Uncovering the influence of commuters' perception on the reliability ratio

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Abstract

The dominant method for measuring values of travel time savings (VOT), and values of travel time reliability (VOR) is discrete choice modeling. Generally, the data sources for these models are: stated choice experiments, and revealed preference observations. There are few studies using revealed preference data. These studies have only used travel times measured by devices such as loop detectors, and thus the perception error of travelers has been largely ignored. In this study, the influence of commuters' perception error is investigated on data collected of commuters recruited from previous research (1, 2). The subjects' self-reported travel times from surveys, and the subjects' travel times measured by GPS devices were collected. The results indicate that the subjects reliability ratio is greater than 1 in the models with self-reported travel times. In contrast, subjects reliability ratio is smaller than 1 in the models with travel times as measured by GPS devices.

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1 Introduction

Two of the most important values obtained from travel demand studies are the *value of travel time savings* (VOT), and the *value of travel time reliability* (VOR). The first refers to the marginal rate of substitution between travel cost and reductions in travel time (i.e. savings). The second refers to the marginal rate of substitution between travel cost, and increases in the predictability (i.e reducing the variability) of travel time. The ratio between these values is known as the *reliability ratio* (RR). This ratio refers to the marginal rate of substitution between reductions in travel time (i.e. savings), and increases in the predictability of travel time (i.e. reduce variability). The *value of travel time savings* has a long established history along with a firm theoretical background (i.e. the time allocation models), and many empirical estimates calculated by practitioners and researchers. Common resources on the theoretical foundations and (brief) empirical discussions are: (3, 4, 5, 6). Readers may also refer to detailed reviews of empirical estimates of VOT such as: (7, 8, 9, 10, 11, 12, 13). The *value of travel time reliability* traces its recent (quantitative) history back to the 1980s and 1990s with important contributions such as: (14, 15, 16, 17, 18, 19). Also, a thorough introduction to the topic is (20). In summary, the theoretical foundation of the *value of travel time reliability* rests on two frameworks: Centrality-Dispersion (or Mean-Variance) proposed by (14); and Scheduling delays under uncertainty proposed by (17, 19). The first is based on the idea that the travel time unreliability (or variability) is concentrated in a statistical measure of the dispersion of the travel time distribution. The second assumes that travelers have a specified time of arrival, and any *expected* late arrivals or *expected* early arrivals incurs disutilities. These disutilities are asymmetric in contrast to the Centrality-Dispersion framework that assumes all disutilities (due to unreliability) are weighted equally. It should be noted that *expected* refers to the first statistical moment of schedule delays due to late arrivals or early arrivals over the travel time distribution. Readers may refer to (21) for an extensive review on the *value of travel time reliability*.

The dominant method for the estimation of these values (i.e. VOT and VOR) is discrete choice analysis typically within the Random Utility framework (22, 23, 24). Generally, the data sources are stated preference experiments, and revealed preference observations. The stated preference experiments present choice scenarios with a variety of presentations (especially in the case of the *value of travel time reliability*) and abstraction (based on real options vs. nondescript options) to travelers. The revealed preference observations refer to actual choices done by travelers in the market (e.g. decisions in the current state of the transportation system of the travelers). Both may also be combined in discrete choice analysis. In revealed preference observations, travel times are experienced by the subjects, and they estimate the travel time through their own cognitive mechanism of perception. This mechanism may be influenced by external sources (e.g. travel information). In essence, there is a mismatch between travel time as reported by a traveler (*subjective travel time distribution*) and travel time as measured from a device (e.g. loop detector; *objective travel time distribution*). It is reasonable that the relationship between subjective travel times and objective travel times may expressed mathematically as: $T_s = T_o + \xi$. T_s is a random variable associated with the probability density given by the *subjective travel time distribution*. T_o is a random variable associated with the probability density given by the *objective travel time distribution*. ξ is the random *perception error* also associated with its own probability density. Thus, it is clear that may overestimate or underestimate the measured travel times, and this is likely to have influence over their valuation of travel time unless $\mathrm{E}(\xi) = 0$, and $\mathrm{Var}(\xi) \approx 0$. In other words, travelers are "optimizing" (i.e. executing decisions on travel choices) according to their own divergent views of the *objective travel time distribution* (20, 21).

The primary objective of this study is a systematic comparison of estimated reliability ratios using self-reported travel times from surveys, and measured travel times by Global Positioning System (GPS) devices. The self-reported travel times represent the travelers' *perceived* travel times or the travelers' *subjective* travel times. The measured travel times represent the travelers' *actual* travel time or the travelers' *objective* travel times. The secondary objective is to calculate confidence intervals for the estimated reliability ratios, and observe whether there are overlaps between the confidence intervals of the reliability ratios from self-reported travel times, and reliability ratios from measured travel times. The objectives are accomplished by analyzing data collected of travelers' self-reported travel times, and travelers' measured travel times by GPS devices from a previous research effort by (1, 2). This data is used to estimate two sets of random utility models: systematic utilities with *subjective travel times* (i.e. self-reported travel times); and systematic utilities with *objective travel times* (i.e. GPS measured travel times). Furthermore, the data set consists of the same subjects, and the self-reported and measured travel times for the same trips. Only direct commute trips (from home to work, and from work to home) are considered. The choice dimension is based on the *hierarchy* of the bridges across the Mississippi river in the Minneapolis-St. Paul region. The term *hierarchy* refers whether travelers choose a bridge that belongs to the Dwight D. Eisenhower National System of Interstate and Defense Highways of the United States of America.

