IDENTIFICATION OF MONETARY TRAVEL TIME VALUATIONS FROM TRAVEL INFORMATION SEARCH PATTERNS

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ABSTRACT

Motivated by the notion that data needed for the estimation of travelers' valuation of travel time (savings) is scarce, we put forward the idea that these valuations may be derived from observed travel time information searches. First, we derive a theoretical model of traveler behavior under uncertainty and information availability, which unambiguously links a traveler's decision whether or not to acquire information to his or her travel time valuation. In theory, this model provides the opportunity to derive travel time valuations from information search. Then, empirical analyses are performed, based on an artificial dataset. The empirical analyses show that information search can indeed be used to empirically identify travel time valuations: estimated parameters for monetary costs and travel time savings are statistically indistinguishable from true values for the majority of generated datasets. Although estimated travel time valuations appear to be below the true value, the differences between the two are small and mostly insignificant.

1. INTRODUCTION

Although for many years now, deriving travel time valuations has received considerable interest in the traveler behavior research community (e.g. *1-3*), interest in the topic is rapidly gaining momentum in recent years (e.g. *4-12*). Travel time valuations are of great use to transport policy makers that wish to evaluate the benefits of policies and infrastructure investments, aimed at combating congestion and inaccessibility of urban centers (e.g. *13*). In order to derive the value of travel time, which itself is a latent construct, data on travel choices is needed: the underlying notion here is that travelers reveal their valuation of travel time by choosing among mode-, route- or departure time-options that differ in terms of their travel times and costs. Given such data, state-of-the-art discrete-choice analyses are applied to obtain econometric estimates of travel time valuations. Traveler behavior researchers are well aware that the needed high quality data on actual travel choices is scarce. In fact, this scarcity can be seen as one of the main reasons for the increasing popularity of stated choice approaches which rely on choices in hypothetical situations (e.g. *10, 11*).

This paper proposes another potential solution to deal with the scarcity of data concerning actual travel choices. We put forward the idea that travelers not only reveal their travel time valuations by choosing from among mode-, route- or departure time-alternatives, but also by choosing whether or not to acquire travel time information.

Picture a scenario where a traveler checks a route's travel time by visiting an internet-page or by calling a traffic information number. By doing so, he provides a signal concerning the importance he attaches to travel time. Roughly put, if travel time weren't important for this traveler, he would not have gone through the trouble of acquiring travel information. Obviously, things are slightly more complicated than this. That is, not only does the acquisition of travel time information provide a signal concerning the importance a traveler attaches to travel time, but also concerning his evaluation the route in terms of other attributes. For example, should the route be very unattractive in terms of a high level of toll, this would make the route relatively unattractive, irrespective of its travel time. Again, the traveler will in this situation not put effort (and potentially money) in acquiring travel time information. Combining these two notions (travel time information acquisition signals a) the importance attached to travel times and b) the evaluation of the travel alternative in terms of other attributes including costs), it becomes clear that data on travel time information acquisition can in principle be used to (help) estimate travelers' monetary valuations of time.

Building on previous theoretical research on the value of (travel time) information acquisition (*14-20*), we propose a model that unambiguously links a traveler's decision whether or not to acquire travel time information under conditions of uncertainty, to his or her travel time valuation. Using this model, we subsequently show how estimates of travel time valuations can be obtained from data on travel time information search patterns.

The outlook of the remainder of this paper is as follows: we first propose our model at the individual level and discuss its properties. We then proceed by providing an econometric specification that is applicable for estimation efforts based on observed information search patterns. Subsequently, we present a fictive example of traveler behavior under conditions of uncertainty and information provision. Artificial datasets of travel time information search behavior are created using Monte Carlo simulation on a predefined set of travel time valuations, and we show how the generated information search patterns can be used to derive these true valuations through model estimation. Finally, we show how the model can be extended towards unreliable information, after which conclusions are drawn.

2. MODEL

A prerequisite for being able to use observed information search behavior to derive travel time valuations is that information search behavior is modeled in terms of the traveler's valuation of travel time, relative to money. A promising candidate to achieve this link is to formulate search for information in terms of a cost-benefit trade-off; the benefits of information search being the difference between the expected utility of the current choice situation and the expected utility of the anticipated choice situation after having received the information (e.g.*14-18*). In addition to theoretical models of information search at the individual level, we need an econometric specification of these models to be able to actually estimate travel time valuations from observed information search patterns. A random-utility-based specification that may be used to this aim has been recently developed by Chorus, Walker and Ben-Akiva (*20*). They propose a model where the unobserved utilities relating to travel alternatives (e.g. intrinsic preferences for different travel modes) are captured in the utility functions of travel information options.

Our approach to derive travel time valuations from observed information search patterns is rooted in these streams of literature. More specifically, we assume i) that a traveler's decision to search for information is based on expected utility maximization, where the expected utility of information is composed out of a cost component and a benefit component; ii) that the benefit of information search can be written in terms of the difference in expected utility of the current and anticipated choice situation; iii) that part of the expected utility of routes and the utility of information cannot be observed by the analyst, leading to additive random error components for travel alternatives that are represented in the utility of information search. In the remainder of this section, we will specify our model at the individual level, discuss its properties, and provide an econometric formulation. For reasons of simplicity, we consider a choice situation where a traveler chooses from among two routes.

