Eliciting travel time perceptions and exploring its impact on value of time

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ABSTRACT

The value of time is crucial to transport policy as it drives the majority of benefits in appraisals. However, individuals can perceive time differently to reality, and this can result in misleading estimates of the value of time in stated preference surveys. Furthermore, there is a lack of methods to determine the distribution of travel time perceptions. This study proposes a model of perceived travel time distribution, including an experimental mechanism to elicit perceived travel time distributions from stated travel time ranges. Two theorems are derived that relate the stated travel time range to the perceived travel time distribution and incentive structure to report accurately. The theorems are validated from a field driving experiment with taxi drivers in Dhaka, Bangladesh, which is also used to study whether stated perceptions elicited with and without incentives are different from actual travel time distributions. The results show that individuals' perceived travel time distributions are significantly different from actual travel times, and that this can result in statistically significant differences in values of time of up to 17% due to perceptions of lower travel times leading to higher values of time. The experiment also validated the assumptions underlying the theorems. Finally, the study shows that ranges stated under clear monetary incentives follow the theoretical predictions, and that Dhaka taxi drivers on average convey a risk of 77% when stating travel time ranges. The theoretical results presented in this study can be applied more broadly in other domains to study perceptions.

KEYWORDS

Perceived distributions; Beliefs; Preferences; Value of time; Experimental economics

1 INTRODUCTION

The concept of a 'value of time'[1] (VOT) is central to transport analysis. It refers to a conversion rate that measures an individual's willingness to trade between time and money. In particular, it is used in the calculation of the generalised cost of a trip, which is an index reflecting all of its monetary and non-monetary costs. This includes travel time, which is converted into monetary units by the VOT, as well as fares, fuel costs and any other measurable attributes. These generalised costs feed many different aspects of transport analysis, for example to determine route choice in transport modelling.

One of the most critical applications of generalised costs is in measuring the benefits of travel time savings. Mackie et al. (2001) estimated that travel time savings constitute around 80% of monetised benefits in appraisals of major road projects in the United Kingdom. Since these appraisals are the primary decision-making tool for comparing options and determining if a proposal is worthwhile to society, it is essential to ensure that the VOT driving them is accurate. Common methods for estimating VOTs include revealed preference (RP) and stated preference (SP) studies, which measure how individuals trade between time and money in existing or experimental scenarios respectively.

However, a complication is that the travel behaviour of an individual is governed by their internal perception of time rather than actual time, and the two may not be the same. In several studies, travel times stated by survey participants were around 1.5 times larger than actual travel times (Burnett, 1978; Henley et al., 1981; MVA Consultancy et al., 1987; O'Farrell and Markham, 1974; Rietveld et al., 1999; van Exel and Rietveld, 2010), which suggests that travel times are generally perceived as longer than reality. Some potential factors for this are summarised in Table 1. Peer et al. (2014) and Parthasarathi et al. (2013) found that network characteristics and types of links may be factors, where higher cognitive load increases the perceived travel time. On the other hand, they found that familiarity leads to underestimation of travel times. This is consistent with a study by Peruch et al. (1989) in which taxi drivers underestimated travel distances. There is also evidence that under emotional stress, people tend to overestimate travel times (Droit-Volet and Meck, 2007). However, under low mental arousal the findings are inconclusive, with some studies claiming underestimation of time (Block and Zakay, 1996), and others reporting overestimation of time (Flaherty, 1999; Glicksohn, 2001).

Table 1: Factors influencing perceptions of travel time

Factors influencing perceptions	Impact on perception	References
Cognitive load	+	Block et al. (2010); Baldauf et al. (2009)
Familiarity	-	Boltz et al. (1998)
Unpredictable	+	Boltz (1998)

Due to the differences between perceived and actual travel times, Brownstone and Small (2005) speculated that SP studies could produce biased estimates of VOT. There is evidence in the literature that RP-based estimates of VOT are higher than SP-based ones (Brownstone and Small, 2005; Ghosh, 2001; Hensher, 2001; Isacsson, 2007; Small et al., 2005), which could be attributed to the overestimation of travel times in perceptions. Despite

[1] In the theoretical frameworks of Becker (1965) and DeSerpa (1971), the 'value of time' and 'value of travel time savings' are distinct. The former refers to the monetary equivalent (in terms of utility gained) of adding a certain amount of time to an individual's day, and the latter refers to the monetary equivalent of reducing time travelling. In transport, the two terms are often conflated, and the value of time in fact refers to value of travel time savings, as in this paper.

this, SP studies are still vital to transport practice to understand scenarios that are not represented in RP data.

A further issue of SP studies identified by Peer et al. (2014) is that stated travel times are prone to reporting errors. However, recent research shows that using monetary incentives (Hensher, 2010), and more specifically using incentive compatible tasks from experimental economics (Arbis et al., 2016; Dixit et al., 2014, 2015), could help significantly reduce these errors and biases.

In addition to perception versus reality, a less-studied aspect of stated travel times is the distribution of travel times perceived by an individual. When an individual is asked about the travel time on a route, it is natural that they would respond with a range rather than a point estimate to convey their perception of the route's travel time variability. However, it appears to be rare that participants are asked about travel time ranges in SP surveys, and even if they were, it is unclear how they should be interpreted. This is an issue that may become more relevant as transport analysis increasingly recognises variability in travel times, for example in measuring the value of reliability in cost benefit analyses.

Therefore, to inform and improve SP methods especially for measuring VOT, this paper investigates what can be understood about perceptions of travel time and its distribution when travel times are stated as a range. In particular, this study addresses the following questions:

1. Do perceptions of travel times differ from actual travel times in experimental conditions?
2. What do stated ranges of travel times reflect about travel time perceptions and their distribution?
3. What is the impact of accounting for perceptions on estimates of VOT?