The study is organized as follows: literature review of the relevant research to the topic at hand; data (description, and methodology); econometric models (specification, and estimation); discussion and results; and conclusions.

2 Literature Review

The literature review for this study encompasses two main areas: travelers' perception of travel time; and travelers' valuation of travel time with a greater emphasis on the valuation of travel time reliability. There are already plenty of studies focusing on each of these areas separately, and thus providing a comprehensive review is a difficult task that is not the purpose of this study. This review focuses only on three subareas: the Centrality-Dispersion framework for valuing travel time reliability; empirical evidence of the valuation of travel time reliability using revealed preference data; and a selective summary of relevant results of travelers' perception of travel time from the transportation research literature, and the psychology research literature. References to further readings are provided for the benefit of the readers.

2.1 Centrality-Dispersion

This theoretical framework is based on the notion that both the mean travel time, and its variance (or unreliability) are sources of disutilities for travelers. It was introduced to the transportation literature by (14). The formulation in a linear-additive form of the model is as follows:

$$U = \gamma_1 \mu_T + \gamma_2 \sigma_T \tag{1}$$

Travelers minimize the sum of the two terms (i.e. objective function for an unspecified choice dimension): the mean travel time of the trip, and the travel time variance of the trip. The mean travel time (μ_T) represents the centrality measure of the travel time distribution. The travel time variance (σ_T) represents the dispersion measure of the travel time distribution. Mean-variance is the usual name of this framework in the transportation literature, despite the fact that centrality and dispersion measures vary across studies. Typically, the mean is the preferred measure of centrality, and the standard deviation the preferred measure of dispersion in travel demand analyses.

The γ parameters in equation (1) are usually estimated using discrete choice methods based on random utility theory. In addition, a travel cost variable ($\gamma_3 C$) is added to the equation to allow the computation of marginals rate of substitution such as the value of travel time savings (VOT), value of travel time reliability (VOR), and the reliability ratio (RR). These are defined mathematically as,

$$VOT = \frac{\partial U/\partial \mu_T}{\partial U/\partial C} \tag{2}$$

$$VOR = \frac{\partial U/\partial \sigma_T}{\partial U/\partial C} \quad (3)$$

$$RR = \frac{\partial U/\partial \sigma_T}{\partial U/\partial \mu_T} = \frac{VOR}{VOT} \quad (4)$$

Readers may refer to (21) for additional details.

2.2 Empirical evidence

There are two common data sources for the estimation of values of travel time reliability: stated choice experiments with a variety of presentations (i.e. designs) for questionnaires; and revealed choices with objective travel time distributions (i.e. travel times measured by devices such as: Global Positioning System [GPS] , loop detectors, and others). Both data sources may also be pooled to overcome some of their own deficiencies. Revealed choices may also be estimated using subjective travel time distributions (i.e. travel times reported by travelers memory). The differences between subjective travel time distributions and objective travel time distributions, as discussed previously, are likely to exist because of perception errors. It should be noted that there are also perception issues with stated choice experiments: the subjects understanding of travel time variability in stated choice experiments versus the subjects understanding of travel time variability in actual observed trips; and survey presentation that matches the survey respondents understanding of the abstract situation with the analysts intentions of the abstract situation. However, the focus of this study is only on the perception error in revealed preference studies. Furthermore, the stated choice experiments are far more common than collected revealed preference observations for the measurement of values of travel time reliability. There are few studies using revealed preference data because of the few examples of experimental settings with significant travel time variation across at least two alternatives (e.g. high occupancy toll lanes); difficulties with measuring travel time data; costs associated with planning (e.g. methodology of experiment) and deployment (e.g. surveys, devices to measure travel time) of revealed preference studies; and others. Readers may refer to (21) for a more thorough review on empirical studies for the valuation of travel time reliability.

