

If only I had taken the other road: Regret, risk and reinforced learning in informed route-choice

Eran Ben-Elia*

Centre for Transport and Society
Dept. of Planning and Architecture
Faculty of Environment and Technology
University of the West of England
eran.ben-elia@uwe.ac.uk

Robert Ishaq

Dept. of Transportation Engineering and Geo-information
Faculty of Civil and Environmental Engineering
Technion – Israel Institute of Technology
roberti@technion.ac.il

Yoram Shiftan

Dept. of Transportation Engineering and Geo-information
Faculty of Civil and Environmental Engineering
Technion – Israel Institute of Technology
shiftan@technion.ac.il

♣ Corresponding author

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1 **Abstract**

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3 This paper presents a study of the effect of regret on route choice behavior when both
4 travel time descriptive information and feedback on post choice outcomes are provided.
5 The relevance of Regret Theory in travel behavior has been well demonstrated in non-
6 repeated choice environments involving decisions on the basis of descriptive
7 information. The relation between regret and reinforced learning through experiential
8 feedbacks is less understood. Using data obtained from a simple route-choice experiment
9 involving different levels of travel time variability, discrete-choice models accounting for
10 regret aversion effects are estimated. The results suggest that regret aversion is more
11 evident when descriptive information is provided ex-ante compared to a pure learning
12 from experience condition. Yet, the source of regret is related more strongly to experiential
13 feedbacks rather than to the descriptive information itself. In addition, payoff variability is
14 negatively associated with regret while regret aversion is more observable in choice
15 situations that reveal risk-seeking, but less in the opposite case of risk-aversion. These
16 results are important to understand the possible behavioral impacts of emerging
17 information and communication technologies and intelligent transportation systems on
18 travelers' behavior.

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22 **Key Words**

23 Expected utility

24 Information

25 Intelligent Transportation Systems

26 Reinforced Learning

27 Regret Route-choice

28 Risk

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1. Introduction

In recent years there has been a growing interest in design and deployment of intelligent transportation systems and especially advanced traveler information services. These systems use information and communication technology to inform, monitor, control and even charge travelers (Bonsall, 2008). It is commonly assumed that providing travelers with more reliable information will improve the individual traveler's route-choice decisions and consequently the networks performance and safety (European Commission, 2008). However, improving our understanding of travelers' response to information is still a key issue to obtain the full benefits from such applications. This response is dependent on travelers' decision making behavior under conditions associated with risk and uncertainty.

Expected Utility Theory (Bernoulli, 1738; Luce and Raiffa, 1957 ;Von Neumann and Morgenstern, 1944), has been the dominant paradigm in analyzing travel behavior under risk and uncertainty and particularly in route-choice (Arentze and Timmermans, 2005; De Palma and Picard, 2005). It suggests that maximization of a linear combination of end states and probabilities of these states normatively represents choice behavior. Random utility models have been widely developed using various specifications to predict route choice decisions providing valuable behavioral insights (see Prashker and Bekhor, 2004 for a detailed review). Chorus et al., (2009), demonstrate the use of a Bayesian EUT framework to assess the effects of travel information on route-choice.

Behavioral decision research has empirically revealed systematic violations of some of the assumptions of Expected Utility Theory (EUT). Some researchers have even raised concern over its validity in forecasting travel behavior (Gärling and Young, 2001). The most common behavioral theory to substitute EUT is Prospect Theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). Prospect Theory (PT) asserts that decision makers frame possible outcomes as gains or losses based on a subjective point of reference and not according to final-states as the classic interpretation of EUT suggests. Whereas in EUT, decision makers are usually assumed as risk-averse, in PT, people will usually reveal risk-averse behavior in the case of gains and risk-seeking behavior in the case of losses. In addition, PT postulates that people are more sensitive to a loss compared to an equivalent gain, implying loss aversion. Furthermore, unlike EUT probabilities are not treated linearly; rather an S-shaped weighting function is applied, whereby small probabilities are overweighed and large probabilities underweighted. PT has also been tested in route-choice contexts and found to have added explanatory value

1 (e.g. Avineri and Prashker, 2004; Avineri and Bovy, 2008; Gao et al., 2010; Katsikopoulos
2 et al., 2002). However, its main caveat is the selection of the perceived reference point
3 which poses a considerable 'headache' for modeling purposes - since it is not well defined
4 in the literature.

5 Regret Theory (RT), is another behavioral decision theory that has been discussed
6 in the literature. Interestingly, RT was originally developed by Loomes and Sugden, (1982)
7 as an alternative theory to PT and particularly to the difficulty in contending with the
8 problem of defining a reference point. RT postulates that choice behavior is affected not
9 only by the attractiveness of a considered alternative as in EUT, but also from the
10 anticipation of regretting not choosing a foregone alternative (i.e. non-chosen). The theory
11 postulates regret aversion i.e. the greater the feeling of regret the less attractive is the
12 chosen alternative i.e., Contrary to PT, RT has a non-arbitrary reference point dependent
13 on the choice set rather than the choice context. Like PT which has been extended to
14 multinomial choice situations with the formulation of Cumulative PT (Tversky and
15 Kahneman, 1992), Quiggin, (1994) has made a similar extension to RT. However, unlike
16 PT, RT still treats probabilities of states-of-the-world linearly. Compared to EUT, RT only
17 makes use of an additional regret aversion parameter, making it more parsimonious than
18 PT which necessitates identifying four additional parameters. Although attracting quite a lot
19 of attention in behavioral decision research (Kahneman and Riepe, 1998; Starmer, 2000),
20 there has been less attention to RT' in travel behavior research as discussed by (Chorus
21 et al., 2006; Chorus et al., 2008; Chorus, 2010).

22 The three aforementioned behavioral theories implicitly assume situations involving
23 one-shot decisions where the outcomes of the choice are not explicitly revealed ex-post. In
24 reality travelers' behavior is influenced not only by descriptive information regarding
25 possible alternative routes, but also by experiential information gained through a process
26 of Reinforced Learning (RL) based on feedbacks. Studies based on RL (Busemeyer and
27 Townsend, 1993; Erev and Barron, 2005) assert that experience leads to adaptive learning
28 but, at the same time, this is also a function of sampling available information on the basis
29 of past experience from memory. Moreover as also demonstrated for route-choice by
30 Avineri and Prashker, (2003) and Ben-Elia et al. (2008), the choice behavior in RL is quite
31 sensitive to the degree of uncertainty in the environment.

32 EUT has been adapted to repeated travel choice situations using the notion of utility
33 updating over time (Horowitz, 1984). Here, route-choice is based on a process of adaptive
34 learning whereby all sources of information either descriptive and / or experiential are

1 applied to update the level of knowledge over the road network (e.g.: Cascetta and
2 Cantarella, 1991; Mahmassani and Liu, 1999; Srinivasan and Mahmassani, 2003; Watling
3 and van Vuren, 1993). PT has also been tested in dynamic contexts. However, unlike
4 EUT, the basic assumptions of PT do not necessarily hold when moving from one-shot to
5 sequences of choices. For example, Barron and Erev (2003) found risk attitude reversals
6 when feedback is introduced in repeated choice experiments. Contrary to one shot
7 decisions, they showed that in repeated choice situations with feedbacks, participants tend
8 to avoid risks when faced with losses and accept more risks when faced with prospective
9 gains. In route-choice, Ben-Elia and Shiftan, (2010) showed that risk seeking behavior is
10 apparent mainly in the short run when knowledge over the network's performance is
11 relatively limited; whereas in the long run, when learning is sufficiently reinforced, the trend
12 is towards risk aversion. Moreover, they did not find, in the context of a choice model
13 behavior completely consistent with PT. Although differences relative to a reference point
14 (mean travel time in this case) seem to have some significance in explaining route-choice
15 behavior, neither was a real difference between gains and losses identified (i.e. no
16 evidence for loss aversion), nor was the PT-based specification better in terms of model fit
17 compared to an EUT specification. However, given that only one reference point definition
18 was tested, it is difficult to generalize from their findings on the appropriateness of PT in
19 dynamic decisions. A recent behavioral study by Erev et al. (2008) asserts that in repeated
20 choice situations with immediate feedback, behavioral tendencies previously related to
21 loss aversion in decisions from experience, are better described as consequences of
22 diminishing sensitivity to absolute payoffs. These studies put a question mark on the
23 appropriateness of PT to explain choice behavior in repetitive situations.