2.1. Individual level model

Consider a choice situation between two routes *i* and *j*. Assume that, in the spirit of Lancaster (*21*), a traveler perceives both routes as a bundle of travel time and travel cost (toll). Travel times are modeled by assuming that a route can experience a good and a bad day. If a route experiences a good day, travel time equals *TT*. On a bad day, travel time equals $TT + \Delta TT$ minutes. If both routes experience a good (or a bad) day at the same time, travel times are (perceived) equal. A constant β_0 reflects an intrinsic preference for route *i* over *j*. Let the utility of *i* and *j* be specified through the following linear additive functions: $U_i = \beta_0 + \beta_{toll} \cdot toll_i + \beta_{good} \cdot good_i$ and $U_j = \beta_0 + \beta_{toll} \cdot toll_j + \beta_{good} \cdot good_j$. Here, β_{toll} reflects the travelers (dis-)utility of a unit of toll. β_{good} represents a traveler's preference for a good day (*good* = 1) over a bad day (*good* = 0), or in other words the utility he or she derives from saving ΔTT minutes travel time. Assume now that the traveler is uncertain whether on this particular day route *i* experiences a good day ($good_i$ = 1), or a bad day with a ΔTT minutes higher travel time ($good_i$ = 0). The traveler is certain that route *j* currently experiences a bad day, i.e. $good_j = 0$. We denote the perceived probability that route *i* experiences a good day as $p(good_i)$. The expected utility the traveler derives from choosing route *i* is then written as:

$$EU_i = \beta_0 + \beta_{toll} \cdot toll_i + p(good_i) \cdot \beta_{good} \tag{1}$$

The expected utility she may derive from the current choice situation as a whole is then given by the maximum of the expected utility of route *i* and *j*.

Let an information search possibility exist concerning the value of $good_i$ (i.e. the traveler may search for information whether or not route *i* experiences a good day). The expected utility of the anticipated choice situation after having received the information, EU^+, can then be formalized as follows: the individual knows that, given fully reliable information, she will receive the message "route *i* experiences a good day" with probability $p(good_i)$ and the message "route *i* experiences a bad day" with probability 1- $p(good_i)$. For example, should our traveler ex ante believe that the probability that route *i* experiences a good day equals 95%, we assume that when acquiring fully reliable information she expects to receive a message, saying that indeed route *i* experiences a good day, with 95% probability as well. She also knows that, after having received one of these messages, she will maximize her utility when choosing between route *i* and route *j*. The following equation gives the notational representation of this argument:

$$EU^+ = p(good_i) \cdot \max\left\{ \underbrace{\beta_0 + \beta_{toll} \cdot toll_i + \beta_{good}}_{\text{Utility of } i \text{ on a good day}}, U_j \right\} + \left(1 - p(good_i)\right) \cdot \max\left\{ \underbrace{\beta_0 + \beta_{toll} \cdot toll_i}_{\text{Utility of } i \text{ on a bad day}}, U_j \right\}$$

(2)

As proposed earlier in this Section, we now conceptualize the expected utility of information as the difference between the expected utility of the current choice situation and that of the anticipated choice situation, minus the cost c of information search: $EU_I = EU^+ - EU - c$. Information is searched for when $EU_I \geq 0$.

2.2. Model properties

Before discussing how the model presented above can be formulated econometrically, let us elaborate on how the proposed model captures some basic intuitions concerning traveler behavior. First, let us consider how traveler information search is influenced by a traveler's intrinsic preference for a route, and its performance in terms of travel costs. We would expect that the expected value of information about travel times (good versus bad days) is relatively high when route *i* and *j* are perceived as comparably attractive in terms of the total of their other attributes (intrinsic preferences and costs). In such a situation, whether or not route *i* experiences a good day will likely determine the traveler's choice. When one of the two routes is superior in terms of intrinsic preferences and/or costs, we expect a traveler to be less interested in knowing route *i*'s travel time, since knowing it will probably not change her preference for the superior route.

The following fictive example illustrates how our model of expected information value captures this intuition. We assume the following settings, based on the choice-situation described above: a traveler chooses between two routes *i* and *j*. The traveler perceives the probability that route *i* experiences a good day, $p(good_i)$, as .5 and is certain that route *j* experiences a bad day. His or her valuation of avoiding the extra ΔTT minutes travel time associated with a bad day, denoted β_{good}, equals 5. Information *I* concerning the value of $good_i$ can be obtained at no costs (i.e., $c = 0$). We now vary the performance of route *i* relative to routed *j* in terms of its alternative specific constant (ASC), representing the traveler's intrinsic preference for *i*. We also vary the difference in toll (positive values indicating that *i* is more expensive than *j*; we assume $\beta_{\text{toll}} = -1/\text{unit}$). We observe how this affects the expected value of searching for information concerning the value of $good_i$.