2.2.1 Revealed preference studies: Objective travel time distribution

Most of the revealed preference studies has been done analyzing data collected from California State Route 91 (SR-91) in greater Los Angeles, and Interstate 15 (I-15) in San Diego, California, United States. (25, 26, 27, 28, 29) are the studies done using data from SR-91, and (30) is the study done using data from I-15. The SR-91 freeway include four untolled lanes, and two high occupancy toll lanes in each direction. The high occupancy toll lanes opened in 1995. The tolls assigned to the lanes vary by time of day. (25) collected revealed choices through mail surveys, and identified the drivers in the corridor by their license plates. The travel time data was collected through loop detectors. However, no toll data was collected, and the travel costs were include through another variable representing wage rate. (25) estimated random utility models of route choice and time of day. They used the Centrality-Dispersion framework with two measures of centrality (mean and median), and two measures of dispersion (standard deviation and the 90th percentile minus the median). They also used the scheduling approach (see (21)) for the random utility models. They estimate values of travel time savings, and values of travel time reliability. However, they express doubt with regards to the estimates, because of the many assumptions used with the loop detector data. (26, 27) collected actual subjects' lane choices, and stated choices from stated preference experiments. Both data sources are combined to enrich their econometric models. The revealed choices were collected using telephone interviews, and mail-back questionnaires. (26, 27) estimate random utility models with systematic utilities containing attributes such as: toll, travel time, and reliability. A set of models focuses on lane choices alone, and another set focuses on lane choices and transponder choices (the transponders are devices required to use the high occupancy toll lanes). The econometric models allow (26, 27) to estimate values of travel time savings, and values of travel time reliability. They use the median as the centrality measure, and the difference of the 80th and 50th percentiles as the dispersion measure. In addition, the travel time data was obtained by in-field measurements (performed by others instead of the subjects) corresponding approximately to the travel periods of the subjects. (28) contains a very detailed account of (26, 27). On the other hand, (29) only uses aggregate counts, and travel times from loop detectors with several assumptions representing the choices depending on origin-destinations from ramps along the freeways. This data is not similar to revealed choices or stated choices. (29)'s VOT and VOT estimates are similar to those found in the previous studies. In the case of I-15, the tolls of the high occupancy toll lanes became responsive to travel demand to maintain free flow traffic conditions in 1998. (30) uses panel data collected by researchers from San Diego State University. The panel contains revealed choices by high occupancy toll lane users, nontolled lane users, and others users from Interstate 8. Travel times are collected from loop detector data based on subjects' movements between ramps across the freeway. (30) estimates random utility models of mode choice (subscriber, nonsubscriber, carpooler, and others similar). He uses the Centrality-Dispersion framework. He uses the median as centrality measure, and the difference between the 90th percentile and median as the dispersion measure. Toll data was also collected in the panel. (30)'s results are similar to the previously discussed studies.

Lastly, studies (31, 32) are also done on the high occupancy toll lanes in Interstate 394 at Minneapolis, Minnesota, and another study (1) is done using bridges crossing the Mississippi river in Minneapolis, Minnesota. (31) uses loop detector data based on the methodology found in (29). An extension of (31) is that the VOT and VOR estimates vary by time of day. (32) introduce a experimental design to analyze subjects choices based on GPS devices, and transponders. Subjects are equipped with GPS devices, and transponders. The subjects are required to drive several weeks on each of the routes alternatives, and the last two weeks the subjects are allowed to freely choose between the route alternatives. The choice dimension of the random utility models are routes: high occupancy toll lanes; untolled lanes; and signalized parallel arterials to the Interstate 394. The revealed choices, and the travel times are collected through the GPS devices. However, the study had a high attrition rate due to the experimental design. (32) estimated random utility models using the Centrality-Dispersion approach with distinct measures (centrality: mean, median; dispersion: standard deviation, 90th percentiles minus median, and interquartile range). The VOT and VOR estimates were lower than previous estimates, but the confidence intervals were wide enough to contain the estimates of previous studies. (1) uses GPS data collected to study the travel behavior of commuters after the Interstate 35W collapse in Minneapolis, Minnesota (2). This data is used to estimate random utility models of bridge choice crossing the Mississippi river where the travelers choose among several possible alternatives. The Centrality-Dispersion framework is used with the mean as the centrality measure, and the standard deviation as the dispersion measure. Only reliability ratios are estimated. Furthermore, the data collected in (1, 2) is also used in this study. This data is described in section 3.

2.2.2 Revealed preference studies: Subjective travel time distribution

At the moment, no studies have been conducted with regard to the travelers' *perceived* travel times (i.e. subjective travel time distribution). Thus, it is currently unknown whether travelers' *perception error* (see the brief discussion in section 1) has a significant impact on estimates of VOT and VOR. The main objective of this study is to contribute results with regards to this unanswered research question.