24 In relation to RT, like in the case of EUT and PT, behavioral research regarding
25 regret aversion - the theory's principle behavioral factor - also demonstrates the
26 importance of expected feedback on the perception of regret. According to the original
27 version of RT (Loomes and Sugden, (1982), before choosing, the decision-maker
28 compares 'what is' under a particular state with 'what might have been' for an alternative
29 under the same state - which results in anticipated regret or rejoice (the opposite of
30 regret). However, as argued by Zeelenberg, (1999), in order to evaluate an alternative by
31 comparing 'what is' with 'what might have been', the decision maker must learn, ex-post
32 choice, 'what might have been' implies. In other words, both the chosen and foregone
33 alternatives must be resolved for anticipated regret or rejoice to influence behavior. The
34 original version of RT does not explicitly account for the resolution of the outcomes of

1 foregone alternatives in stimulating anticipated regret. A different view is expressed by
2 Humphrey (2004) suggesting that the resolution of foregone alternatives is less cardinal
3 than the ability of the decision maker to learn exactly which state-of-the world has
4 occurred. This is especially relevant in situations where only the outcome of a chosen
5 alternative is revealed ex-post (i.e. experiential feedback) but not those of foregone
6 alternatives, and the decision maker is not fully informed which state-of-the world has
7 actually occurred. In comparing the importance of expected regrets that will be
8 experienced ex-post with those that will not, Larrick, (1993) suggests that it seems
9 reasonable to assume that feedback about what definitely would have occurred could well
10 have a greater potential for regret than abstract knowledge of what was statistically likely
11 to occur as assumed in original RT. This assertion forms the rationale of a revised theory
12 of RT called Feedback-conditional RT (Humphrey, 2004). This theory postulates that the
13 effect of feedback (following a choice) on the anticipated emotion of rejoice or regret
14 depends on whether the state-of-the world is revealed (i.e. is the foregone alternative
15 resolved). More specifically, it predicts for any outcomes x and y , where the utility of x is
16 larger than the utility of y , *rejoice* for x is greater when having x fully reveals the state-of-
17 the world than when it is not, whereas *regret* for y is smaller when having y does not fully
18 reveal the state of the world.

19 Returning to the transportation realm, in most situations, it is highly likely that the
20 traveler receives feedback on their chosen route but not necessarily on the non-chosen
21 routes. Feedback on a chosen route is almost immediate – e.g. the travel time
22 experienced to have reached the destination, whereas discovering what were the travel
23 times on non-chosen routes requires active search for information and is not immediately
24 available. Since RT has shown a considerable potential for explaining travel behavior,
25 there is added value in investigating its salience in as real to life environment as possible
26 such as the case of experiential feedback on the chosen route.

27 In order to test the impact of RT on route choice we reinvestigate the route-choice
28 behavior data collected in the experiment conducted by Ben-Elia et al., (2008). We apply a
29 RT-based modeling framework as suggested by Chorus, (2010) and incorporate the effect
30 of experiential feedbacks in the specification of regret based on the rationale of Feedback-
31 Consistent RT (Humphrey, 2004). The rest of the paper is organized in the following way:
32 Section 2 presents the experimental method; Section 3 describes the modeling
33 frameworks and the tested specifications; Section 4 presents the results and a discussion;
34 and in Section 5 we present some conclusions and future research directions.

1 **2. Experiment and data**

2 **2.1 Design**

3

4 A route-choice experiment was designed on the basis of a simple binary network
5 and one origin-destination pair (work and home). Route A is on average faster than route
6 B. The faster route has a mean of 25 minutes and the slower one – 30 minutes. Three
7 traffic scenarios were designed by manipulating the routes' travel time ranges (i.e.
8 deviation around the mean value). These ranges are ± 5 or ± 15 minutes for each route.
9 Table 1 presents the three travel time scenarios applied in the experiment. The experiment
10 consists of 100 choice trials in each scenario. Each trial simulates a daily trip. The order of
11 the scenarios follows a counterbalanced (blocked randomization) design. The treatment
12 condition (here: informed) in the experiment consisted of the provision of ex-ante travel
13 information in the form of a travel time range corresponding to a particular traffic scenario
14 simulating a simple variable message sign (VMS) presented to travelers before a route
15 diversion. This information is not provided in the control condition (here: non-informed).

16

17 *** Table 1 – about here ***

18 **2.2 Participants and procedure**

19

20 49 participants (undergraduate Technion students – 30 men and 19 women)
21 arriving in random order to the lab were divided randomly into two groups between the
22 treatment condition (N=24) and the control group (N=25). Each participant was also
23 allocated randomly to one of the six (that is 3! blocks) possible orders. Table 2 presents
24 the descriptive statistics of the participant sample.

25 Each participant was seated in front of a computer terminal and provided with
26 written on-screen instructions about the task ahead. The instructions were also read out
27 loud by the assistant. The task was to choose (by selecting a radio button) among two
28 routes to return home after a day's work. They were explained that this task is to be
29 repeated several times for different commuting days and in several different scenarios.
30 Participants were not informed in advance how many 'days' or how many scenarios they
31 are expected to complete. However, they were told when one scenario would end and a
32 new scenario is about to begin. In the treatment condition only, participants were also told
33 that they will receive travel information before each daily choice. No other explanation was
34 given as to the nature of the experimental task. Each participant had a budget of 100 ILS

1 (Israeli Shekel, where 1 ILS equals about 0.26 USD) and for each minute spent travelling
2 0.01 ILS is deducted from the budget. If he/she saves time during the experiment then
3 they can keep the money left over. An addition flat rate of 20 ILS was paid after completing
4 the experiment as a participation reward. Participants were instructed to complete the task
5 by themselves and were forbidden to communicate with each other while seated before
6 the terminal screens.

7 Before commencing the experiment, participants filled in a simple onscreen
8 questionnaire regarding their socio-demographic characteristics and their usual travel
9 behavior patterns to campus. Once the experiment started, in each trial participants in the
10 treatment condition received ex-ante information about the travel time range (the minimum
11 and maximum travel times) predicted for each of the two routes according to the design.
12 However, a small degree of random variation was programmed (between 0-5 minutes
13 around the daily mean) so that the information was not seen constant throughout the entire
14 scenario. This information was unavailable in the control condition. In addition, all the
15 participants, after confirming a choice, were shown onscreen the 'experienced' travel time
16 (in minutes) for that day on the chosen route. This travel time was randomly drawn from
17 the distribution of the chosen route's travel time range according to the particular scenario.
18 This also guaranteed that participants in the treatment condition would have confidence in
19 the accuracy of the provided ex ante information. Foregone payoffs (i.e. feedback on the
20 non-chosen route) were not provided. After the real travel time was revealed, participants
21 were asked to press a button to go to the route-choice for the next day. When the last
22 scenario was completed participants were revealed how much time they spent travelling in
23 total and what was the total monetary cost of their travel time.. Overall the average
24 duration of a typical session lasted no more than 15 minutes per participant. For further
25 details on the experiment design see Ben-Elia et al., (2008).

26

27 *** Table 2 – about here ***

28

29 **2.3 Reducing possible threats to validity**

30 A common concern in longitudinal designs is the problem of participant fatigue
31 confounding treatment effects or alternatives' attributes thus threatening the validity of the
32 obtained estimates and results. Fatigue occurs when participants tire over time causing
33 performance to deteriorate in later conditions or assessments. Some marketing and

1 psychology studies find that the precision of respondents' choices declines moderately
2 with repeated choice tasks because they become fatigued (Elrod et al., 1992). Conversely,
3 learning effects manifest themselves in participants becoming better the more often they
4 do the experimental task.

5 Proper experiment design, is the first step in reducing the magnitude of fatigue
6 problems e.g. by counterbalancing treatment orders so that order effects can be assessed.
7 If order effects are not distinguished the problem of carryover effects can be regarded as
8 less detrimental on the internal validity of the results (Shadish et al., 2002). The second
9 step is careful analysis of the obtained results. The approach typically used to distinguish
10 between the two effects is based on the assertion that learning implies a smaller noise to
11 signal ratio from observed choices whereas fatigue results in a larger noise to signal ratio.
12 A typical measure is to examine the change over time in the variability of the response
13 (e.g changes in the standard deviation). Third, in choice modeling terms, learning is
14 usually observed by a decrease (increase) in the magnitude of the variance (scale)
15 parameter as the respondent progresses through the sequence of questions or (at least)
16 until fatigue sets in. Fatigue, in contrast, is evident when by an increasing value for the
17 variance of the error term in later choices, or equivalently, by decreasing its scale
18 (Bateman et al, 2008). Several studies have been carried out to investigate the magnitude
19 of fatigue and or learning in choice models. However to most parts, the evidence remains
20 inconclusive. Bradley and Daly (1994) find fatigue effects in SP choice experiments
21 involving a small number of repetitions. In contrast, Brazell et al. (1995) suggest fatigue
22 effects may be minimal whereas learning may sometimes occur as respondents are
23 exposed to more replications. Furthermore, Brazell and Louviere (1997) reveal equivalent
24 survey response rates and parameter estimates for respondents answering 12, 24, 48 and
25 96 choice questions in a particular choice task. Swait and Adamowicz (1996), show that
26 task complexity is inversely related to fatigue. Savage and Waldman (2008) find that
27 delivery formats whether online surveys or mail back questionnaires result in different
28 scales with fatigue more apparent in online formats. Hess et al, (2012) provide strong
29 evidence that the concerns about fatigue in the literature are possibly overstated, with no
30 clear decreasing trend in scale across choice tasks in any of their studies, while evidence
31 of significant attribute level (as opposed to scale) heterogeneity across choice tasks
32 suggests possible learning effects. Fatigue and boredom, though different in nature, have
33 a similar impact on results, and in practice confounded, making it virtually impossible to
34 distinguish between them. Notwithstanding, the discussion in the choice modeling

1 literature relates to studies involving description-based decisions without feedbacks on
2 choice outcomes and usually involving multiple attributes, whereas the effects of fatigue in
3 experiential-based decisions, as is in our study, remains an open question.