Figure 1 shows how the expected value of information, given our conceptualization, is low or even non-existing in situations where either i) route *i* is substantially more expensive than *j* AND the traveler holds a strong intrinsic preference for *j*, OR ii) route *i* is substantially cheaper than *j* AND the traveler holds a strong intrinsic preference for *i*. In situations with no strong differences in intrinsic preferences or toll, or where they cancel out, expected value of information is relatively high. Note that in fact, since we assumed that route *j* experiences a bad day, the expected value of information is highest when *j* is slightly more attractive than *i* in terms of toll and intrinsic preference. Completely in line with intuition, our model predicts that travelers derive the most value of information search concerning uncertain travel times (good versus bad day) when the information will determine their choice between the two routes.

Second, let us consider how information search concerning uncertain travel times is influenced by the degree of uncertainty and the traveler's valuation of travel times. We would expect that the more uncertain a traveler is concerning route *i*'s true travel time, i.e. the occurrence of good or bad days, the more she will be inclined to search for information, ceteris paribus. We also expect that the higher the traveler's value of time, the more she will be inclined to search for travel time information, ceteris paribus. In notation, we would expect that higher values for β_{good} induce higher expected values of information and that when $p(good_i)$ approaches either 0 or 1, the expected value of information decreases.

Figure 2 visually shows how our model captures these intuitions, by plotting the expected value of information against travel time valuation and the level of uncertainty. We adopt the following settings: there is a small intrinsic preference for route *j* over *i* ($\beta_0 = -3$), both routes are toll-free. We vary $p(good_i)$ within [0,1], and β_{good} (the traveler's valuation of avoiding the ΔTT minutes of extra travel time associated with a bad day) between 0 and 7.5. As expected, expected information value is low or non-existing when the individual is relatively certain that route *i* does (not) experience a good day, and for low values of β_{good}. In these situations, there is little uncertainty, and the uncertainty that does exist does not influence traveler choice due to the low valuation of travel time. However, when $p(good_i)$ approaches .5, and β_{good} increases, the expected value of information increases as well: travel time becomes more important, and its value more uncertain, so the information becomes more valuable. Again, the proposed model of expected information value appears to behave in line with our intuitions regarding the behavioral determinants of travel information search.

Summarizing, the proposed model of expected information value appears to provide an intuitive account of traveler behavior. This provides first confidence that the model may be applied to derive travel time valuations from observed information search patterns. However, in order to become applicable for data-analysis, we need an econometric specification of our individual-level model of information search. Such a specification is presented in the remainder of this Section.

2.3. Econometric model specification

Assume that an analyst observes information search from *N* travelers, one choice per traveler *n*, and wishes to derive (average) travel time valuations from these observations. Adopting a random-utility framework, we assume that the analyst is only able to observe part of the (expected) utility that a traveler derives from the available routes, or from information search. That is, these utilities are – from the analyst's point of view - composed out of an observed and an unobserved (random) part. We assume the following distributions for the random utility components: δ_i^n represents the part of the utility of route *i* that is unobservable by the analyst and reflects variation across travelers concerning intrinsic preferences for route *i* over route *j* (the average intrinsic preference is given by β_0). We assume that δ_i^n is normally distributed across individuals: $\delta_i^n \sim N\left(0,\sigma_i\right)$. Furthermore, ε_I^n represents the part of the utility of information search that is unobservable by the analyst and reflects an inclination to (not) acquire information. We assume that ε_I^n is i.i.d. Extreme Value Type I distributed with standard deviation $\pi/\sqrt{6}$. For ease of presentation, we assume also that the level of *toll* is perceived and evaluated equally by each traveler. However, different travelers may attach different probabilities $p^n\left(good_i\right)$ concerning the occurrence of a good day on route *i*. Together, this leads to the following reformulation of equation (2) concerning the expected utility of the anticipated choice situation, after having received information:

$$EU^{n+} =$$

$$p^n\left(good_i\right)\cdot \max\left\{\underbrace{\beta_0+\beta_{toll}toll_i+\beta_{good}+\delta_i^n}_{\text{Utility of } i \text{ on a good day}},U_j\right\}+\left(1-p^n\left(good_i\right)\right)\cdot \max\left\{\underbrace{\beta_0+\beta_{toll}toll_i+\delta_i^n}_{\text{Utility of } i \text{ on a bad day}},U_j\right\}$$

(3)

The expected utility of information becomes $EU_I^n = EU^{n+} - EU^n - c^n + \varepsilon_I^n$. Given these formulations, computing the probability that an observed traveler *n* will search for travel time information now involves the evaluation of two integrals: one to integrate out δ_i^n relating to the traveler's intrinsic preference for route *i*, another one to integrate out ε_I^n relating to his or her inclination to search for information.