2.3 Perception of travel time

Psychologists have showed clear interest into the behavioral and cognitive mechanism of perception of time. They have classified the perception of time into three main categories: subjective time passage (i.e. perception of the speed that time passes); estimation of time duration; and simultaneity and succession of time. The estimation of time duration is the most frequently studied category by psychologists, and thus it is better understood. It is also the dimension of time perception that will be focus of this study, and it has been the focus of most studies investigating perception of travel time in the transportation literature. Main factors identified in the duration of time are: temporal relevance, temporal uncertainty, affective elements, arousal, task complexity, temporal expectancies, absorption and attentional deployment. *Temporal relevance* refers to the significance of time for performing a task in an optimal way. *Temporal uncertainty* refers to how well the subject can estimate the duration of the task given previous experiences. Thus, results indicate that when a task is commonly performed, its uncertainty is low, but when a task is uncommonly performed, its uncertainty is high. In addition, tasks with high levels of relevance and uncertainty are associated with estimates of duration of time tend to be longer. In contrast, tasks with low levels of relevance and uncertainty are associated with shorter duration of time (33, 34). *Affective elements* represent emotional levels of the individuals while performing a task. For example, subjects experience fear estimate the duration of time to be shorter than those neutral (35, 36, 37). *Arousal* refers to a state of physical activation. For example, subjects under the influence of drugs may overestimate the duration of time in comparison to others without such influence (38, 39, 40). *Task complexity* refers to the effort and the characteristics of the task. Research indicates that high complexity leads to overestimation of the duration of time. In general, subjects that process more events during the time at hand will tend to overestimate as they will have more memories (41). *Temporal expectancies* refer to the accumulated previous experiences that allow the subject to generate an estimate of the duration of time for a task. Results indicate that previous durations of time will guide the duration of time for a new task (previously performed), and also update experiences (42, 43). *Absorption and attentional deployment* refer to the focus of subjects and their understanding of the task that must be performed. Subjects that do not focus and/or do not understand how to perform the task at hand will take further time figuring the details of it, and thus may overestimate the duration of time (44, 45). Readers may refer to (46) for more details.

In the case of perception of travel time in the transportation literature, most of the studies as previously mentioned have focused on the estimation of time duration of the travelers. In essence, the travel times reported by the travelers are analyzed through several methods with the actual travel times that the subjects experienced. Transportation researchers may have control over the environment similar to psychological researchers through computer-based simulations, and/or fixed-base vehicle simulators (47, 48). On the other hand, transportation researchers may collect data from field observations through questionnaires, cameras, GPS devices, and others (49). It should be noted that there is an obvious trade-off between the analyst's control over the environment, and the realism of the environment to the subjects.

In the case of studies using simulators, (47, 48) study the travelers' preferences towards waiting times during distinct traffic conditions (e.g. free flow traffic). They used computer administered stated choice experiments with written travel times and stated choice experiments based on subjects' travel times inside vehicle simulators. The results indicated that subjects perception of the travel times as presented in the computer administered experiments, and the experiments with vehicle simulators are significantly different.

In the case of field observations, (49) studied the travelers' perception of their morning commute. The data sources are reported travel times by subjects from questionnaires, and travel times as observed from cameras. The reported travel time distributions are compared to the camera travel time distributions. The results indicate that perception error is relevant.

3 Data

3.1 Recruitment

Subjects were recruited through announcements posted in different media including: *Craigslist.org*, and *CityPages.com*; the free local weekly newspaper *City Pages*; flyers at grocery stores; flyers at city libraries, postcards handed out in downtown parking ramps; flyers placed in downtown parking ramps; and emails to more than 7000 University of Minnesota staff (students and faculty were excluded). More than 900 subjects responded, and consequently they were randomly selected among those the following requirements:

1. Age between 25-65,
2. Legal driver,
3. Full-time job and follow a "regular" work schedule
4. Travel by driving alone
5. Likelihood of being affected by the reopening of the new I-35W Mississippi River bridge.

Potential subjects (randomly selected from the original pool) were instrumented with logging-type GPS devices (QSTARZ BT-Q1000p GPS Travel Recorder powered by DC output from in-vehicle cigarette lighter) about 2 weeks before the replacement I-35W bridge opened to the public. The GPS devices record the position of the vehicles at a frequency of 25 meters per location point (latitude and longitude coordinates) between engine-on and engine-off events. The subjects remained instrumented for 8 weeks. The subjects received no instructions with the exception of filling the periodic surveys. In addition, subjects completed two types of web-based surveys: a survey at the end of the study to evaluate their driving experience on routes using different bridges crossing the Mississippi river, and provide socio-demographic information; and periodic surveys about three times per week to collect information with regards to their route preferences, and route information (e.g. self reported travel times).

A total of approximately 97 subjects had usable complete day-to-day GPS data, and survey data. For this study, only 39 subjects had the required data according to the subsequent Section 3.2.

3.2 Methodology

The data analysis process can be divided in four phases:

1. Identification of commute trips per subject from GPS data on the bridges of interest (see Figure 1);
2. Matching of the commute trips from GPS data to the trips from periodic survey data;
3. Information extraction (e.g. travel time) of commute trips per subject from GPS and survey data;
4. Specification and estimation of econometric models using travel times from GPS and from survey data.

The first phase uses the coordinates (latitude and longitude) of the trips per subject, and the *TLG network* in order to identify the trips crossing bridges, and the bridges crossed. The *TLG network* refers to a digital map maintained by the Metropolitan Council and The Lawrence Group (TLG). It covers the entire 7-county Minneapolis-St. Paul Metropolitan Area and is the most accurate GIS map of this network to date. The TLG network contains 290,231 links, and provides an accurate depiction of the entire Minneapolis-St. Paul network at the street level. The identification is done by spatial matching the coordinates of each bridge of interest to the coordinates of each set of trips for each subject. Also, subjects' trips must start at their home/work and end at their work/home locations in order to be considered commute trips (only *direct* commute trips). The distance tolerance between origins (destinations) to home (work) locations was set to 600 meters. The home and work locations are geocoded (transformed into latitude and longitude coordinates) from the actual addresses provided by the subjects on the web-based surveys. The origin and destination pair of each trip is obtained by mapping the coordinate points into trajectories of engine-on and engine-off events. Moreover, inaccurate points due to GPS "noise", and out-of-town trips (e.g. during Thanksgiving) were excluded. Lastly, only the trips after September 18th are considered as this is the date the new I-35W Bridge opened to the public at 5 AM.