4 As fatigue or boredom are always a plausible alternative explanation that could
5 confound the treatment effects, we have conducted a separate analysis of fatigue threats
6 based on the state-of-the-art, which is presented following the results in Section 4.2.

7 **3. Behavior modeling**

8 **3.1 Approach**

9 The data collected by Ben-Elia et al. (2008) consists of a series of choices under
10 different conditions of risk. This data were not designed with the objective of a priori testing
11 RT or any other behavioral theory. Therefore, if regret appears as a significant effect, it
12 provides a strong indication to the relevance of regret in similar route-choice decisions.

13 Since the data contains a panel of choices for each participant we use a modified
14 version of the mixed logit discrete choice model. Mixed Logit (MXL and also referred to as
15 Logit Kernel or Mixed Multinomial Logit Model) is an advanced and highly flexible discrete
16 choice model. MXL accommodates random taste variation, substitution patterns, and
17 correlation in unobserved factors unrestricted over time (McFadden and Train, 2000) and
18 can be derived under a variety of different specifications (Ben-Akiva and Bolduc, 1996;
19 Bhat, 1998) It is also easily generalized to allow for repeated choices i.e. panel data, as
20 well as lagged variables (Bhat, 1999; Revelt and Train, 1998; Train, 1999).

21 For our purposes two types of models are specified: the first for expected utility
22 (EU) and the second for expected modified utility (EMU) which includes the regret effect
23 based on the formulation of Chorus (2010). We use the term 'modified utility' (MU) to
24 distinguish the utility function according to RT from the term 'utility' (U) according to EUT.

25 Formally the utility (U) of alternative i for person n in response t is (eq. 3):

$$26 \quad U_{int} = \beta_{in}X_{int} + \varepsilon_{int} \quad (3)$$

27 where: β is a vector of fixed and random coefficients for alternatives' attributes - X ; ε is a
28 vector of independently, identically distributed (iid) extreme-value type one error term. β
29 has some distribution f (β_0 mean and a covariance matrix Σ_β). This term also capture the
30 panel effects - varying between participants but remaining constant within the observation

1 panel set of each participant. Often a normal distribution is assumed i.e. $\beta \sim N(\beta_0, \sigma_\beta^2)$.
 2 Accordingly, the expected utility (*EU*) of alternative *i* for person *n* in response *t* is (eq. 4):

$$3 \quad EU_{int} = \sum_{j=1, j \in S}^J (p_{jt} U_{ijnt}) + \varepsilon_{int} \quad (4)$$

4 where: $p_j [0,1]$ is the probability that state-of-the-world *j* will occur at response *t* out of the
 5 set of *J* possible states of the world – *S*.

6 Conversely, *MU* depends on both the considered and foregone alternatives. Following
 7 Chorus (2010), the modified utility (*MU*) of alternative *i* for person *n* in response *t* is (eq.5):

$$8 \quad MU_{iknt} = \beta_{in} X_{int} + \{1 - e^{[-\rho(\beta_{in} X_{int} - \beta_{in} X_{knt})]}\} + \varepsilon_{int} \quad (5)$$

9 where: β , X and ε , are similar to eq. 3 and the term in curly brackets represents the effect
 10 of regret towards alternative *k* when considering *i*. That is, in considering *i*, person *n*
 11 accounts also for the utility difference attributed to X for the foregone alternative *k*.
 12 $\rho \in [0, +\infty]$ is a regret aversion parameter. Higher values imply that person *n* will become
 13 more and more sensitive to regret compared to an equivalent rejoice. In other words a
 14 higher value suggests that if for attribute X , *k* is outperforming *i* (i.e. a regret emotion) this
 15 will decrease the attractiveness of *i* more than in the reverse case where *i* outperforms *k*
 16 (i.e. a rejoice emotion).

17 Similarly, the expected modified utility (*EMU*) of alternative *i* for person *m* in response *t* is
 18 (eq. 6):

$$19 \quad EMU_{iknt} = \sum_{j=1, j \in S}^J (p_{jt} MU_{ijknt}) + \varepsilon_{int} \quad (6)$$

20

21 **3.2 Assumptions and considerations**

22 The purpose of the model estimation here is to test whether regret influences route-
 23 choice behavior as it appears in the data by comparing various model specifications. To
 24 accomplish this several simplifications were allowed and further assumptions were made:

25 First, given both the small (49 participants) and homogenous nature of the sample
 26 used in the experiment (undergraduates) it is not possible to include individual-specific
 27 factors (see also discussion in Ben-Elia et al., 2010).

28 Second, to allow a smooth comparison between alternative specifications (with and
 29 without Regret) we decided to include travel time as the only attribute explaining the route
 30 choice. The data provides us with two sources of travel time: ex-ante travel time
 31 information (description) and “actual” travel time (feedback). The latter is specified as a

1 lagged variable. To keep the specifications simple a generic coefficient is used for all
2 sources of travel time. That is, in relation to eq.3 and eq.5, β corresponds to the travel time
3 coefficient and is specified as the same coefficient for both routes and for all sources.
4 Initially we also tested different coefficients for the two sources of travel time; however they
5 were not found to be significantly different from each other suggesting that the generic
6 form is sufficient. For examples of more comprehensive models using the same data see
7 Ben-Elia and Shiftan, (2010).

8 Third, in the treatment condition, the information received by the participants, in
9 each trial of the experiment, simulates a simple Variable Message Sign (VMS) presenting
10 a description of the expected travel time in a range from a minimum to a maximum value.
11 This range creates the possible states of the world that a participant would anticipate in
12 his/her decision making process. Although the inherent assumption in both EUT and RT is
13 that the decision maker can mentally produce the matrix of state-contingent outcomes
14 even if it is not explicitly provided in the description of the decision problem, it is unlikely
15 that a human mind would be able to mentally account for a large number of states-of-the-
16 world. Likewise, given a range of possible outcomes, it is also unlikely that only the mean
17 value (the mid range) would be considered as the only state-of-the world accounted for.
18 Hence, it is assumed that participants would regard as a minimum two points on the range
19 as being identified with the possible states of the world – one below (i.e. the first quarter)
20 and the other above (i.e. the 3rd quarter) the mean value (see Figure 1). Naturally, any
21 assumption regarding these or other sets of points suggested by the modeler is valid.
22 However, it is reasonable to assume that participants would view extreme outcomes as
23 less likely than the middle one. It should also be noted that the participants were not aware
24 that the travel time distribution was in fact uniform meaning that all outcomes had the
25 same probability to occur. Moreover, using extreme values such as the best and worst
26 travel time on the range might well lead to inflating the estimates of regret we are looking
27 for which seems counterproductive. Therefore, if these mid points reveal significant
28 evidence for regret this should provide a safe bet regarding what most participants
29 consider as a base for comparing possible outcomes. Cognitive limitations would likely
30 inhibit the number of combinations that travelers could mentally reproduce. For example
31 splitting the range by an additional point for each percentile, increases the number of
32 possible states to 8 for each considered route making the number of combinations quite
33 difficult to contend with.

34

1 *** Figure 1 – about here ***

2

3 Fourth, as presented in the Introduction, the behavioral literature suggests the
4 plausibility that emotions of regret or rejoice, can be also triggered by the expected
5 feedback received after a choice is made. It is then likely that in anticipating regret,
6 participants would factor in some way both the experiential feedbacks and the information
7 describing the expected outcomes. In this respect Bar-Hillel and Neter (1996) have shown
8 that in some cases regret effects generated by counterfactual thinking can be as strong as
9 those generated by actual feedback. In each choice trial the participant receives the actual
10 experienced travel time on the chosen route as an ex post feedback, but not
11 simultaneously that of the foregone route. Consequently, he/she cannot know for certain
12 which state-of-the-world occurred at a specific trial on the route not chosen. Therefore, it is
13 assumed that participants can compare the outcome of the considered route in the last
14 trial with the memory of what had been experienced the last time that the alternative route
15 was actually chosen. Accordingly, one can assume that regret emotions can be triggered
16 not only by the differences attributed to descriptive information (as in the original version of
17 RT) but also by the comparison between what was experienced the last time the
18 considered route was chosen (i.e. experiential feedback) and the memory of what had
19 occurred when the alternative route had been chosen. This can be regarded as a kind of
20 variant on feedback conditional RT). Weights can also be specified for descriptive and
21 experiential information to account for the difference in the cognitive importance given to
22 expected and experienced regret (or rejoice) in the choice behavior.