The distributional assumptions of the random errors result in a mixed binary logit model; the closed form solution of the integral associated with ε_I^n (resulting in binary logit) is mixed over the probability density function of δ_i^n. Acknowledging that the non-random part of the utility of not acquiring information equals zero by definition, the choice probability for information search by traveler *n* may thus be denoted as:

$$p\left(I^n\right)=\int_{\delta_i^n}\left(\frac{\exp\left(EU_I^n\right)}{\exp\left(EU_I^n\right)+1}\right)\cdot f\left(\delta_i^n\right)d\delta_i^n \tag{4}$$

Let us denote observed information search as y_I^n, assuming it takes one the value 1 when the traveler chooses to acquire information, and 0 otherwise (remember that we observe only one choice per traveler). We can now estimate the parameters of the choice model, β_0, β_{good} and β_{toll}, by maximizing the (log of) the sample likelihood *L* for the observed information search patterns:

$$L=\prod_{n=1}^{N}\left(\left[p\left(I^n\right)\right]^{y_I^n}\cdot\left[1-p\left(I^n\right)\right]^{1-y_I^n}\right) \tag{5}$$

The parameter ratio $\beta_{good}/\beta_{toll}$ now gives the econometric estimate of the average monetary valuation of (avoiding) ΔTT minutes of extra travel time associated with a bad day. Note that a negative number is expected as we expect that β_{good} is expected to have a positive, and β_{toll} a negative sign. In other words: we estimate the amount of money a traveler would be willing to give up in order to achieve a travel time saving ('exchange' a bad day for a good one).

The above model *theoretically* provide us with a tool to derive travel time valuations from observed travel information search patterns. However, it is yet unclear whether this theoretical notion holds empirically. A look at the sub-section on model properties suggests that the assumed relation between travel time valuations and the resulting information search patterns is rather subtle and indirect. This certainly holds when compared to the relation, assumed in conventional choice models, between travel time valuations and choices among routes. In other words, it is not clear whether the parameters (travel time valuations) that underlie a data-generating process (information search behavior) that is characterized by the above equations can be *empirically* identified by maximum likelihood estimation based on the observed data. In the next section, we will address these questions concerning empirical identification by estimating our model of information search on artificial datasets.

3. EMPIRICAL ANALYSES

This section consists of two parts: first, we will generate artificial data concerning information search patterns. This is done by feeding a set of true parameters β (and Monte-Carlo-generated random error components δ and ε) in the model presented above, in order to simulate information search. Second, we will use the artificially generated data on information search for maximum likelihood estimation and investigate whether the obtained parameter estimates $\hat{\beta}$ correspond to the true β's used to generate the data. See Figure 3 for a visual overview of this process.

3.1. Data generation

We assume the following hypothetical situation: travelers are faced with a choice between two routes A and B, and perceive them as a bundle of the attribute TOLL, an attribute denoted GOOD_DAY. On average, there is no intrinsic preference for one of the two routes. Route A has a higher level of toll than route B, travelers are aware of this difference. The two routes can experience good or bad days. If a route experiences a good day, travel time equals *TT*. On a bad day, travel time equals $TT + \Delta TT$ minutes. If both routes experience a good (or a bad) day at the same time, travel times are (perceived) equal. Travelers know that route B currently experiences a bad day (GOOD_DAY = 0 for route B) and they attach a probability *p*(GOOD_DAY = 1) to the event that route A experiences a good day; this probability differs between travelers, and we assume that they perceive it as independent from the attribute TOLL. Traveler preferences are as follows: -1 util per unit regarding the attribute TOLL and 50 utils for the attribute GOOD_DAY. That is, travelers are willing to pay (no more than) 50 units for a travel time difference of ΔTT minutes. In case travelers are certain that route A has a bad day (*p*(GOOD_DAY=1) = 0), then route B is preferred, due to the lower level of toll. In case travelers are certain that A has a good day (*p*(GOOD_DAY=1) = 1), the traveler's preference depends on the toll difference between the two computers. Under conditions of uncertainty (0 < *p*(GOOD_DAY=1) < 1) route A may or may not be preferred to B, depending on the toll difference between the two and the exact value of *p*(GOOD_DAY=1). By replacing the attribute TOLL by TOLL_DIFF (reflecting the difference in toll between A and B), we normalize the utility of route B to zero.

Adding δ_A^n to reflect that traveler *n* may have an intrinsic preference for route A, we arrive at the following expected utility function for route A: $EU_A^n = \beta_{TOLL\_DIFF}$ * TOLL_DIFF + β_{GOOD_DAY} * *p*(GOOD_DAY=1) + δ_A^n . Travelers now face a choice whether or not to acquire fully reliable information concerning the value of GOOD_DAY, denoted INFO_SEARCH. The information comes at a certain information cost, denoted COST and perceived by travelers to equal –4 utils. Note that COST may consist of monetary as well as non-monetary components.