Answers to these questions can provide insights into the impact of perceptions on travel choices, as well as help understand traveller uncertainties in travel time when accounting for risk attitudes in decision making.

To address these questions, this paper proposes an incentivised experimental mechanism, utilising experimental economics techniques, in which participants provide travel times as a range to elicit their perceived travel time distribution. Two theorems are derived to understand what is meant by the given range, and to demonstrate that their true travel time perceptions and distribution can be derived from it. A field driving experiment was conducted in Dhaka, Bangladesh, to test the mechanism and validate its assumptions. Like previous studies by Peruch et al. (1989), the experiment involved recruiting a pool of taxi drivers who had significant experience about the traffic network in the experiment. Although taxi drivers were found to underestimate travel distances in the earlier studies (Peruch et al., 1989), the use of incentives in this approach should help to effectively reduce such bias. Furthermore, choosing taxi drivers as the subjects helped to control for any impact of experience on travel time perceptions, and provided statistical power to isolate the impact of travel time perceptions on behaviour and choices. The findings from this study can inform experimenters, researchers and policy makers on a method to elicit perceptions and their role on choice, and demonstrates the impact of perceptions differing from reality on estimates of VOT.

The paper is organised as follows. Section 2 presents theory relating to stated travel time ranges. Section 3 describes the experimental design and the data collection procedure, followed by the estimation process using the experiment data, to test and validate the theory and its assumptions. Section 4 discusses the estimation results and Section 5 concludes the paper.

2 THEORY

This section explores what information is communicated when an individual states a travel time range. For this paper, a travel time range is defined as two travel times t_0 and t_1 which form the lower and upper bounds of an individual's 'expectation'[2] of the true travel time. It is assumed that the individual can be incentivised to give their true perception by being rewarded with value $k(t_0, t_1)$, which is a function of t_0 and t_1, if the actual travel time lies within t_0 and t_1.

Two theorems are derived regarding the stated travel time range. The first theorem shows that when people are incentivised to tell the truth and their underlying perceived travel time distribution is symmetric and concave, the midpoint of the range is the mean of their perceived travel times. The second theorem is a relationship between the stated travel time range and the travel time distribution. These theorems are useful in verifying the distribution and understanding its nature, and are validated using the data collected from the driving experiment. Furthermore, while these theoretical results have been formulated in the context of travel times, they can be easily generalised to study perception over any other domains with continuous states of nature.

2.1 Theorem 1

Theorem 1: Assuming (a) that the perceived travel time distribution is symmetric and concave, and (b) that the gradient of the utility w.r.t. to the incentive over the reported range $[t_0, t_1]$ is constant, the midpoint of the range $[t_0, t_1]$ reported by an individual is the mean of their perceived travel time distribution.

Proof: Let $f(t)$ be the perceived travel time distribution for an individual with mean $\bar{t}$ and standard deviation σ. Then, t_0 and t_1 can be rewritten as $t_0 = \bar{t} - \alpha\Delta$ and $t_1 = \bar{t} + (1-\alpha)\Delta$, where α represents the skewness in reporting of the travel time range, and Δ is the size of the range, i.e. $\Delta = t_1 - t_0$. Let $U(vt + m)$ denote the expected utility of choosing the route, where v and m are the coefficients determining the expected utility based on travel time t.

The base expected utility of the route $EU(0)$ is constant for a given preference and perceived travel time distribution, and is written as:

$$\begin{aligned} EU(0) &= \int_{0}^{\infty} U(vt+m) f(t) dt \\ &= \int_{0}^{\bar{t}-\alpha\Delta} U(vt+m) f(t) dt + \int_{\bar{t}-\alpha\Delta}^{\bar{t}+(1-\alpha)\Delta} U(vt+m)\, f(t) dt \\ &\quad + \int_{\bar{t}+(1-\alpha)\Delta}^{\infty} U(vt+m) f(t) dt \end{aligned} \tag{1}$$

Let $k(t_0, t_1)$ be an incentive (for example, as in Equation (14)) provided to the individual for stating a travel time range $[(\bar{t} - \alpha\Delta), (\bar{t} + (1-\alpha)\Delta)]$ that contains the observed travel time. For consistency, $k(t_0, t_1)$ can be rewritten as $k(\bar{t}, \Delta)$. With the incentive, the expected utility EU is then:

[2] The confidence level of this expectation can be determined, and was estimated for taxi drivers in Dhaka in the experiment.

$$EU = \int_{0}^{\bar{t}-\alpha\Delta} U(vt+m)f(t)dt + \int_{\bar{t}-\alpha\Delta}^{\bar{t}+(1-\alpha)\Delta} U\big(vt+m+k(\bar{t},\Delta)\big)\, f(t)dt + \int_{\bar{t}+(1-\alpha)\Delta}^{\infty} U(vt+m)f(t)dt \quad (2)$$

Using Equation (1), Equation (2) can be rewritten as:

$$EU = EU(0) + \int_{\bar{t}-\alpha\Delta}^{\bar{t}+(1-\alpha)\Delta} \Big(U\big(vt+m+k(\bar{t},\Delta)\big) - U(vt+m)\Big)\, f(t)dt \quad (3)$$

By the mean value theorem, there exists a $0 \leq \beta \leq 1$ such that:

$$EU = EU(0) + k(\bar{t},\Delta) \int_{\bar{t}-\alpha\Delta}^{\bar{t}+(1-\alpha)\Delta} \frac{\partial U\big(vt+m+\beta k(\bar{t},\Delta)\big)}{\partial k(\bar{t},\Delta)}\, f(t)dt \quad (4)$$