23 The fifth consideration relates to the treatment of risk perception (i.e. risk aversion
24 or risk seeking tendencies) and how risk is related to regret. In his formulation, Chorus
25 (2010) accounts for constant risk aversion by assuming a non-linear convex EU function.
26 We initially tested the effect of constant risk aversion on EU, but found it not significant.
27 Consequently all our models applied a linear specification of utility. The literature suggests
28 that risk aversion and regret aversion are often confounded in many experimental settings
29 (Zeelenberg, 1999). This can make the differentiation between the two effects quite
30 difficult. Moreover, Zeelenberg et al. (1996) report an experiment where regret aversion
31 can induce both risk-averse and risk-seeking choices depending on the type of feedback -
32 experiential or foregone. The latter induces more risk seeking behaviors than the former.
33 Therefore, we decided to test indirectly for a relation between risk and regret by specifying
34 different coefficients of regret aversion for each of the three travel time scenarios. By

1 design, each scenario frames the two routes either as risky or as reliable depending on the
2 level of variability represented in the travel time range (See Table 1).

3 Last, in all the discussions of Regret Theory the inherent assumption is that the
4 decision maker is presented with a description of the possible alternatives she can choose
5 from. As noted above, feedback received following a choice can also be considered, but
6 so far only in addition to the initial description. However, there is no apparent reason why
7 regret cannot be triggered by an outcome of a choice which is not based on a complete
8 description of the alternatives but rather on a gradual process of sampling and reinforced
9 learning based on experiential feedback information. One can assume that ex-post regret
10 could well occur regardless of the type of information provided, especially when the choice
11 environment allows participants to test more than once each of the two alternative routes.
12 Hence, there is added value to verify whether there is a real difference in the strength of
13 regret emotions triggered by exposure to descriptonal versus experiential feedback
14 information. Given that the experimental design consists of two groups i.e. conditions with
15 and without descriptonal information, it is possible to jointly estimate the strength of regret
16 emotions under both conditions simultaneously.

17 **3.3 Specifications**

18 Based on the above discussion, six models are specified. Model A through D are
19 based on the descriptonal information (i.e. travel time ranges) and, therefore, are only
20 applicable for the group of participants in the informed condition (N=24). Models E and F
21 are based on the full dataset and include a joint estimation of regret under both the
22 informed and non-informed conditions (N=49).

23 ***Model A: Description-based expected utility***

24 Model A corresponds to a simple EU model where only the considered route
25 influences its perceived attractiveness and utility is based on the provided descriptonal
26 information. This model is estimated as a control for comparing to more sophisticated
27 specifications based on regret. The two points corresponding to two states of the world
28 assumed for a given route i as described above (and see Figure 1), are referred as mean-
29 high (MH_i) and mean-low (ML_i) whereby $Mean_i < MH_i < Max_i$ and $Min_i < ML_i < Mean_i$. For
30 example, if for a certain trial Route A has a travel time mean of 25 min with a range of 10
31 min (as in Scenario 1), then $MH_A = 27.5$ and $ML_A = 22.5$, which are exactly the lower and
32 upper quartiles of the travel time range. Since EUT, assumes the decision makers treat
33 probabilities linearly (unlike e.g. PT which uses subjective weights) and since the

1 distribution of travel times in the experiment is uniform, the probabilities of the states of the
 2 world are assumed to be equally distributed. Therefore, there is a probability of 0.5 to be in
 3 the high or low state-of-the world for each route. Consequently the appropriate
 4 specification (for simplification we removed the person and trial notations) for *Route-A*
 5 (Route B is similar only with subscript B) is (eq. 7):

$$6 \quad EU_A = 0.5(\beta MH_A + \beta ML_A) + \varepsilon_A \quad (7)$$

7 where: β , and ε – are as defined in eq.3.

8 **Model B: Description-based regret**

9 Model B corresponds to RT under the assumptions of the original theory (Loomes
 10 and Sugden, 1982). In this case, the modified utility function – *MU* - is influenced by both
 11 the attributes of the considered route and the alternative one. The choice between the two
 12 routes is influenced only by the description of the alternatives i.e. the information
 13 presented by the VMS prior to the actual choice. Each route is assumed to have two
 14 possible outcomes (MH_i , ML_i) and four states of the world are generated (according to the
 15 2x2 combination of high and low values). Each state of the world has an equal probability
 16 of 0.25 to occur. This combination is also illustrated in Figure 1. Consequently, the
 17 appropriate specification for *Route-A* is (eq. 8):

$$18 \quad EMU_A = 0.25(\beta MH_A + 1 - e^{[-\rho(\beta MH_A - \beta MH_B)]}) + 0.25(\beta MH_A + 1 - e^{[-\rho(\beta MH_A - \beta ML_B)]}) \\
 19 \quad + 0.25(\beta ML_A + 1 - e^{[-\rho(\beta ML_A - \beta MH_B)]}) + 0.25(\beta ML_A + 1 - e^{[-\rho(\beta ML_A - \beta ML_B)]}) + \varepsilon_A \quad (8)$$

19 where: β , ρ and ε – are as defined in eq.5

20

21 *** Figure 1 – about here ***

22

23 **Model C: Description and experienced-based regret**

24 As presented in the previous section, it is quite possible that participants can be
 25 influenced by both descriptonal information as presented by the VMS and by the ex-post
 26 feedback information provided following each route choice. Accordingly, for each state-of-
 27 the-world as defined in Model B, we can specify the regret function as composed of the
 28 differences in the descriptonal information (the four points on the travel time ranges) and
 29 the difference in the feedback information. The latter is based on the assumption that
 30 participants can recall the recent outcomes the last time each of the two routes was

1 chosen. Weights are assigned to both types of information to capture difference in
2 cognitive importance. The appropriate specification for *Route-A* is (eq. 9):

$$\begin{aligned}
EMU_A = & 0.25(\beta MH_A + 1 - e^{\{-\rho[w(\beta MH_A - \beta MH_B) + (1-w)(\beta F_A - \beta F_B)]\}}) \\
& + 0.25(\beta MH_A + 1 - e^{\{-\rho[w(\beta MH_A - \beta ML_B) + (1-w)(\beta F_A - \beta F_B)]\}}) \\
& + 0.25(\beta ML_A + 1 - e^{\{-\rho[w(\beta ML_A - \beta MH_B) + (1-w)(\beta F_A - \beta F_B)]\}}) \\
& + 0.25(\beta ML_A + 1 - e^{\{-\rho[w(\beta ML_A - \beta ML_B) + (1-w)(\beta F_A - \beta F_B)]\}}) + \varepsilon_A
\end{aligned} \tag{9}$$

4 where: $0 < w < 1$ is the weight attributed to the descriptive information (MH_i , ML_i) and $1-w$ is
5 the weight for feedbacks; F_i is the feedback received for *Route i* the last time i is chosen;
6 β , ρ and ε – are as defined in eq.8.
7

8
9 Note that $w=1$ would mean that only descriptive information influences regret and
10 in this case the formulation would be the same as Model B. Conversely, $w=0$ would mean
11 that only feedbacks influence regret or rejoice emotions but descriptive information
12 provided ex-ante does not. In this case, the descriptive information enters the utility but
13 does not appear in the regret function and the formulation collapses to two states of the
14 world. The appropriate specification, for *Route-A*, in Model C, is now (eq. 10):

$$EMU_A = 0.5(\beta MH_A + 1 - e^{\{-\rho(\beta F_A - \beta F_B)\}}) + 0.5(\beta ML_A + 1 - e^{\{-\rho(\beta F_A - \beta F_B)\}}) + \varepsilon \tag{10}$$

16 where: β , ρ and ε – are as defined in eq.5

17 **Model D: Description and experienced-based regret with risk effects**

18 Model D expands the specification to include the effect of risk by specifying different
19 regret coefficients for each of the travel time scenarios (and see Table 1 for the definition)
20 (eq. 11):

$$\begin{aligned}
EMU_A = & \sum_{s=1}^3 [0.25(\beta MH_{As} + 1 - e^{\{-\rho_s[w(\beta MH_{As} - \beta MH_{Bs}) + (1-w)(\beta F_{As} - \beta F_{Bs})]\}}) \\
& + 0.25(\beta MH_{As} + 1 - e^{\{-\rho_s[w(\beta MH_{As} - \beta ML_{Bs}) + (1-w)(\beta F_{As} - \beta F_{Bs})]\}}) \\
& + 0.25(\beta ML_{As} + 1 - e^{\{-\rho_s[w(\beta ML_{As} - \beta MH_{Bs}) + (1-w)(\beta F_{As} - \beta F_{Bs})]\}}) \\
& + 0.25(\beta ML_{As} + 1 - e^{\{-\rho_s[w(\beta ML_{As} - \beta ML_{Bs}) + (1-w)(\beta F_{As} - \beta F_{Bs})]\}})] + \varepsilon_A
\end{aligned} \tag{11}$$

22 where: β , and ε – are as defined in eq.9, and ρ_s ($s=1,2,3$) is the coefficient of regret
23 aversion in scenario s ($s=1,2,3$).