Based on the described choice situation, we generate 10 datasets of 200 cases each. Each case presents a choice, made by a different traveler, whether or not to acquire the available travel time information. The data generation process consists of three steps:

1. Each case is systematically assigned TOLL_DIFF from the set $\{10, 20, 30, 40, 50\}$ - reflecting that A is always more expensive than B. Also, each case is randomly assigned a probability *p*(GOOD_DAY=1) drawn from the 0-1 interval, representing the individual's belief strength that route A experiences a good day.
2. We then apply Monte Carlo simulation to draw random error components for each case. One error component, reflecting the traveler's intrinsic preference for route A over B, is drawn from a standard normal distribution and added to the (expected) utility of route A. Two other errors, reflecting the individual's inclination (not) to search for information, are drawn from an i.i.d. Extreme Value Type I distribution with standard deviation $\pi/\sqrt{6}$, and added to the expected utility of (not) acquiring information.
3. Finally, using our model, we compute for each case the expected utility EU_I^n of information search and based on this utility simulate a traveler's choice whether or not to acquire the available information. For the given model settings, roughly half of the 2000 hypothetical travelers choose to search for information, denoted INFO_SEARCH = 1.

3.2. Model estimation and comparison of estimates with true values

The generated datasets contain four columns each: three independent variables (TOLL_DIFF, *p*(GOOD_DAY=1), COST) and one dependent variable (INFO_SEARCH). We now present an attempt to estimate parameters β_{GOOD_DAY} and β_{TOLL_DIFF} (and their ratio: the implied value of travel time), by relating these independents to INFO_SEARCH using our econometrical model of information search. The likelihood function and estimation process were coded in GAUSS 7.0, using the MaxLik-module. Note that calculation of the likelihood function involves integration of a binary logit function over a standard normal probability density function, for which there is no closed form solution. We compute the integral through simulation, using 500 intelligent Halton draws for each case. This number of intelligent draws results in a sufficiently high level of coverage of the probability density function and a high level of stability of parameter estimates.

It turns out that, notwithstanding the subtlety and indirect nature of the assumed relation travel time valuations and information search behavior, we are able to empirically identify from the generated data the parameters that were used for data generation. That is, β_{GOOD_DAY} and β_{TOLL_DIFF} are empirically identified. As Table 1 shows, estimated parameters and implied travel time valuations seem to be very close to the true values (respectively -1, 50, -50), although the implied valuations of travel time appear to be slightly below the true value. Perhaps more importantly than assessing whether the estimated parameters and travel time valuations seemingly correspond to the true ones is to assess whether they are statistically indistinguishable from the true values.

We first test, for each of the 20 estimated parameters β_{GOOD_DAY} and β_{TOLL_DIFF}, the following hypothesis through a one-sample *t*-test: the estimated parameter is equal to the true value. See Table 1 as well for the results of this test, *t* = (estimated value – true value) / SE. Acknowledging that a significance level of 5% implies that absolute values of *t*-values smaller than 1.96 signal that the hypothesis cannot be rejected, it becomes clear that for 8 of 10 datasets the estimated parameters appear as statistically indistinguishable from their true values. For the two datasets where parameters can be distinguished from their true value at a 5% significance level, t-values remain close to 1.96.

We go on to test whether the travel time valuations implied by the estimated parameters can be distinguished, in a statistical sense, from the true value. First, we estimate the standard error of the implied estimates of travel time valuation using the Delta-method for confidence bound estimation of parameter ratio’s. Following this method, the standard error of a ratio of parameter estimates $\hat{\alpha}/\hat{\beta}$ can be approximated by the following measure:

$$\mathrm{SE}\left(\frac{\hat{\alpha}}{\hat{\beta}}\right)=\sqrt{\frac{1}{\left(\hat{\beta}\right)^{2}}\cdot\left(\left(\mathrm{SE}\left(\hat{\alpha}\right)\right)^{2}-\frac{2\hat{\alpha}}{\hat{\beta}}\cdot\mathrm{COV}\left(\hat{\alpha},\hat{\beta}\right)+\left(\frac{\hat{\alpha}}{\hat{\beta}}\right)^{2}\cdot\left(\mathrm{SE}\left(\hat{\beta}\right)\right)^{2}\right)} \quad (6).$$

Applying this approximation on our estimation results yields the SE’s for the implied value of travel time, as presented in Table 1. Similarly to the significance tests displayed above, we test whether the implied value of travel time is indistinguishable from its true value in a statistical sense. See Table 1 for the results of this test: it appears that for seven out of ten datasets, the estimated value of time is indistinguishable from its true value at a significance level of 5%. However, for three datasets, there is a statistical difference between true and estimated value of travel time at any reasonable level of significance. Notably, it appears that all estimated travel time valuations are below the true value. We have not found a good explanation for this. Notwithstanding this, it appears that the differences between the two are small and, as said, mostly insignificant.

4. EXTENSION TOWARDS PARTIALLY RELIABLE INFORMATION

In the remainder of this section, we explore how our approach may be extended to cover situations where information is (perceived as) only partially reliable.

4.1. Extension towards partially reliable information

Until here, we have assumed that available information is (perceived as) fully reliable. In practice, this assumption will not always hold. Information may often be (perceived as) only partially unreliable, which is likely to result in lower inclination to search for information than our model predicts. Should the model that the analyst uses for deriving travel time valuations from observed information search be – erroneously - based on the premise of fully reliable information, this would lead to biased estimates. In the following, we show that there is a straightforward way to incorporate the notion of perceived information unreliability in our model of information search, based on the concept of Bayesian perception updating (e.g. *22*).