The second phase is done by matching the dates of the commute trips from GPS data to the dates of commute trips from survey data. The subjects completed the information of commute trips within the same day that they took their trips. Thus, times of departure of the commute trips must be earlier than the time of completing the periodic survey by the subjects. Furthermore, any trips that are not considered commute trips according to the subjects in the survey data are excluded.

The third phase extracts usable information from the matched trips such as: statistics of travel time distribution of all trips (e.g. mean, standard deviation, and others used in the Centrality-Dispersion framework) for each subject from GPS data and periodic survey data. This process is performed for both home to work trips, and work to home trips.

The fourth phase is explained in section 4.

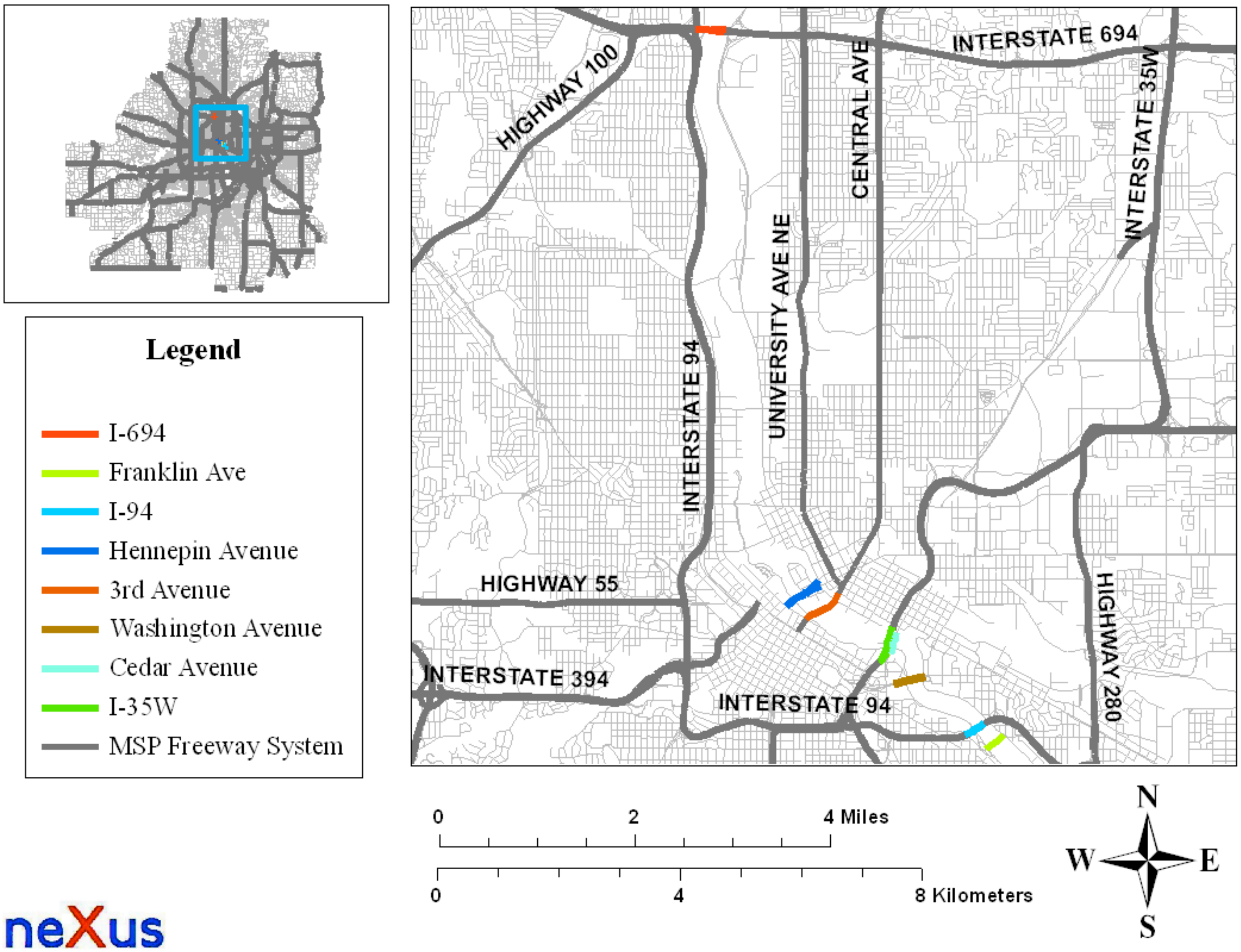

Figure 1: Bridge locations (Source: (1))

3.3 Descriptive statistics

Table 1, summarizes socio-demographic information of the subjects. The sample differs from the population of the Minneapolis-St. Paul region in several ways: subjects are older, more educated and have a more uniform distribution of income.