24 Here, significantly different values estimated for ρ_s would imply that regret aversion
25 is not risk neutral.

26 **Model E: Regret aversion with and without descriptive information**

27 Model E uses the full dataset to estimate the effect of regret for each of the
28 experiment's groups - treatment and control - i.e. with and without (descriptive)
29 information. Here, the motivation is not to identify if the source triggering regret is

1 description or experience based as in the previous models. Rather, it is to verify if by
 2 exposing travelers to descriptive information as simulated in the VMS and in addition to
 3 information gained from experience, would result in different degrees of regret aversion.
 4 Accordingly the model utilizes a scale parameter to estimate the group effect on the rest of
 5 the parameter estimates. This scale multiplies all the estimates relating to the non-
 6 informed group. It is similar to the approach used in a joint estimation of a discrete choice
 7 model based on revealed and stated preference data sources (Ben Akiva and Morikawa,
 8 1990; Bhat and Castellar, 2002). Moreover, whereas the modified utility of informed
 9 participants remains similar to Model C (as in eq. 9), the modified utility of the non-
 10 informed participants is specified as composed only of the experiential feedback
 11 information and since here there is no possible way to identify the state-of-the-world
 12 occurring the only effect is that of the recent outcomes the last time one of the two routes
 13 was chosen. The appropriate specification, for *Route-A*, in Model E, is now (eq. 12)

$$14 \quad EMU_A^{NI} = \beta F_A + 1 - e^{[-\rho(\beta F_A - \beta F_B)]} + \varepsilon_A \quad (12)$$

15 where: F_i , β , ρ and ε – are as defined in eq.9. Superscript *NI* indicates this
 16 corresponds to the non-informed group.

17 **Model F: Joint estimation of regret with risk effects**

18 Model F, expands Model E to account for the effects of risk as in Model D. The only
 19 change is the modified utility for the non-informed condition which is now specified for
 20 Route A as (eq 13):

$$21 \quad EMU_A^{NI} = \sum_{s=1}^3 (\beta F_{As} + 1 - e^{\{-\rho_s[\beta F_{As} - \beta F_{Bs}]\}}) + \varepsilon_A \quad (13)$$

22 where: F_i , β , ρ and ε – are as defined in eq.11. *NI* indicates this corresponds to the non-
 23 informed group.

24 **3.4 Model estimation**

25 In all the models EU and EMU are estimated using a log-likelihood (*LL*) maximization
 26 procedure. The EMU model's *LL* function (for *EU* replace EMU with EU) for the probability
 27 (*P*) to choose route *i* is (eq. 14):

$$28 \quad LL(\beta_0, \sigma_\beta, \rho, \lambda) = \sum_{n=1}^N \ln(P_{ni}) = \sum_{n=1}^N \ln \left\{ \int_{\beta} \left[\prod_{t=1}^T \left(\frac{e^{\lambda_{nt} EMU_{it}}}{\sum_{k=1, i \in K}^K e^{\lambda_{nt} EMU_{kt}}} \right) \right] d\beta \right\} \quad (14)$$

29 where:

30 $\beta \sim N(\beta_0, \sigma_\beta^2)$ is a normally distributed vector of random coefficients with β_0 mean and σ_β^2
 31 variance for the travel time attribute;

1 ρ is the regret aversion coefficient to be estimated;
 2 λ is the non-informed group's scale and $\lambda_{nt}=[(1-\delta_{nt,l})\times\lambda]+\delta_{nt,b}$, $\delta_{nt}=1$ if person n and trial t
 3 belong to an observation from group I (i.e. informed) and 0 otherwise;
 4 $N=49$ is the number of participants (=24 in Models A-D), $T=300$ is the number of route-
 5 choice trials, $K=2$ is the number of alternative routes.

6 As the unconditional probability is obtained by integration over the random
 7 coefficients and this integrand has no closed form, simulated log likelihood (SLL) is applied
 8 using random draws (Bhat, 1999; Train, 2003) (eq. 15):

$$9 \quad SLL(\beta, \rho, \sigma_\beta, \lambda) = \sum_{n=1}^N \log \frac{1}{R} \left\{ \sum_{r=1}^R \left[\prod_{t=1}^T \left(\frac{e^{\lambda_{nt} EMU_{it}}}{\sum_{k=1, i \in K}^K e^{\lambda_{nt} EMU_{kt}}} \right) \right] \right\} \quad (15)$$

10 where: R is the number of draws (r).
 11

12 We used BIOGEME version 2.1 (Bierlaire, 2003; Bierlaire, 2010) for model
 13 estimation. Simulated log likelihoods of all models were estimated with 1,000 Halton draws
 14 (Halton, 1960) which significantly reduce the number of draws required compared to
 15 pseudo-random draws (Bhat, 2003; Train, 2000). The models were estimated with 100,
 16 500 draws and 1,000 draws. The differences between the last two sets were negligible.
 17 The results presented here are for the set of 1,000 draws. We also applied appropriate
 18 guidelines to assure proper identification (Walker et al., 2004). The CFSQP optimization
 19 algorithm was used (Lawrence et al., 1997). Since the weight parameter in Model C can
 20 be confounded with the attribute coefficient (β), they cannot be estimated simultaneously.
 21 Therefore, the weights were specified as constants with a linear constraint equal to 1.
 22 Different sets of weights were tested in increments of 0.1 through a trial and error process.

23 **4. Results and discussion**

24 **4.1 Estimation results**

25 The estimation results are presented in Table 3 and Table 4. Goodness of fit (final
 26 log-likelihood) is measured with the log likelihood ratio test. When computed for the
 27 informed group only (see Table 3) - Models A through D – it shows that models B, C and
 28 D, which account for regret, are significantly better than Model A - the simple EU model
 29 ($\chi^2_{B,A}= 310.06$, $p<0.001$; $\chi^2_{C,A}= 152.83$, $p<0.001$; $\chi^2_{D,A}= 341.36$, $p<0.001$). The goodness of
 30 fit of Model D, which also accounts for risk effects is the best of the four models and the
 31 likelihood ratio test in relation to Model B, the second best, is significant ($\chi^2_{D,B}= 31.3$,

1 $p < 0.001$). When comparing the joint estimated models for both groups (see Table 4) –
2 Model E and F, the goodness of fit of Model F accounting for the risk effects is better
3 ($\chi^2_{E,F} = 258.87$, $p < 0.001$). Naturally the goodness of fit of the joint models cannot be
4 compared with the single group models.

5 All the coefficients in all the six models are significant. The coefficient σ_β is
6 significant ($p < 0.001$) implying the specification of the panel is appropriate for the data
7 structure. The coefficient for the mean travel time (β) is negative as expected and
8 significant in all the models ($p < 0.001$). The coefficients for general regret (ρ) are all
9 significant ($p < 0.001$). However, in Model B the sign of the coefficient is negative and
10 incorrect according to the assertions of RT. A negative sign for ρ implies that a considered
11 alternative is preferred when it is outperformed by a foregone alternative, which seems
12 unreasonable.

13 In contrast, the estimate obtained for the regret aversion coefficient in Model C has
14 the correct sign and seems reasonable and comparable with the values used by Chorus
15 (2010). However, in terms of weighting of the descriptive and the feedback information, the
16 best result was obtained with $w=0$. This implies that the descriptive information does not
17 seem to influence regret; but rather the feedbacks are apparently responsible for
18 generating the emotion of regret aversion.

19 This result suggests that regret aversion is important and has a behavioral effect in
20 the experimental data. Moreover, it is evident that here regret aversion is more associated
21 with the ex-post feedback information compared to the ex-ante descriptive information.
22 When accounting only for the descriptive information (Model B) the wrong sign of the
23 regret parameter indicates that RT, in its original formulation, is not quite the appropriate
24 theory to account for the observed behavior in this case. The high t-stat of the coefficient
25 suggests it is capturing some variability in the data, but with the wrong specification.