Assume the exact same choice situation that is described in the model-section above – we here focus on the individual-level model for simplicity of notation. Assume that the information *I* concerning the value of attribute $good_i$ is not (perceived as) fully reliable. That is, there is a perceived non-zero probability $p\left(I : good_i = 1 \middle| good_i = 0\right)$ that the information *I* received by the traveler states that $good_i = 1$ (route *i* experiences a good day) when in fact $good_i = 0$. Similarly, there may be a perceived non-zero probability $p\left(I : good_i = 0 \middle| good_i = 1\right)$. What are the effects of these non-zero probabilities on the expected value of information?

First, the probabilities that govern a traveler's perception of what message he or she thinks he or she will receive when acquiring information will change. In case the information is perceived as completely unreliable, the traveler will perceive the information service's messages to be random draws, irrespective of her initial perceptions concerning the uncertain attribute $p\left(good_i = 1\right)$ and $p\left(good_i = 0\right)$. In case of fully reliable information, his or her initial perceptions concerning the occurrence of a good day fully determine her perceived probability of receiving particular messages: $p\left(I : good_i = 1\right) = p\left(good_i = 1\right)$ and $p\left(I : good_i = 0\right) = p\left(good_i = 0\right)$; In general, we can write the perceived probability of receiving particular messages as follows:

$$p\left(I : good_i = 1\right) = p\left(good_i = 1\right) p\left(I : good_i = 1 \middle| good_i = 1\right) + p\left(good_i = 0\right) p\left(I : good_i = 1 \middle| good_i = 0\right)$$

$$p\left(I : good_i = 0\right) = 1 - p\left(I : good_i = 1\right)$$

(7).

Note that the following must hold: $p\left(I:good_i=1\middle|good_i=0\right)+p\left(I:good_i=0\middle|good_i=0\right)=1$ and $p\left(I:good_i=0\middle|good_i=1\right)+p\left(I:good_i=1\middle|good_i=1\right)=1$. It can be seen that the perceived probabilities of receiving partially reliable messages reduce to the probabilities associated with the case of fully reliable information when $p\left(I:good_i=1\middle|good_i=0\right)$ = $p\left(I:good_i=0\middle|good_i=1\right)$ = 0.

Besides that information unreliability affects travelers' beliefs about what message may be received when searching for information, it is expected that the unreliability also affects the impact of a received message on traveler perceptions concerning the occurrence of good or bad days. The more reliable the information is perceived to be, the more a traveler will take messages seriously, up to the point that he or she is willing to replace here initial perceptions completely by received fully reliable information. Information that is believed to be fully unreliable will be disregarded by travelers. Using Bayes' law of conditional probabilities, we arrive at the following general formulation for a traveler's perception updating process, where p' stands for an updated perception conditional on receiving a particular message (we give the probabilities for $good_i=1$, subsequent derivation of those for $good_i=0$ is straightforward):

$$\begin{aligned} p'\left(good_i=1\middle|I:good_i=1\right) &= p\left(I:good_i=1\middle|good_i=1\right)p\left(good_i=1\right)\big/p\left(I:good_i=1\right) \\ p'\left(good_i=1\middle|I:good_i=0\right) &= p\left(I:good_i=0\middle|good_i=1\right)p\left(good_i=1\right)\big/p\left(I:good_i=0\right) \end{aligned} \quad (8).$$

Based on the above two equations, it is seen that in case of partial unreliability of information, traveler choice after having received the information remains a choice under uncertainty. This in contrast to the case of fully reliable information, where all uncertainty is removed upon receiving a message. The updated expected utility of route *i*, denoted $EU_i^{'}$, is based on the updated perceptions p' concerning the occurrence of good versus bad days.

Combining our derivations concerning i) what message is expected to be received and ii) the effect of received messages on traveler perceptions of the uncertain attribute, we can now write the expected utility of the anticipated choice situation after having searched for partially reliable information as follows:

$$EU^+ = p\left(I:good_i=1\right)\cdot\max\left\{EU_i^{'}\left(I:good_i=1\right),U_j\right\}+\left(1-p\left(I:good_i=1\right)\right)\cdot\max\left\{EU_i^{'}\left(I:good_i=0\right),U_j\right\}$$

(9).

Subtracting from (9) the expected utility of the current choice situation and the costs of information acquisition yields the expected utility of searching partially reliable information.

As an illustration of the workings of this model extension towards including partially reliable information, consider the following choice situation: a traveler chooses between two routes *i* and *j*. She perceives the probability that route *i* experiences a good day $p(good_i = 1) = .8$ and is certain that route *j* experiences a bad day. The utility associated with a good day, denoted β_{good}, equals 5. There is an intrinsic preference for route *j* over *i*: $\beta_0 = -3$. Toll levels of the two routes are equal. Thus, the expected utility of the current choice situation equals max (-3 + .8 * 5 , 0) = 1. Information *I* concerning the value of $good_i$ can be obtained at no costs (i.e., $c = 0$). However, information is perceived as only partially reliable in the sense that there is a perceived probability that a received message claims that $good_i = 1$ where in fact $good_i = 0$, and vice versa.