If the partial derivative of the utility w.r.t. $k(\bar{t},\Delta)$ (denoted as $\frac{\partial U}{\partial k}$ for simplicity) does not change significantly in the range $[\bar{t}-\alpha\Delta,\ \ \bar{t}+(1-\alpha)\Delta]$, then Equation (4) can be written as:

$$EU = EU(0) + k(\bar{t},\Delta)\frac{\partial U}{\partial k} \int_{\bar{t}-\alpha\Delta}^{\bar{t}+(1-\alpha)\Delta} f(t)dt \quad (5)$$

It should be noted that the gradient of the utility w.r.t. $k(\bar{t},\Delta)$ can vary significantly when starting from different times. However, the assumption of a constant gradient within the stated time interval is made since the stated time interval is small relative to the entire set of possible travel times.

Each individual is assumed to maximise their expected utility, and thus the first and second order conditions for maximisation w.r.t. α must be satisfied. The first order condition w.r.t. α is:

$$\frac{\partial EU}{\partial \alpha} = k(\bar{t},\Delta)\frac{\partial U}{\partial k}[-\Delta f(\bar{t}+(1-\alpha)\Delta) + \Delta f(\bar{t}-\alpha\Delta)] = 0 \quad (6)$$

This implies that $f(\bar{t}+(1-\alpha)\Delta) = f(\bar{t}-\alpha\Delta)$. The only solution that satisfies this is for $\bar{t}$ to be the mean of the symmetric distribution, i.e. $\alpha = 0.5$.

The second order maximisation condition is:

$$\frac{\partial^2 EU}{\partial \alpha^2} = k(\bar{t},\Delta)\frac{\partial U}{\partial k}[\Delta^2 f'(\bar{t}+(1-\alpha)\Delta) - \Delta^2 f'(\bar{t}-\alpha\Delta)] \quad (7)$$

In a concave symmetric distribution where $\bar{t}$ is the mean, $f'(\bar{t}+(1-\alpha)\Delta) < 0$ and $f'(\bar{t}-\alpha\Delta) > 0$. Therefore, $\frac{\partial^2 EU}{\partial \alpha^2} < 0$ and the second order maximisation condition is satisfied w.r.t. α. It is notable that this result holds irrespective of the structure of the incentive $k(\bar{t},\Delta) > 0$. Therefore, when individuals report a travel time range, the midpoint of the range is the mean of their perceived travel time distribution.

2.2 Theorem 2

Theorem 2: The size of the reported travel time range Δ, i.e. $t_1 - t_0$, maximises their expected utility if it satisfies the following condition:

$$-\frac{\frac{\partial k(\bar{t},\Delta)}{\partial \Delta}}{k(\bar{t},\Delta)} = \frac{\left(f\left(\bar{t}+\frac{\Delta}{2}\right)+f\left(\bar{t}-\frac{\Delta}{2}\right)\right)}{2\left(F\left(\bar{t}+\frac{\Delta}{2}\right)-F\left(\bar{t}-\frac{\Delta}{2}\right)\right)}$$

Proof: Taking the partial derivative of EU w.r.t. Δ in Equation (5) and substituting $\alpha = 0.5$ yields:

$$\begin{aligned}\frac{\partial EU}{\partial \Delta} = k(\bar{t},\Delta)\frac{\partial U}{\partial k}\Bigg[&\frac{f\left(\bar{t}+\frac{\Delta}{2}\right)+f\left(\bar{t}-\frac{\Delta}{2}\right)}{2} \\ &+\frac{\partial k(\bar{t},\Delta)}{\partial \Delta}\left(F\left(\bar{t}+\frac{\Delta}{2}\right)-F\left(\bar{t}-\frac{\Delta}{2}\right)\right)\left(\frac{1}{k(\bar{t},\Delta)}+\frac{\frac{\partial^2 U}{\partial k^2}}{\frac{\partial U}{\partial k}}\right)\Bigg]\end{aligned} \tag{8}$$

With the first order maximisation condition $\frac{\partial EU}{\partial \Delta} = 0$:

$$-\frac{\frac{\partial k(\bar{t},\Delta)}{\partial \Delta}}{k(\bar{t},\Delta)} = \frac{\left(f\left(\bar{t}+\frac{\Delta}{2}\right)+f\left(\bar{t}-\frac{\Delta}{2}\right)\right)}{2\left(F\left(\bar{t}+\frac{\Delta}{2}\right)-F\left(\bar{t}-\frac{\Delta}{2}\right)\right)} + \frac{\frac{\partial^2 U}{\partial k^2}}{\frac{\partial U}{\partial k}}\frac{\partial k(\bar{t},\Delta)}{\partial \Delta} \tag{9}$$

If the cultural and/or monetary incentive structure relies on individuals being accurate, then $k(\bar{t},\Delta)$ will be decreasing w.r.t. Δ, i.e. $\frac{\partial k(\bar{t},\Delta)}{\partial \Delta} < 0$. For cases where $k(\bar{t},\Delta)$ is linear or a power function of $1/\Delta$, it is trivial to show that $\frac{\partial^2 EU}{\partial \Delta^2} < 0$, i.e. the second order condition is satisfied. Therefore, Equation (9) is the maximisation condition.