Table 1: Socio-Demographics attributes of the sample

Number of Subjects		39	
		Sample	Twin Cities
Sex	Male	46.15%	49.40%
	Female	53.85%	50.60%
Age (Mean, Std. Deviation)		(50.44, 10.81)	(34.47, 20.9)
Education	11th grade or less	0.00%	9.40%
	High School	17.95%	49.60%
	Associate	15.38%	7.70%
	Bachelors	61.54%	23.20%
	Graduate or Professional	5.12%	10.10%
Household Income	$49,999 or less	23.08%	45.20%
	$50,000 to $74,999	20.51%	23.30%
	$75,000 to $99,999	25.64%	14.60%
	$100,000 to $149,999	23.07%	11.00%
	$150,000 or more	7.69%	5.90%
Race	Black/African American	7.69%	6.20%
	White or Caucasian	79.49%	87.70%
	Others	12.81%	6.10%

Minneapolis' Population statistics are obtained from the (50)

4 Econometric models

In this study, the data set is analyzed through random utility models (22, 23, 24). The data set is composed of two observations per subject. There are 39 distinct subjects, and thus 78 observations (see section 3.1). Each two observation per subject represent the consolidation of all the home to work trips, and all the work to home trips of a subject. The set of home to work trips per subject, and the set of work to home trips per subject allow to obtain travel time distributions for these same trips (see section 3.2) from GPS (*objective travel time distribution*) and survey data (*subjective travel time distribution*) per subject. Thus, centrality and dispersion measures are calculated on the travel time distributions, and are included as attributes in the systematic utilities of the random utility models. The choice dimension is based on the *hierarchy* of the bridges across the Mississippi river in the Minneapolis-St. Paul region (see figure 1). The term *hierarchy* refers whether travelers choose a bridge (from those listed in figure 1) that belongs to the Dwight D. Eisenhower National System of Interstate and Defense Highways of the United States of America. It should be noted that only 39 subjects had enough observations on Interstate bridges, and nonInterstate bridges. Thus, the set of home to work trips and the set of work to home trips are further disaggregated to two alternatives (or choices). The first alternative represents the *most used* bridge that belongs to the Interstate category, and the second alternative represents the *most used* bridge that belongs to the nonInterstate category. The term *most used* refers to the bridge with the highest number of commute trips. The bridge with the smallest travel time by centrality measure and dispersion measure is selected in the case that two or more bridges have the same number of commute trips. Furthermore, an alternative is considered chosen by a subject according to whether the number of trips on the alternative is strictly higher compared to the other alternative.

4.1 Random utility models

The random utility models considered in this study can be formulated as binomial logits (22). Assume that the utility function a decision-maker k in the set of decision-makers $\mathcal{N}$ associates with alternative j in the set of choices $\mathcal{J}$ (for this study $\mathcal{J}$ only have two alternatives) is given by:

$$U_j^k = V_j^k + \epsilon_j^k \tag{5}$$

For this case of binomial logit model, the functional form is given by equation (5). The first term (V_j^k) is the systematic utility, and the second (ϵ_{jt}^k) is a random vector identically and independently distributed (i.i.d.) over alternatives and decision-makers following a extreme value type 1 (or Gumbel) distribution with 0 location, and scale set to 1. For this study, the systematic utility is linear in parameters; $V_j^k = \beta^T x_j^k$, where β is the coefficient vector, and x_j^k are the vectors of explanatory variables in the regressors matrix.
The estimation of binomial logits are straightforward, and it is done by maximizing the loglikelihood, which is of closed form. The details are standard and are found in Train (22), Ortuzar and Willumsen (23), Ben-Akiva and Lerman (24). The models are estimated using STATA (51).
The likelihood for these binomial logit models is given by:

$$L(\beta) = \Pi_{\forall k \in \mathcal{N}} \Pi_{\forall j \in \mathcal{J}} \left(\frac{e^{V_j^k(\beta)}}{\sum_{j=1}^{J} e^{V_j^k(\beta)}} \right)^{\gamma_{kj}} \tag{6}$$

Where the γ_{kj} variable is one for the chosen j alternative of the k decision-maker, and zero otherwise.

4.2 Hypothesis testing

There are two hypothesis tests that are considered for the random utility models in this study. For the nested models, the *Wald tests* are used as they only depend on the covariance matrix of the unrestricted models, and do not require estimation of the restricted models. These tests are asymptotically equivalent to the *likelihood ratio tests*. For the nonnested models, the *Akaike information criterion* (AIC), and *Bayesian information criterion* (BIC) are used in order to compared the statistical fit of the binomial logits with travel times from survey data to the binomial logits with travel times from GPS data. Furthermore, the confidence intervals for the *reliability ratio* of the models are calculated using the *Delta method*. see (52, 53, 54) for more details.