Figure 4 shows the expected information value for varying levels of magnitude of the probabilities of receiving incorrect messages $p(I : good_i = 1 | good_i = 0)$, denoted P_1_false, and $p(I : good_i = 0 | good_i = 1)$, denoted P_0_false. It is directly seen that the expected value of information increases as the perceived probability of receiving incorrect messages approaches zero. As the perceived probability of receiving incorrect messages increases, expected information value drops, as would be expected. Note that should the perceived probability of receiving incorrect messages approach 1, information value would rise again. This is in fact logical, as travelers then know that when faced with a message, they may derive the true value of $good_i$ with certainty: when a message $I : good_i = 0$ is received, the updated perception consists of knowing with certainty that $good_i = 1$. Information value is lowest when the probability of receiving incorrect messages is around .5. In summary, it appears that extending the proposed model with Bayes' law of conditional probabilities makes it possible to provide a meaningful account of the way in which travelers deal with partially reliable information.

5. CONCLUSIONS

Motivated by the notion that data needed for the estimation of travelers' valuation of travel time (savings) is scarce, we put forward the idea that these valuations may be derived from observed travel time information searches. In addition to a theoretical underpinning of this idea within an expected utility framework, we provide an empirical example of how this process may work in practice. The empirical analyses show that information search can indeed be used to empirically identify travel time valuations: estimated parameters for monetary costs and travel time savings are statistically indistinguishable from true values for the majority of generated datasets. Although all estimated travel time valuations appear to be below the true value, the differences between the two are small and mostly insignificant. It is also shown how the model can be extended to cover the case of unreliable information.

Directions for further research include: i) incorporating unreliable information in empirical estimation efforts, ii) incorporating non-expected utility perspectives on travel choice, and last but certainly not least iii) empirical estimation on a dataset of actual travel behavior.

Finally, we wish to acknowledge here that, although this research is rooted in a real world problem (putting to use potential data to derive travel time valuations for transport planning purposes), the paper has a rather theoretical scope. Notwithstanding this, we feel that, from the perspective of data-efficiency, it makes sense to always try to identify ways to gain insight into traveler behavior from (potentially) available data. This paper puts forward one particular way of doing so.

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LIST OF TABLES & FIGURES

Table 1: Estimation results

Set	**β**$_{TOLL\_DIFF}$ *True = -1*	SE	***t***	**β**$_{GOOD\_DAY}$ *True = 50*	SE	***t***	**Value of travel time** *True = -50*	SE	***t***
1	-1.04	0.07	-0.57	51.09	3.02	0.36	-49.04	1.19	0.80
2	-1.09	0.07	-1.27	53.10	2.97	1.04	-48.72	1.09	1.16
3	-1.15	0.07	-2.08	56.21	3.09	2.01	-49.02	1.08	0.91
4	-1.02	0.07	-0.36	48.97	2.80	-0.37	-47.80	1.18	1.87
5	-1.03	0.07	-0.40	49.29	2.75	-0.26	-47.99	1.15	1.74
6	-1.16	0.09	-1.83	54.57	3.51	1.30	-47.04	0.90	3.29
7	-1.17	0.08	-2.11	53.62	3.18	1.14	-45.97	0.82	4.93
8	-1.01	0.07	-0.21	49.58	2.91	-0.15	-48.86	1.17	0.97
9	-1.14	0.08	-1.76	53.76	3.21	1.17	-47.16	1.05	2.71
10	-1.07	0.07	-0.93	52.00	3.05	0.66	-48.76	1.24	1.00