As in Theorem 1, under the assumption $\frac{\partial U}{\partial k}$ does not change significantly in the range $[\bar{t} - \alpha\Delta, \bar{t} + (1-\alpha)\Delta]$, then $\frac{\partial^2 U}{\partial k^2} = 0$ and Equation (9) can be rewritten as:

$$-\frac{\frac{\partial k(\bar{t},\Delta)}{\partial \Delta}}{k(\bar{t},\Delta)} = \frac{\left(f\left(\bar{t}+\frac{\Delta}{2}\right)+f\left(\bar{t}-\frac{\Delta}{2}\right)\right)}{2\left(F\left(\bar{t}+\frac{\Delta}{2}\right)-F\left(\bar{t}-\frac{\Delta}{2}\right)\right)} \tag{10}$$

For the case when $k(\bar{t},\Delta) = (100-\bar{t})/\Delta$ or in general when $k(\bar{t},\Delta)$ is a linear function of $1/\Delta$, Equation (10) is written as:

$$\frac{1}{\Delta} = \frac{\left(f\left(\bar{t}+\frac{\Delta}{2}\right)+f\left(\bar{t}-\frac{\Delta}{2}\right)\right)}{2\left(F\left(\bar{t}+\frac{\Delta}{2}\right)-F\left(\bar{t}-\frac{\Delta}{2}\right)\right)} \tag{11}$$

The first and second order conditions imply that the Δ determined by Equation (11) maximises the expected utility when $k(\bar{t},\Delta)$ is a linear function of $1/\Delta$.

3 EXPERIMENT

A natural field driving experiment was conducted in Dhaka, Bangladesh, from November 2012 to January 2013 to validate the theoretical model in Section 2, collect data for its calibration and demonstrate its use. This section describes the experimental design and methods for the model estimation.

3.1 Study area

The study area for the field driving experiment was the southeast part of Dhaka near Ramna Park. This is one of the most congested areas of Dhaka with commercial entities, residential units, government offices and public service centres in the vicinity. Two mutually exclusive alternative routes in this area were chosen for the driving tasks in the experiment, as shown in Figure 1. Route 1 was 1.2 kilometres long and consisted of Minto Road and Hare Road (shown in red in Figure 1). Route 2 was 1.5 kilometres long and consisted of Ramna Road and Bhashani Road (shown in blue in Figure 1). The two routes were chosen based on their similarity of length and travel time from origin to destination, and the lack of favourable alternative routes other than the two in the study.

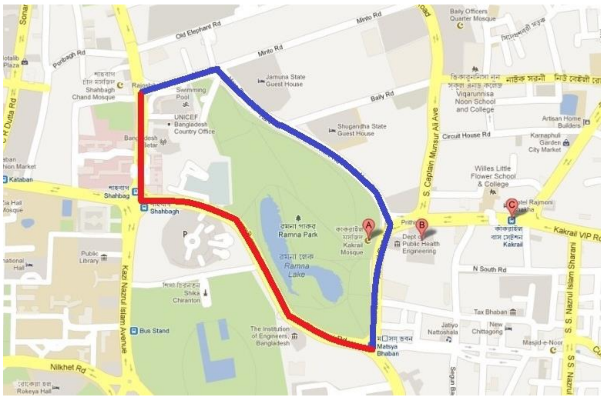


Figure 1: Network used in the experiment

3.2 Subject recruitment

The participants of the study were randomly recruited taxi drivers in Dhaka. A strong motivation for choosing a sample of taxi drivers was that they undertake decisions under uncertain travel time and costs in their professional life, and have more experience of the network than the rest of the population. Therefore, their perceptions should be more stable.

Table 2: Summary of participant demographic variables

Variables	Mean	Std.Dev.	Binary variable	Description
Rental_ amount	500	318.17	-	Car rental cost per month.
Own	-	-	71%	Binary variable, with car ownership status = 1 if the participant owns the car.
Nhh	3.92	1.18	-	Number of people living in the participant's household.
Safe_ Route1	-	-	77%	Binary variable, with perception of route safety =1 if the participant believes Route 1 is safer.
Safe_ Route2	-	-	23%	Binary variable, with perception of route safety =1 if the participant believes Route 2 is safer.

A total of 101 taxi drivers were randomly hired from the origin of the selected road network during morning peak periods. Only taxi drivers born between 1958 and 1993 were invited, thereby restricting the age range of the target population to be from 20 to 55 with all holding a driving licence for 1 to 30 years. Table 2 describes the demographics of these participants.

All participants were given an "Informed Consent Form" before the experiment began and were made aware of the "Revocation of Consent" right if they wished to withdraw from the experiment. None of the taxi drivers refused to participate or revoked their consent.

3.3 Experiment protocol

The experiment comprised four tasks: (1) a lottery choice task, (2) a questionnaire, (3) an assigned route task, and (4) a chosen route task (see Table 3). All tasks were conducted in the field, and participants took approximately 35 to 55 minutes to complete the entire experiment. All payments were made in Bangladeshi taka (BDT).

Each session began with the participant being informed that they would be paid a minimum of 15.00 BDT for their participation. They were also informed that they could earn additional money based on the outcomes of other tasks (the lottery, assigned route and chosen route tasks).

Instructions for the experiment were provided in handouts and subjects read through the instructions while the experimenter read them aloud. For ease of subjects' understanding, the instructions were translated into the local language of Bengali by a professional translator.

Table 3: Data collection method summary

Task	Section	Collected Data	Purpose
1	Lottery choice	Lottery choices.	Elicit risk attitude.
2	Demographics & hypothetical questionnaire	Participants' demographics to observe heterogeneity, and stated travel time ranges with no incentive.	Observe any heterogeneity regarding risk attitudes, value of time and perception.
3	Assigned route task	Incentivised travel time ranges.	Compare perceived and actual travel time distributions. Validate the proposed theorems.
4	Chosen route task	Revealed preference data of route choice.	Determine the real value of time.