26 However, when regret aversion is specified to the feedbacks obtained by the
27 participants from the actual travel time payoffs, (as in Model C) the results suggest that it is
28 really the feedback information that better explains the choice behavior. This leads us to
29 assert that emotions of regret are likely generated by the experiential feedback information
30 rather than the descriptive information. A possible explanation for this result is that the
31 feedbacks are more closely related in the traveler's mind with the objective of minimizing
32 travel costs and less so to the description of the alternatives themselves. To our best
33 knowledge, this result has not been demonstrated before in an empirical travel behavior

1 study. As noted by Ben-Elia and Shiftan, (2010) the effect of information was mostly
2 relevant for the short run, when participants lacked experience and had little knowledge
3 about the payoff distribution of each route, whereas over time the effect of feedbacks and
4 experience became more dominant. The results regarding the effect of regret seem to
5 concur with these findings as well.

6 The results obtained for Model D suggest that regret aversion is evident but
7 changes between the different scenarios. Recall, that each participant concludes all three
8 scenarios (in different orders). The estimates obtained for ρ indicate that regret aversion is
9 stronger when the risk associated with the choice environment is low, as demonstrated in
10 scenario 3 where both routes have low variability. Conversely, in scenarios 1 and 2, where
11 one of the two routes is associated with more risk, regret seems to be weaker. This
12 suggests that increasing the variability in the choice environment (what behavioral
13 psychologists have referred to as the effect of payoff variability), decreases regret
14 aversion. Regret seems stronger when it is more certain to occur. Low variability makes
15 regret appear more certain to the participant. In contrast high variability makes the loss of
16 not choosing the alternative route appear less obvious. It is likely that this is attributed to
17 hampering of learning as also demonstrated by Ben-Elia et al. (2008). That is, as variability
18 in the choice environment increases, the rate of learning which route provides on average
19 a better payoff decreases.

20 In addition, the results seem to suggest that risk seeking might correspond to more
21 regret aversion compared to risk aversion. In the case of scenario 1, where Route A, which
22 is also on average faster, is associated with low variability and the slower Route B with
23 high variability - the estimate of regret aversion is not significant. This suggests that when
24 the alternative resulting in better payoffs, on average, is also regarded as safer, regret is
25 not observed. Nonetheless, it is also possible that the effect of risk aversion here is also
26 confounding regret aversion. In comparison, in Scenario 2 where the faster route (A) is
27 associated with greater risk, regret aversion is significantly higher. We recall that Ben-Elia
28 and Shiftan (2010) demonstrate that attitudes towards risk in scenario 2 reveal on average
29 more risk seeking tendencies. One possible explanation is that when facing a choice in a
30 domain of losses, (which also induces risk seeking behavior i.e., gambling), the emotional
31 amplitude of regret is greater when contending with a negative affective state i.e. an
32 outcome that leads to a possible loss. Conversely, when choosing the safer alternative
33 also results in good outcomes (as in scenario 1) negative affect is not induced and regret
34 is likely to be much weaker and even masked by risk aversion. In sum, these results assert

1 that *payoff variability* in the choice environment appears to be negatively associated with
2 the strength of regret aversion. Moreover, attitudes towards risk related to regret appear to
3 be quite relevant as demonstrated by Zeelenberg et al., (1996) and especially in the case
4 of risk seeking.

5 The results of the joint estimated models do not contradict the results above and
6 present the same trends for the estimated coefficients. In particular the assertions that
7 regret is associated more closely with feedback information and with the level of payoff
8 variability appears to hold for both groups. However, an additional result is demonstrated
9 by the estimate obtained for the non-informed group scale (λ). λ is significant in both
10 Model E ($p < 0.001$) and Model F ($p < 0.001$). The estimates for λ suggest that without
11 descriptive information (the non-informed group), regret is significantly weaker. This
12 means that regret aversion can be triggered even without any available description of the
13 travel time distributions (i.e. without the VMS) simply from a gradual trial and error
14 sampling of available alternatives and learning reinforced through experiential feedback
15 information. However, in the presence of descriptive information (the informed group)
16 regret emotions become much stronger. This leads us to the assertion that informed
17 travelers are more likely to experience higher levels of regret aversion than non-informed
18 ones.

19 In terms of theory, though not a concrete proof, the results seem to indicate the
20 relevance of the recent theoretical contributions such as feedback-conditional regret theory
21 (Humphrey, 2004). However, it is not possible with the data we hold to completely
22 investigate FCRT given that the experiment did not allow for foregone payoffs. This is left
23 for future research endeavors. In addition the results obtained for models D and F
24 demonstrate that risk levels and corresponding attitudes are likely to be correlated with
25 regret.

26 **4.2 Analysis of fatigue threats**

27 As noted in Section 2.3, a common threat in repeated choice designs is the threat of
28 fatigue or boredom confounding the results and threatening their validity. To verify whether
29 fatigue might have interfered with our estimates we applied the methods suggested in the
30 literature. First, an analysis of the robustness of the design. Second, we measured the
31 signal to noise ratio obtained in the results by plotting the mean standard deviation (SD) of
32 the maximization rate (i.e. the share of the Fast route in each trial. Third, following the
33 debate in the choice modeling literature, we estimate the logit scale for different stages of
34 the experiment, per group in blocks of 10 trials.

1 Beginning with an evaluation of the design, Ben-Elia et al. (2008) who studied the
2 same dataset, did not find significant order effects in their analysis. This asserts that the
3 within-subjects repeated design was successful in counterbalancing the treatment orders,
4 therefore minimizing the risk of carryover effects threatening validity. This implies that the
5 participants did in fact relate to each scenario independently and hence the risk that
6 fatigue and learning were carried over from one scenario to the next is relatively small.

7 Next, regarding the signal to noise ratio, Figure 2 shows the mean standard-
8 deviation of the maximization rate over 100 trials (averaged out for all three scenarios in
9 blocks of 10 trials). The results show that for both groups, informed and non-informed, the
10 signal to noise ratio is decreasing as the experiment progresses. This indicates that
11 learning is indeed taking place, at a faster rate with the informed group, whereas fatigue is
12 much less evident. In fact we can assert that after the first 10 trials on average,
13 participants' become quite experienced in making the correct route choice that minimizes
14 their time penalties. As demonstrated by Ben-Elia and Shiftan (2010), the learning curve,
15 as seen in the mean maximization rate suggests that providing descriptive information
16 does expedite the learning rate for the informed group while the trial and error learning of
17 the non-informed group takes a longer time. The graphs of the SD demonstrate similar
18 trends.

19
20 *** Figure 2 – about here ***

21
22 Last, we estimated a very simple mixed logit model similar to Model A (i.e. EU)
23 without regret effects. For consistency considerations, in both groups, the only attribute
24 include in this tested specification is the obtained travel time payoff (i.e. the experiential
25 feedback in each route F_i). The expected utility function for Route A is (eq. 16):

$$26 \quad EU_A = \beta F_A + \varepsilon_A \quad (16)$$

27 Ten scale parameters are specified for each experimental group (in total 20
28 parameters) each of these corresponding to a block of 10 trials out of 100. For
29 normalization purposes the first block i.e for trials 1-10 in each group is set to 1. Scenarios
30 are ordered according to the treatment orders initially assigned for each participant. Like
31 all the previous estimations, the model is estimated with 1000 Halton draws. The simulated
32 log likelihood function is (eq. 17):

$$SLL(\beta, \sigma_\beta, \lambda_{g1}, \dots, \lambda_{g20}) = \sum_{n=1}^N \log \frac{1}{R} \left\{ \sum_{r=1}^R \left[\prod_{g=1}^G \prod_{t=1}^T \left(\frac{e^{\lambda_{gnt} EU_{it}}}{\sum_{k=1, i \in K}^K e^{\lambda_{gnt} EU_{kt}}} \right) \right] \right\} \quad (17)$$

where: λ_{gnt} is the group scale for group g out $G=20$ groups; $\lambda_{1nt} = \lambda_{11nt} = 1$ and all other parameters are as in equations 14 and 15.

*** Figure 3 – about here **

Figure 3 presents the scale estimates (detailed results can be obtained from the authors by request). Scale estimates that are not significantly different from 1 (i.e. $p > .05$) are marked with empty markers and the values in italics. To facilitate understanding of the results polynomial regression lines are plotted alongside the raw estimates ($R^2 = 0.91, 0.92$ respectively). The scales' estimates show that the non-informed group scales are gradually increasing as the experiment progresses indicating a learning effect. Where there is a decrease it appears in most of the blocks quite small and does not change the overall trend. It may be that there is some element of fatigue towards the end of the session. The informed group has a rapid increase in scale (indicating expedited learning) and then a period where scales are going up and down but with no clear trend. This stage is likely indicative of neither learning nor fatigue. It suggests informed participants are relying on the descriptive information to make their choices, whereas non-informed participants are still learning from trial and error. Towards the final blocks of trials the scale increases once more indicating further learning. Here, informed participants have gained sufficient confidence based on the combined effects of description and experience to choose efficiently as can also be seen in Figure 2.