4.3 Systematic Utility for the models

The additive linear in parameters systematic utility for the alternatives for all models is:

$$V_j^k = f(T, V, S, D, A; \beta) \tag{7}$$

where

- T: Centrality measure of travel time
- V: Dispersion measure of travel time
- S: Socio-demographic
- D: Type of work trip
- A: Alternative specific constants (ASC)

4.3.1 Centrality measure of travel time

The centrality measures are calculated for the travel time distributions for the set of home to work trips, and work to home trips for each alternative per subject as described in section 4. For this study, the mean, and the median are considered as centrality measures. These variables are alternative specific. The variables are measured in minutes.

4.3.2 Dispersion measure of travel time

The dispersion measures are calculated for the travel time distributions for the set of home to work trips, and work to home trips for each alternative per subject as described in section 4. For this study, the standard deviation (a typical measure in the Centrality-Dispersion framework), and the difference between the 90th percentile and the median (DMP90) are considered as dispersion measures. These variables are alternative specific. The variables are measured in minutes.

4.3.3 Socio-demographic

These are extracted from the socio-demographic questions in the web-based surveys.

- Gender (1 = Male; 0 = Female).
- Income. Four categories: $(\$0, \$49,999]$, $(\$50,000, \$74,999]$, $(\$75,000, \$99,999]$, and $(\$100,000, \infty+)]$. The first category is the base case. (2008 US dollars).

4.3.4 Type of work trip

It is a binary variable indicating whether the trip originates from home (1 = from home to work) or from work (0 = from work to home).

4.3.5 Alternative specific constants

For these binomial logits, the alternative specific constant of the Interstate alternative is set to 0.

5 Discussion and results

Table 2 presents the estimates of the random utility models (binomial logits) along with the reliability ratios, and goodness of fit statistics. There are four types of models estimated according to distinct centrality and dispersion measures of travel time: Mean/Standard Deviation (SD); Mean/Difference between 90th percentile and median (DMP90); Median/SD; and Median/DMP90. The four types of models are estimated with self reported travel times from surveys, and with measured travel times from GPS devices. The results indicate that the estimates of the centrality measures and dispersion measures of travel times are negative, and highly statistically significant across all models. The goodness of fit statistics indicate that the models with self reported travel times from surveys fit the data better in contrast to models with measured travel times from GPS devices. Both the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC) favor the models with self-reported travel times over the models with measured travel times. Thus, the models estimated with self reported travel times are preferred by statistical basis, and more specifically the Mean/SD model.

The reliability ratios in the models with self reported travel times are higher than 1, except for the Mean/DMP90. The 95% confidence intervals of these models indicate that values greater than 1 are more plausible. In contrast, the reliability ratios in the models with measured travel are less than 1. The 95% confidence intervals of these models indicate that values less than 1 are more plausible. In addition, there are few overlaps of the 95% confidence intervals for the same models with self reported travel times vs. measured travel times. This is an important finding as it gives different results with regards to the subjects valuing of travel time savings, and travel time reliability.

The reliability ratio is defined as the marginal rate of substitution between the travel time variability, and the expected travel time. Thus, the centrality-dispersion models with the self reported travel times indicate that the subjects are valuing higher the travel time variability over the expected travel time, except for the Mean/DMP90 model. In contrast, the centrality-dispersion models with measured travel times indicate that the subjects are valuing higher the expected travel time over the travel time variability. Therefore, questions arise about which of the travel times (self reported or measured) should be trusted. This leads back to the previous discussion about perception error. It is known that perception error is a factor that distorts the travelers' interpretation of the actual travel times. It is more than likely that the travelers execute their travel decisions based on their perceived travel times, and not the actual travel times. This perception also is linked to the valuation of travel time, and thus the reliability ratios may be inflated or deflated depending on the level of distortion or magnitude of the perception error.

Lastly, the socio-demographic (e.g. income and gender), and type of work trip variables were not found statistically significant. Thus, the subjects were more influenced by the travel time measures in their choices. This result agrees with the findings in (1) with the same data source, albeit not the exact same data set.

6 Conclusion

This study presents novel results that are starting to scratch the surface of the influence of perception on the valuation of travel time. At the moment, there is none to little effort in favor of intersecting two main research areas in the transportation literature: travelers' perception of travel time; and travelers' valuation of travel time with a greater emphasis on the valuation of travel time reliability. There are already many studies identifying that subjects' perception of travel times has been found to be a significant factor in studies. Travelers overestimate or underestimate the actual travel times they experience. Therefore, it is likely that revealed preference studies may be underestimating or overestimating the value of travel time savings, and value of travel time reliability as the objective travel time distributions (measured from devices) differ from the subjective travel time distributions (self reported by travelers).

In this study, the influence of commuters' perception error is investigated by estimating random utility models (i.e. econometric models) on data collected of commuters recruited from a previous research study in the Minneapolis-St. Paul region (1, 2). This data (surveys, and Global Positioning System [GPS] points) consists of work trips (from home to work, and from work to home) of subjects . For these work trips, the subjects' self-reported travel times, and the subjects' travel times measured by GPS devices were collected. The results indicate that the subjects value travel time reliability more than travel time savings (i.e. reliability ratios greater than 1) in the econometric models with self-reported travel times. In contrast, subjects value travel time savings more than travel time reliability (i.e. reliability ratios smaller than 1) in the econometric models with travel times as measured by GPS devices. Furthermore, the models with self reported travel times are found to statistically fit the data better in comparison to the models with measured travel times.