3.3.1 Lottery choice task to elicit risk attitudes

The first task (lottery choice) was conducted to elicit the risk attitudes of participants. This task comprised a modified Holt and Laury (2002) lottery choice structure, from which it has been theoretically and empirically shown that under expected utility theory, risk attitudes can be inferred. For the task, participants were presented with a series of binary lottery choice scenarios as shown in each row of Table 4. In each scenario, the subject could choose either Option A or Option B. Each Option A consisted of a low outcome of \$6.0 with a probability of p (given as the probability of payoff 2 in Table 4) and a high outcome of \$8.0 with a probability of *1-p* (given as the probability of payoff 1 in Table 4). Each Option B had a low outcome of \$1.0 with a probability of p and a high outcome of \$20.0 with a probability of $1-p$. The value of p varied between choice tasks. Therefore, the expected utilities for the two options in each scenario could be determined as follows:

$$EU_A = p \times U(6.0) + (1-p) \times U(8.0) \tag{12}$$

$$EU_B = p \times U(1.0) + (1-p) \times U(20.0) \tag{13}$$

These expected utilities EU_A and EU_B for each scenario are shown in Table 4.

The risk attitudes of each participant could be inferred by their choices. For example, a risk neutral individual would choose the alternative with a higher expected utility, while a risk averse individual would also consider the alternative with a lower variance in payoff.

Table 4: Adaptation of Holt and Laury lottery task

Prob. payoff 1	**Prob. payoff 2**	**Option A**		**Option B**		**EU$_A$**	**EU$_B$**	**(EU$_A$ – EU$_B$)**
		Payoff 1	**Payoff 2**	**Payoff 1**	**Payoff 2**			
1/10	9/10	8.0	6.0	20.0	1.0	6.2	2.9	3.3
2/10	8/10	8.0	6.0	20.0	1.0	6.4	4.8	1.6
3/10	7/10	8.0	6.0	20.0	1.0	6.6	6.7	-0.1
4/10	6/10	8.0	6.0	20.0	1.0	6.8	8.6	-1.8
5/10	5/10	8.0	6.0	20.0	1.0	7.0	10.5	-3.5
6/10	4/10	8.0	6.0	20.0	1.0	7.2	12.4	-5.2
7/10	3/10	8.0	6.0	20.0	1.0	7.4	14.3	-6.9
8/10	2/10	8.0	6.0	20.0	1.0	7.6	16.2	-8.6
9/10	1/10	8.0	6.0	20.0	1.0	7.8	18.1	-10.3
1	0	8.0	6.0	20.0	1.0	8.0	20	-12.0

The payoffs were determined at the end of the experiment by randomly selecting one of the ten lottery scenarios for which the participant had provided a response, and then playing out the lottery they selected. Although the descriptions here are in terms of dollars, the payments themselves were made in BDT.

3.3.2 Demographics questionnaire

The second task was a questionnaire to collect two types of information from each participant. The first section collected demographic information such as household size, taxi ownership and taxi rental prices to capture heterogeneity in preferences and attitudes. The second section collected personal beliefs regarding travel time ranges on the two routes and which of the two routes they thought was safer. There were no incentives associated with this questionnaire, and no information about the future incentivised tasks was given to the participants at this stage.

3.3.3 Assigned route task to elicit travel time perceptions

In the first driving task and third task overall in the experiment, the drivers were asked to state a travel time range for each route. They were informed that they would earn a monetary payoff only if they reached the destination within their stated travel time range for the route later assigned to them.

The monetary payoff $k(t_0, t_1)$ for this and the following driving task was a function of the size of the travel time range $(t_1 - t_0)$ and the mean of the range $((t_0 + t_1)/2)$, where t_0 was the minimum expected travel time and t_1 was the maximum expected travel time as in Section 2. This function was given as:

$$k(t_0, t_1) = \frac{100 - \frac{t_1 + t_0}{2}}{(t_1 - t_0)} \tag{14}$$

The incentive was designed to encourage drivers to report as narrow and low a range as possible. This was to prevent them from specifying a wide range to ensure the incentive was captured, as well as discourage them from driving slowly to target the stated range. Section 2 shows that this incentive mechanism can be used to elicit perceived travel times under expected utility theory.

Once the participants stated the travel time ranges for both routes, the route to be driven on was randomly determined by the flip of a coin. For example, if a driver had previously selected 20 to 25 min as the travel time range for the randomly determined route, and he or she was successful in reaching the destination within the range, the driver's final payoff for the driving task was $\frac{100 - (25+20)/2}{25-20}$ = 15.50 BDT. Participants were informed that they must follow all traffic rules.

3.3.4 Chosen route task to study route choice preferences and value of time

The second driving task and fourth task overall in the experiment involved participants making a choice between the two routes. The difference between this driving task and the previous one is that drivers chose their preferred route in this task, while they had to use the randomly determined route in the previous one. Subjects were then paid based on whether or not they reached their destination along their chosen route within their stated ranges, according to the incentive mechanism in Section 3.3.3.

3.3.5 Final payoff

Since the participants were taxi drivers, they earned a fare in addition to the payoffs from the experiment tasks. Each taxi trip had a base fare of 50.00 BDT for the first 2 km, followed by a fare of 1.50 BDT/min.

The final payoff for the experiment was the summation of the fixed participation fee (15.00 BDT), the payoff from the lottery task, the payoff for the assigned route task (if earned), the payoff for the chosen route task (if earned), and the actual taxi fare.

3.4 Model estimation

This section describes the methods developed to validate the proposed theorems and generate results for the study using the experimental data.