To summarize, the analysis of fatigue risks does not provide sufficient evidence to suggest a significant threat to the validity of the results. Moreover, the analysis here shows similar patterns to those already demonstrated by Ben-Elia and Shiftan (2010) and Ben-Elia et al. (2008) who discuss the key role of learning in informed and feedback-based route-choice situations. The estimated scales raise another interesting issue related to how regret is influenced by learning. One possible hypothesis is that learning mitigates the amplitude of regret emotions as participants' subjective confidence in their choices gains strength. Our results on regret aversion show that on average, regret does seem to be an issue that arises under certain conditions. However, with the current data limited to 49 participants there is not enough variation to allow a proper analysis of this issue (i.e. to

1 estimate regret aversion parameters for the different learning stages). We leave this for
2 future researchers to ponder on.

3 **5. Conclusions**

4 Regret Theory (RT) has been recently suggested as a viable behavioral theory, in
5 addition to traditional Expected Utility Theory and the well documented Prospect Theory,
6 to explain travel behavior phenomena including route-choice. These three theories have
7 also been adapted or at least tested in situations involving sequences of repeated choices
8 where the decision makers can learn by being provided with experiential feedbacks.
9 Repeated choices also characterize the day to day dynamics of travelling such as
10 commuting.

11 In this study we made use of an existing dataset collected by Ben-Elia et al. (2008)
12 in a relatively simple binomial repeated route-choice experiment where participants could
13 make their decision based both on descriptive information and experience. This dataset
14 was not designed a-priori to account for the occurrence of regret. Different model
15 specifications accounting for different sources of regret were applied and compared to a
16 simple choice model based on expected utility. In addition a joint estimation was
17 conducted for comparing the strength of regret with and without descriptive information.

18 The results assert that emotions of regret do appear to occur in the observed data
19 and that regret aversion is likely generated by the experiential travel time feedbacks
20 received by the participants ex-post their route choices rather than the descriptive
21 information provided to them ex-ante. This result also concurs with the assertions of the
22 more recent theories involving regret which account for feedbacks, such as conditional
23 feedback-based RT (Humphrey, 2004). However, regret aversion is much more evident
24 when participants are provided with descriptive information whereas without such
25 information, regret aversion exists but is significantly weaker. Therefore it is the
26 combination of both descriptive and experiential information that results in higher levels
27 of regret aversion. These results suggest that with the proliferation of emerging
28 technologies for intelligent transport systems in road networks, it is likely that travelers will
29 experience more regret in their route choices. Increasing emotions of regret aversion can
30 have significant impacts on network equilibrium as also demonstrated theoretically by
31 Chorus (2010). This needs to be further investigated in a congested network like
32 experimental setting which accounts for equilibrium (e.g. Lu et al., 2011). Furthermore, in
33 accounting for effects of risk, it seems that regret aversion is more apparent in situations

1 involving less risk, whereas riskier choices seem to inhibit regret, perhaps due to the
2 difficulty in perceiving the differences in outcomes (the payoff variability effect) and due to
3 other emotional effects linked to affective states related to risk attitudes.

4 Notwithstanding several limitations and future research directions to this study
5 should be noted. First, it is necessary to obtain further evidence for the importance of
6 reinforced learning in route choice behavior in experimental settings that also provide
7 feedback on foregone (i.e. non-chosen) alternatives. This would allow a better comparison
8 with the feedback-theoretical stream in Regret Theory such as FCRT. It would also provide
9 an indication to the behavioral effects of future intelligent information and communication
10 technologies that could well provide immediate foregone feedback. In addition, although
11 fatigue does not seem to play a major issue in repeated route choice, learning effects and
12 their influence in partially informed choice environments, such as transportation, are
13 clearly an important topic worth further research. Moreover, it is of added value to
14 understand how regret, risk perceptions and regret are influenced by long-term learning. It
15 is possible that with learning these effects might decline. Currently we can demonstrate
16 that regret (and to certain extent risk perception) is, on average, an emotion which is likely
17 to rise when both descriptive and experiential information are provided. However
18 whether and how regret changes over time is still an open question. A study involving a
19 larger panel of participants would make it possible to investigate the hypothesis that
20 learning could well mitigate the amplitude of regret aversion.

21 Second, in this study descriptive information was presented to participants as a
22 travel time range. Though useful to allow a visualization of travel time variability this is not
23 necessarily the only way to describe expected travel times. The framing effect illustrated
24 by Kahneman & Tversky (1979), suggests that different forms of presenting information
25 will likely affect how choices are made. Recently, Waygood and Avineri, (2011) have also
26 observed framing effects in mode choice when provided with different information formats
27 regarding their environmental-friendliness (CO₂ emissions). Moreover, we used a relatively
28 strong assumption regarding how the information of travel time ranges would be
29 processed (the upper and lower quartiles) and how this in turn corresponds to regret
30 aversion estimates. However, there is nothing to preclude from other possible assumptions
31 such as the best and worst travel times on the range or even a greater degree of
32 heterogeneity in how travelers are likely to view travel time ranges. There is, therefore, a
33 place to study more flexible travel information representations that do not result in
34 cognitive overload and how these could assist perhaps in mitigating regret.

1 Third, as shown by Gao et al., (2010) travelers could well anticipate the provision of
2 information on a route downstream resulting in more strategic behavior involving routing
3 policies. There is added value to investigate how emotions of regret could be related to
4 choosing among routing strategies and how this corresponds to the evolution of
5 equilibrium in simulated networks.

6 Nevertheless, our study provides additional empirical support to warrant further
7 investigations of regret in other travel behavior settings and especially in relation to the
8 possible behavioral impacts of intelligent transportation systems.

9

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11

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19

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Table 1: Description of travel time scenarios

Scenario	Description	Travel Time Ranges (minutes)	
		Route A	Route B
1	Lower variability on A	25±5	30±15
2	Higher variability on A	25±15	30±5
3	Equal variability	25±5	30±5

Table 2: Descriptives of the participants

Variable	Category	N	%	Stat.
Gender	Male	30	61	
	Female	19	39	
Age	Median			24
Drivers licence	Median No. of years holding			6
Car availability	Yes	18	37	
	No	31	63	
Employment	Yes	22	45	
	No	27	55	
Family composition	Single	47	96	
	Cohabiting with children	2	4	
Car Use	Never	4	8	
	once a week	11	22	
	Twice a week	8	16	
	3 times a week	7	14	
	almost every day	5	10	
	Every day	14	29	
Travel mode to campus	Walk	20	41	
	Bike	1	2	
	Drive alone	16	33	
	Share a ride	3	6	
	Bus	8	16	
	Other	1	2	

Table 3: Model estimation results – Informed group

Coe f.	Definition	Model A: Description-based EU				Model B: Description-based regret				Model C: Description & experienced-based regret				Model D: Description & experienced based regret with risk effects			
		Est.	Std err*	t-test	p-value	Est.	Std err*	t-test	p-value	Est.	Std err*	t-test	p-value	Est.	Std err*	t-test	p-value
β	Travel time mean	-0.542	0.0591	-9.17	<0.001	-1.42	0.0844	-16.8	<0.001	-0.461	0.0537	-8.58	<0.001	-0.467	0.0544	-8.58	<0.001
σ_{β}	Travel time s.d	0.259	0.0383	6.77	<0.001	0.646	0.0553	11.68	<0.001	0.211	0.0385	5.48	<0.001	0.185	0.03	6.19	<0.001
ρ	Regret aversion (general)					-0.108	0.00507	-21.28	<0.001	0.0925	0.0179	5.17	<0.001				
ρ_1	Regret aversion (scen. 1)													0.0364	0.0241	1.51	0.130
ρ_2	Regret aversion (scen. 2)													0.105	0.0189	5.53	<0.001
ρ_3	Regret aversion (scen. 3)													0.403	0.0908	4.44	<0.001
LL_0	Initial LL	-4940.8				-4940.8				-4940.8				-4940.8			
LL_{β}	Final LL	-2086.3				-1931.3				-2009.9				-1915.7			
ρ^2	Rho sq.	0.578				0.609				0.593				0.612			
$\overline{\rho^2}$	Adj. Rho sq.	0.577				0.608				0.593				0.611			