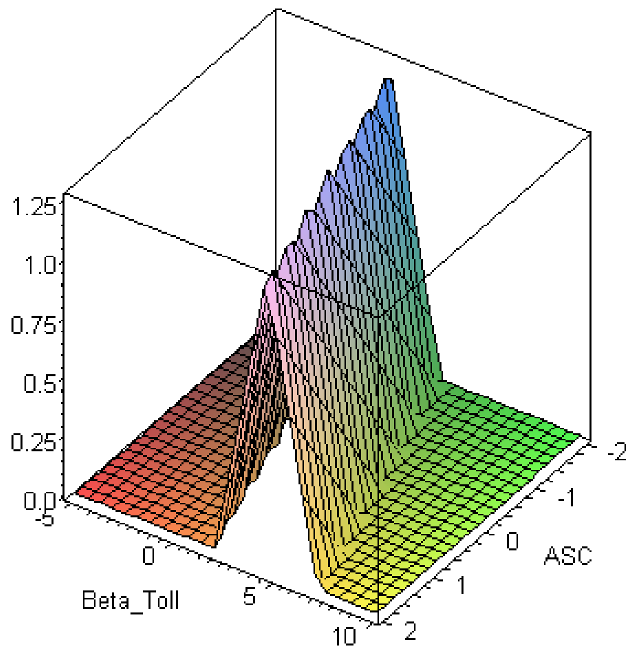

Figure 1: Information value as a function of attribute values

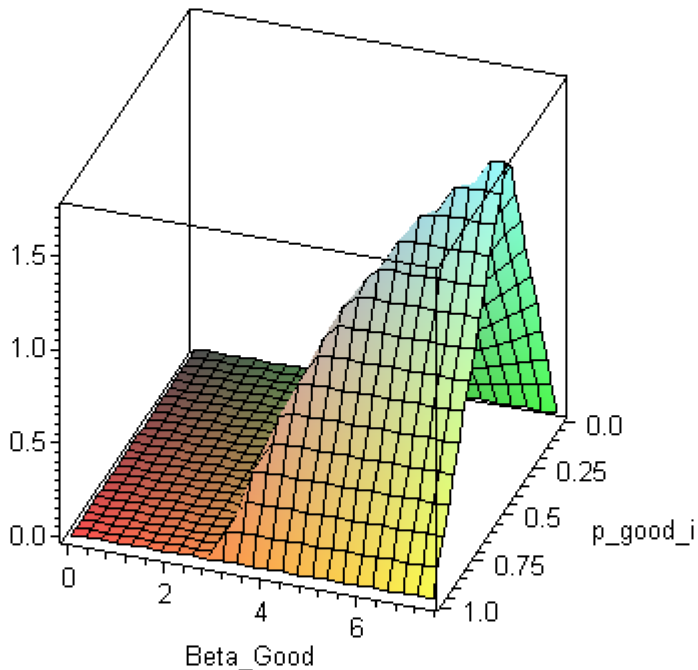

Figure 2: Information value as a function of attribute importance and uncertainty

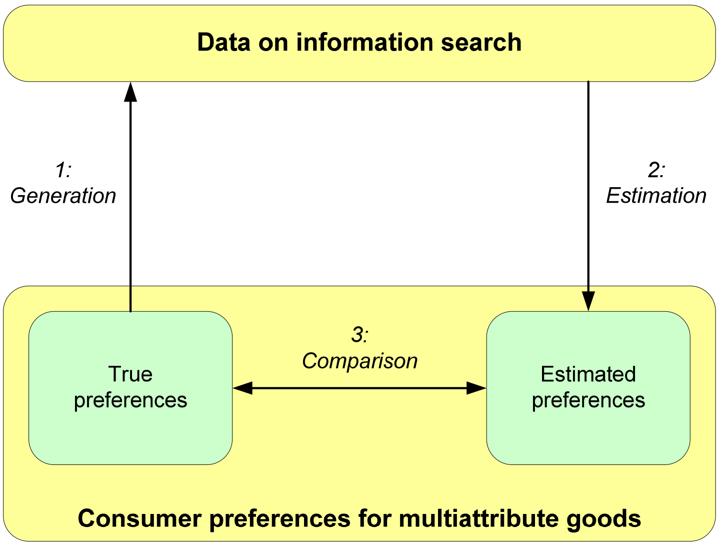

Figure 3: Schematic overview of empirical analyses

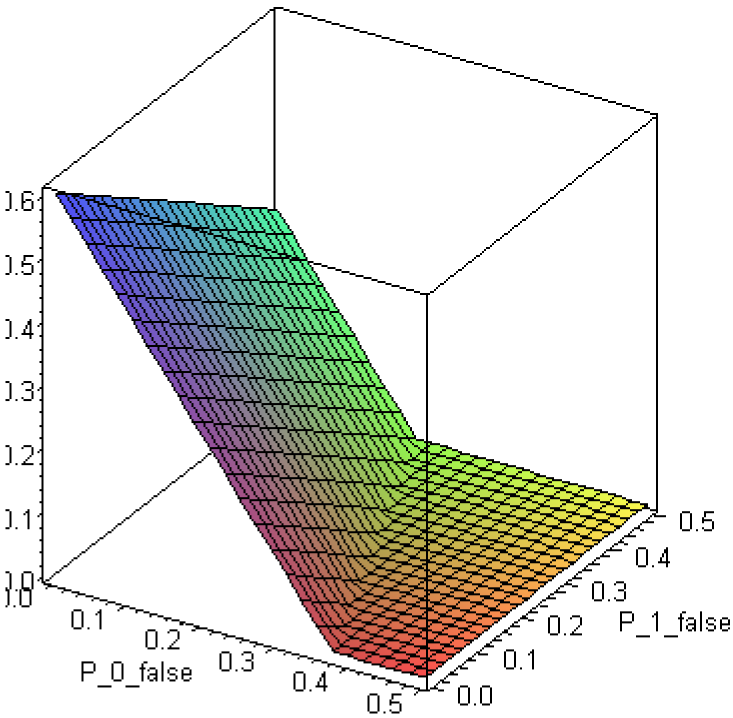

Figure 4: Information value as a function of information unreliability