3.4.1 Estimating preferences over lotteries

The risk attitudes of individuals were first estimated using data from the lottery choice task. Individual preferences were assumed to follow an exponential utility function, i.e.:

$$U(x) = 1 - e^{-rx} \tag{15}$$

In the above equation, r represents the constant absolute risk aversion. An increase in r can be interpreted as an increase in risk aversion.

The utility function was estimated using maximum likelihood on the choices made in the lottery task. These choices were discussed in Section 3.3.1, where Equations (12) and (13) defined the expected utilities EU_A and EU_B for the two options.

Let ∇EU be a latent index defined as the difference in expected utility between the two options, normalised by a structural noise parameter μ:

$$\nabla EU = (EU_A - EU_B)/\mu \tag{16}$$

This noise parameter μ was introduced to account for behavioural errors, where the choice between alternatives becomes more random as μ gets larger, and was assumed to follow a standard normal distribution.

The log-likelihood for the lottery choices to be maximised was:

$$\ln L(r, \mu : X) = \sum_i \left[\ln\left(\Phi(\nabla EU) \times \boldsymbol{I}(A)\right) + \ln\left(\left(1 - \Phi(\nabla EU)\right) \times \boldsymbol{I}(B)\right)\right] \tag{17}$$

In Equation (17), $\boldsymbol{I}$ is an indicator function equal to one when the condition is satisfied, and equal to zero otherwise. The argument in this function is the participants' lottery choice, i.e. Option A or Option B. In addition, X is a vector of individual characteristics based on the demographic questionnaire.

To estimate the heterogeneity of risk attitudes, the maximum likelihood analysis was generalised such that the core parameter r was a linear function of X, i.e. $r = r_o + \gamma X$ where r_o is a fixed parameter and γ is a vector of effects associated with the socio-demographic variables X.

3.4.2 Estimating perceptions of travel time

To generate results for this study, three distributions were required to be estimated: (1) the distributions of actual travel times observed from the field, (2) the perceived distributions stated with no incentives (from the questionnaire), and (3) the perceived distributions stated with incentives (from the driving tasks). The perceived travel time distributions were assumed to follow a gamma distribution with parameters α and β, which is:

$$f(t: \alpha, \beta) = \beta^{\alpha} \frac{1}{\Gamma(\alpha)} t^{\alpha - 1} e^{-\beta t} \tag{18}$$

The gamma distribution was chosen due to its flexible symmetry. From fitting the gamma distribution to the data, it was possible to determine whether the assumption of symmetricity required for the theorems in Section 2 was reasonable.

For easier interpretation, the gamma distribution in Equation (18) can be parameterised by its mean (μ) and standard deviation (σ), i.e.:

$$f(t: \mu, \sigma^2) = \left(\frac{\mu}{\sigma^2}\right)^{\left(\frac{\mu^2}{\sigma^2}\right)} \frac{1}{\Gamma\left(\frac{\mu^2}{\sigma^2}\right)} t^{\left(\frac{\mu^2}{\sigma^2} - 1\right)} e^{-\left(\frac{\mu}{\sigma^2}\right)t} \tag{19}$$

In Equation (19), $\alpha = \frac{\mu^2}{\sigma^2}$ and $\beta = \frac{\mu}{\sigma^2}$. Therefore, the original parameters α and β can be recovered from the mean and standard deviation, and used exogenously to estimate preferences. The parameters of the perceived distribution were determined using maximum likelihood estimation, based on the means of stated travel time ranges.

3.4.3 Estimating preferences over routes

The chosen route task was further utilised to analyse the perception of travel time incorporating risk attitudes.

In the case of route choice, the argument x for the utility function shown in Equation (15) involves money and travel time. Generalising this utility function to incorporate preferences over route travel time and other route characteristics yields:

$$U(t) = 1 - e^{-r(50+1.5t+k-VOT*t)} \tag{20}$$

In Equation (20), r is the risk attitude, 50 is the basic payment, 1.5 is the taxi fare per minute, t is the travel time, k is the payoff if the participant successfully reaches the destination within the reported travel time range, and VOT is the value of time which captures the individual's marginal substitution between travel time and money. Let v denote the product of VOT and r. Equation (20) can then be rewritten as:

$$U(t) = 1 - e^{-r50-r1.5t+vt-rk} \tag{21}$$

From Section 3.3.3, k was an experimental input determined by the reported travel time range, and was calculated as follows:

$$k(t) = \begin{cases} \dfrac{100-(t_1+t_0)/2}{(t_1-t_0)} & if\ t_0 \le t \le t_1 \\ 0 & else \end{cases} \tag{22}$$

An individual's expected utility given their reported travel time range $[t_0, t_1]$ was then:

$$\begin{aligned} EU_R &= \int_0^\infty \beta^\alpha \frac{1}{\Gamma(\alpha)} t^{\alpha-1} e^{-\beta t}(1 - e^{-r50-r1.5t+vt-rk})dt \\ &= 1 - \frac{\beta^\alpha e^{-r50}}{(\beta+1.5r-v)^\alpha}\left(1 + (e^{-rk}-1)\frac{\gamma(\alpha,(\beta+r1.5-v)t_1) - \gamma(\alpha,(\beta+r1.5-v)t_0)}{\Gamma(\alpha)}\right) \end{aligned} \tag{23}$$

Similar to the lottery choice analysis, a latent index ∇EU was defined as the difference in expected utilities between the two routes:

$$\nabla EU = (EU_{R1} - EU_{R2})/\mu \tag{24}$$

Route choice was then jointly modelled with lottery choice by maximising the log-likelihood of the sample. As well as allowing for heterogeneity in risk attitudes of individuals, the analysis accounted for heterogeneity in VOT by specifying v as $v = v_o + \theta X$ where v_o is a fixed parameter and θ is a vector of effects associated with the socio-demographic variables X. VOT was then calculated as v/r.