* Robust estimate

Table 4: Model estimation results – Joint estimation

Coef.	Definition	Model E: Regret aversion with and without descriptive information				Model F: Joint estimation of regret with risk effects			
		Est.	Std err*	t-test	p-value	Est.	Std err*	t-test	p-value
β	Travel time mean	-0.875	0.239	-3.67	<0.001	-0.991	0.217	-4.57	<0.001
σ_β	Travel time s.d	-0.38	0.0914	-4.15	<0.001	0.334	0.0675	4.95	<0.001
ρ	Regret aversion (general)	0.0431	0.00839	5.13					
ρ_1	Regret aversion (scen. 1)					0.0159	0.00955	1.66	0.1
ρ_2	Regret aversion (scen. 2)					0.0449	0.0124	3.63	<0.001
ρ_3	Regret aversion (scen. 3)					0.166	0.0398	4.18	<0.001
λ	Group scale (non-informed)	0.147	0.0395	-21.62**	<0.001	0.127	0.0275	-31.68**	<0.001
LL_0	Initial LL	-10087.4				-10087.4			
LL_β	Final LL	-4763.5				-4634.1			
ρ^2	Rho sq.	0.528				0.541			
$\overline{\rho^2}$	Adj. Rho sq.	0.527				0.540			

* Robust estimate

** t-test for $H_0: \lambda=1$

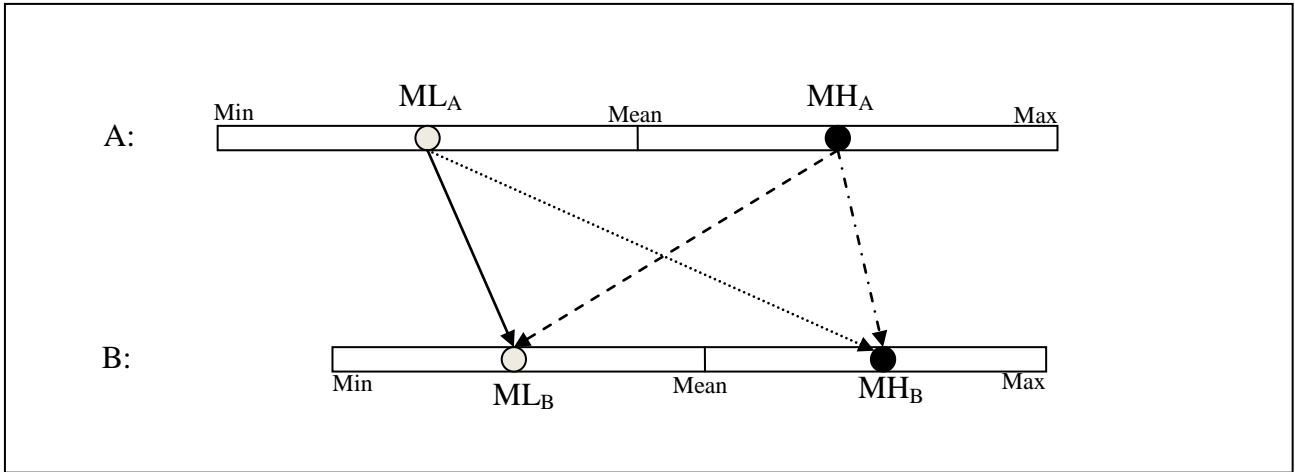


Figure 1: Illustration of two and four possible states-of-the world

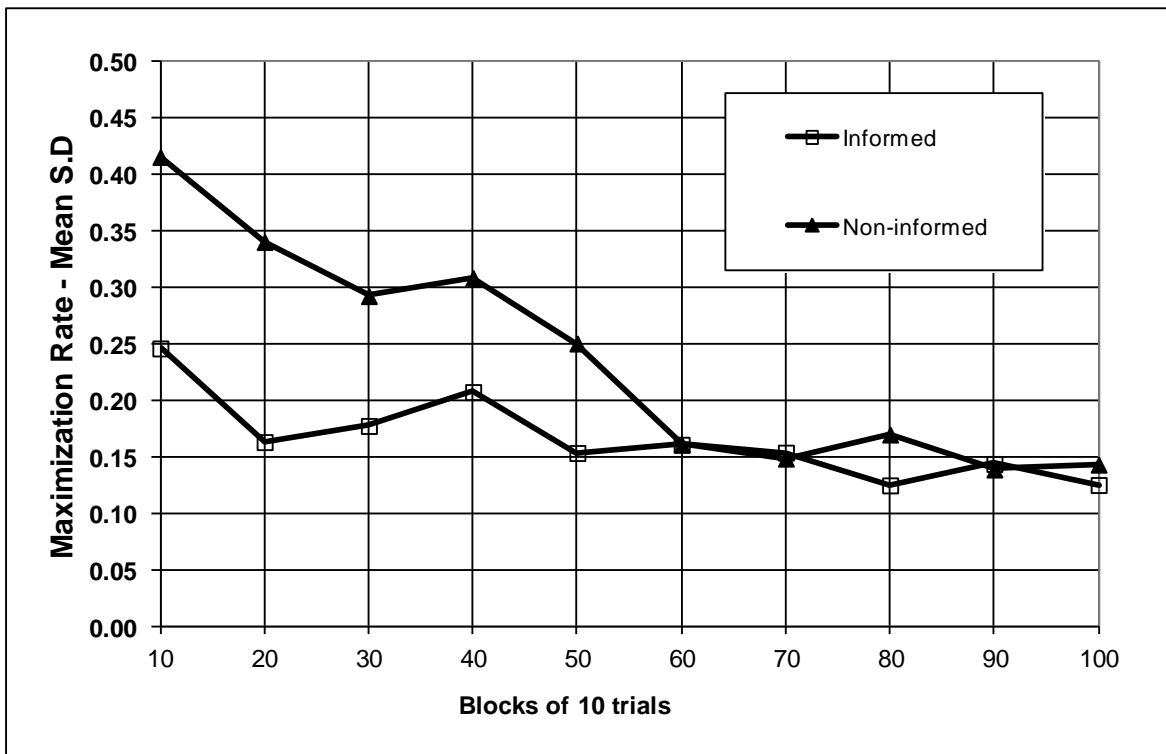


Figure 2: Mean Standard-Deviation of the Maximization Rate (Share of 'Fast' route choices)

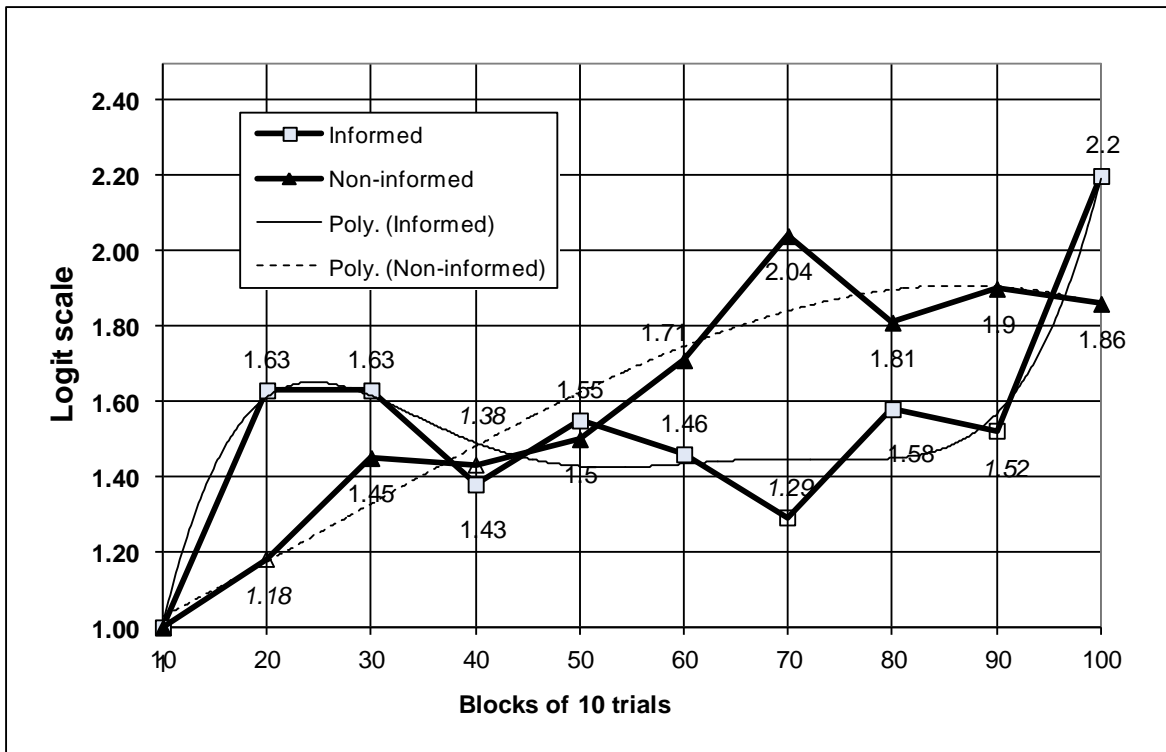


Figure 3: Logit scale estimates and corresponding polynomial regressions in blocks of 10 trials