Finally, these initial results are actually a harbor for the departure of new studies trying to "unpack" the factors governing the perception error of the travelers ((55) contains promising results) , and also for studies focusing on the influence of external sources of information (e.g. travel information) on the magnitude of the values of travel time savings, and values of travel time reliability.

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Table 2: Random Utility Models

Variables	Survey (Mean/SD)	Survey (Mean/DMP90)	Survey (Median/SD)	Survey (Median/DMP90)	GPS (Mean/SD)	GPS (Mean/DMP90)	GPS (Median/SD)	GPS (Median/DMP90)
	Estimates (T-Stats)	Estimates (T-Stats)	Estimates (T-Stats)	Estimates (T-Stats)	Estimates (T-Stats)	Estimates (T-Stats)	Estimates (T-Stats)	Estimates (T-Stats)
Centrality - Travel time - [Interstate/nonInterstate]	-1.19 (-2.89) ***	-0.46 (-3.72) ***	-1.20 (-2.90) ***	-0.70 (-3.56) ***	-0.33 (-3.88) ***	-0.31 (-3.86) ***	-0.19 (-3.39) ***	-0.17 (-3.31) ***
Dispersion - Travel time - [Interstate/nonInterstate]	-1.54 (-2.89) ***	-0.38 (-3.41) ***	-1.93 (-3.05) ***	-0.61 (-3.71) ***	-0.14 (-3.01) ***	-0.12 (-2.75) ***	-0.15 (-3.41) ***	-0.11 (-2.91) ***
Gender - [nonInterstate] 1 = Male; 0 = Female	1.25 (0.85)	1.54 (0.103)	2.02 (1.46)	1.84 (1.69) *	-0.54 (-0.75)	0.25 (0.52)	0.09 (0.14)	0.55 (0.94)
Income - [nonInterstate] $[\$50,000, \$74,999]$ 1 = In; 0 = Out	1.32 (0.76)	0.400 (0.36)	0.66 (0.42)	0.05 (0.04)	0.68 (0.71)	-0.13 (-0.14)	-0.39 (0.44)	-0.63 (-0.76)
Income - [nonInterstate] $[\$75,000, \$99,999]$ 1 = In; 0 = Out	1.52 (0.86)	-0.042 (-0.04)	0.66 (0.42)	-0.29 (-0.26)	0.14 (0.14)	-0.80 (-.78)	-0.27 (-0.31)	-0.79 (-0.92)
Income - [nonInterstate] $[\$100,000, \infty+)]$ 1 = In; 0 = Out	-1.75 (-0.77)	-1.03 (-0.89)	-3.73 (-1.65) *	-1.66 (-1.16)	1.07 (1.17)	0.25 (0.30)	0.08 (0.10)	-0.32 (-0.43)
Type of work trip - [nonInterstate] 1 = from home to work; 0 = from work to home.	-0.19 (-0.14)	0.49 (0.62)	0.29 (0.80)	0.75 (0.80)	-0.29 (-1.37)	0.35 (0.52)	-0.16 (-0.28)	0.31
Alternative Specific Constant - [nonInterstate]	-2.07 (-1.13)	-2.02 (-1.86) *	-2.04 (-1.48)	-2.35 (-1.85) *	-1.03 (-1.37)	-1.20 (-1.66) *	-0.22 (-0.31)	-0.60 (-0.90)
Reliability Ratio RR	1.30	0.83	1.60	1.14	0.42	0.39	0.77	0.65
95% Confidence Interval	[1.08, 1.51]	[0.59, 1.08]	[1.32, 1.89]	[0.95, 1.35]	[0.18, 0.69]	[0.16, 0.61]	[0.37, 1.16]	[0.28, 1.02]
Intercept Log-Likelihood $ll_{\hat{ASC}}$	-51.472515	-51.472515	-51.472515	-51.472515	-51.472515	-51.472515	-51.472515	-51.472515
Final Log-Likelihood $ll_{\hat{\beta}}$	-9.4065462	-22.884538	-10.486297	-18.352769	-30.111183	-31.944981	-36.652578	-39.258894
Likelihood ratio index ρ^2	0.81725109	0.55540276	0.79627386	0.64344525	0.41500463	0.37937789	0.28791942	0.23728433
Akaike Information Criterion AIC	34.81309	61.76908	36.97259	52.70554	76.22237	79.88996	89.30516	94.51779
Bayesian Information Criterion BIC	59.21194	86.16792	61.37144	77.10439	100.6212	104.2888	113.704	118.9166
Number of observations	78	78	78	78	78	78	78	78
Number of subjects	39	39	39	39	39	39	39	39

* is 10% significance level, ** is 5% significance level, *** is 1% significance level

See the section 4 for details on the econometric models.