4 RESULTS AND DISCUSSION

Using the experimental data and theoretical results, this section (1) compares the distributions of perceived and actual travel times, (2) estimates the impact of differences in perception and actual travel times on estimates of travel time preferences, and (3) validates the predictions of Theorem 2.

4.1 Perceived travel times

Table 5 shows the mean perceived travel times elicited through the stated and incentivised tasks compared to the actual travel times. From these results, participants tended to underestimate the travel time for both routes, and this difference between the actual and perceived travel times was found to be statistically significant. However, no statistically significant difference was observed between the perceived travel times elicited by the stated and incentivised methods.

Table 5: Comparison of perceived mean travel time and actual travel time

Route	Mean of stated perceived travel time in minutes (standard deviation)	Mean of incentivised perceived travel time in minutes (standard deviation)	Actual travel time in minutes (standard deviation)
Route 1	13.248 (1.506)	13.069 (1.526)	16.044 (1.827*)
Route 2	16.545 (2.301)	17.847 (1.762)	21.354 (2.275*)

*The perceived travel times were based on 101 data points, while the actual travel times were based on 139 data points for Route 1 and 63 data points for Route 2.

The perceived and actual travel time distributions were estimated based on the methods described in Section 3.4.2. The full set of results is shown in Appendix A. Figure 2 presents the kernel density distributions of the mean perceived travel times from the stated and incentivised tasks as well as the distribution of the actual travel time spent for the two routes. This figure supports the earlier conclusion that the perceived distributions are significantly different from the actual travel time distributions.

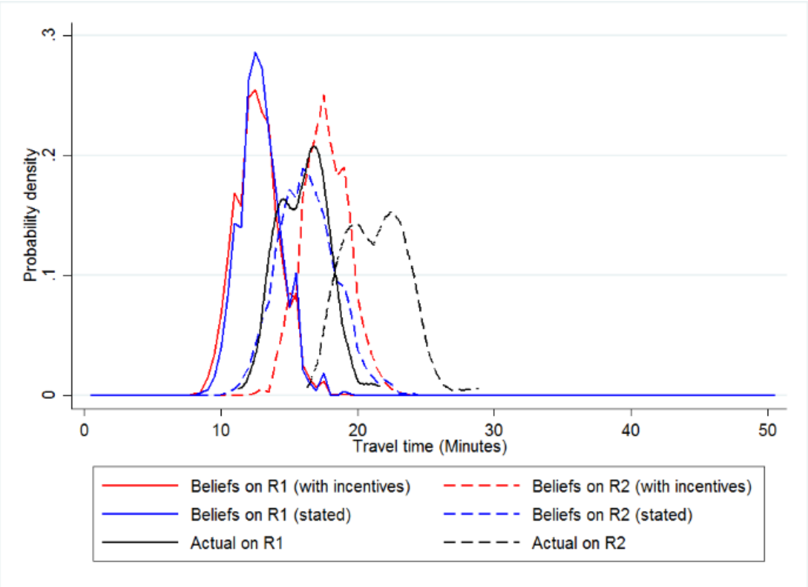


Figure 2: Comparison of perceived and actual travel time distributions

Table 6 shows the skewness of the distributions in Figure 2. The skewness values of all six distributions are within the acceptable limits of +/- 2 to conclude that the distributions are symmetric (Field, 2009; Gravetter and Wallnau, 2016; Trochim and Donnelly, 2001). This validates the assumption underlying the theorems in Section 2.

Table 6: Skewness of perceived and actual travel time distributions

	Route 1			Route 2		
	Incentives	**Stated**	**Actual**	**Incentives**	**Stated**	**Actual**
Skewness	0.6753	1.2218	0.1625	0.3458	0.7763	0.4309

4.2 Preferences over risk and time

The results of the joint models for choices over lotteries and routes are shown in Appendix B. These results indicate significant heterogeneity in risk attitudes and VOT. Table 7 summarises the risk attitudes and VOT based on (1) stated travel times, (2) incentivised travel time estimates, and (3) actual travel times.

Table 7: Comparison of estimates of value of time and risk attitudes

	Stated (standard deviation)	**Incentivised (standard deviation)**	**Actual (standard deviation)**
Risk attitudes (r)	0.0469 (0.010)	0.0459 (0.010)	0.0456 (0.009)
Value of time (VOT)	-3.4541 (2.8755)	-3.5764 (2.4089)	-2.9508 (2.0117)

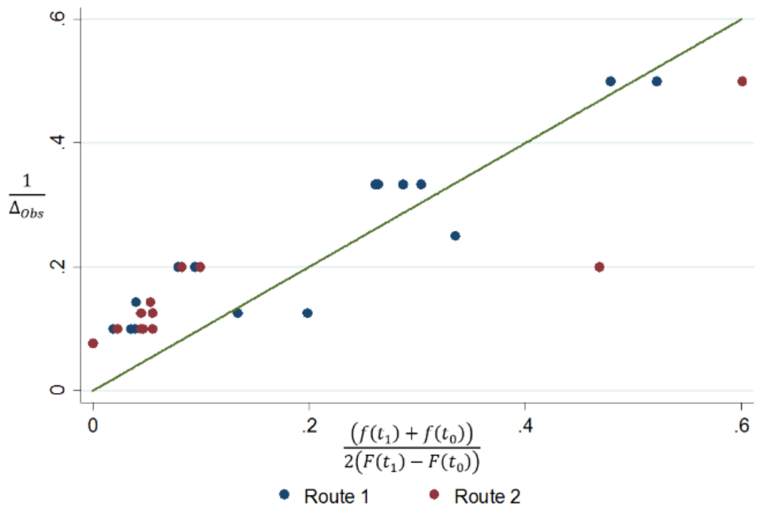
As seen in Table 7, the risk attitudes based on a pooled t-test are not statistically significantly different at a 95% confidence interval between the three models. Furthermore, no statistically significant difference was found between the VOT estimated from the stated ranges and that from the incentivised tasks. However, the VOT estimated using actual travel times was almost 17% lower than that estimated using the incentivised perceived travel times. This difference is statistically significantly different at a 95% confidence interval. On the other hand, while the VOT estimated using actual travel times was approximately 15% lower than that estimated using the stated travel times, the difference was not found to be statistically significant (p-value of 0.15).

4.3 Travel time ranges

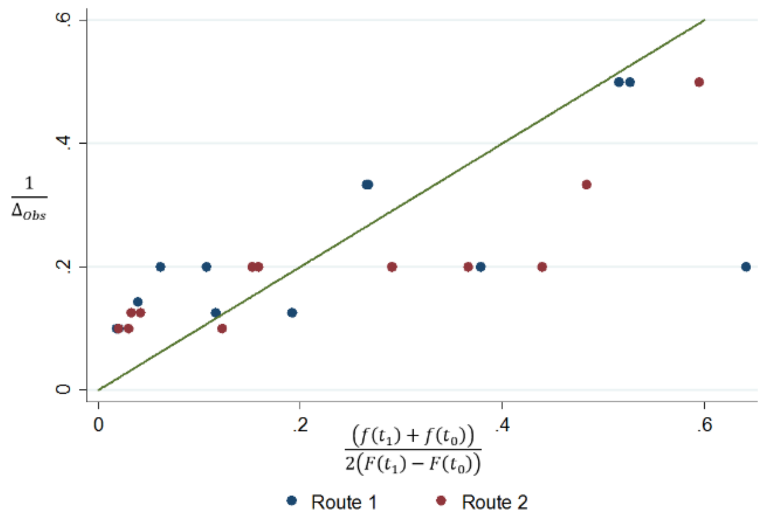
Theorem 2 in Section 2.2 presented a result in Equation (11), as shown again below, that related the travel time range Δ to the perceived travel time distribution. This theorem was claimed to provide useful information about an individual's perceived travel time distribution.

$$\frac{1}{\Delta} = \frac{\left(f\left(\bar{t}+\frac{\Delta}{2}\right)+f\left(\bar{t}-\frac{\Delta}{2}\right)\right)}{2\left(F\left(\bar{t}+\frac{\Delta}{2}\right)-F\left(\bar{t}-\frac{\Delta}{2}\right)\right)}$$

To validate this theorem, the value of the right hand side of Equation (11) was compared with the left hand side ($1/\Delta$) calculated using actual reported ranges Δ_{obs}, for both stated and incentivised perceived travel time distributions on both routes. The results and corresponding RMSE values are shown in Figure 3, with Figure 3(a) showing results for incentivised travel time ranges and Figure 3(b) showing results for stated ranges. The results of the predictions are reasonable and consistent when the perceptions are elicited using incentives (Figure 3(a)). Though the exact structure of the incentives may not be known, when individuals state travel time ranges, there appears to be a high correlation between the predicted and observed values.



(a) Stated travel times, with an RMSE of 0.09 on both routes



(b) Incentivised travel times, with an RMSE of 0.13 on Route 1 and of 0.08 on Route 2

Figure 3: Comparison of the model predictions with observed values

From the incentives to elicit beliefs in conjunction with the theory, this study concludes that the elicited distribution is a reliable representation of the perceived travel times. Under this assumption, it is possible to determine the risk that individuals convey when they state a range. To address this, the risk P_i each individual communicates is calculated using the cumulative perceived distribution F and their stated range $[t_0^i, t_1^i]$ as:

$$P_i = F(t_1^i) - F(t_0^i) \tag{25}$$

Using Equation (25), the average value of the risk communicated on both routes was found to be very similar, with a value of 0.78 (and a standard deviation of 0.23) on Route 1 and a value of 0.76 (and a standard deviation of 0.29) on Route 2. This suggests that taxi drivers in Dhaka when reporting ranges tend to provide a 77% confidence interval.

5 CONCLUSION

This study was motivated by three aims: (1) to determine if perceptions and actual travel times differ, (2) to determine what stated ranges of travel times reflect about travel time perceptions and their distribution, and (3) to determine the impact of accounting for perceptions on estimates of VOT. In particular, the accurate calculation of VOT is crucial to transport policy as it drives the majority of benefits in appraisals, and the reliance on SP-based estimates without accounting for the difference between perceptions and reality may have produced misleading results.

This study proposed a model of perceived travel time distribution and derived two theorems relating an individual's stated travel time range to the distribution, in accordance with the second study aim. Theorem 1 showed that the midpoints of stated travel time ranges are an individual's estimate of the mean travel time irrespective of an incentive structure for accurate reporting. Theorem 2 was a relationship between the stated ranges, their perceived travel time distributions and the incentive structure to report accurately. Furthermore, the theoretical results of Theorem 1 and Theorem 2 can be generally applied to any continuous event where perceptions need to be studied.

The theorems were then validated with data collected in a field driving experiment with taxi drivers in Dhaka. This experiment was also used to study whether stated perceptions elicited with and without incentives are different from actual travel time distributions. In relation to the first study aim, the results from the experiment showed that individuals' perceived travel time distributions are significantly different from the actual travel times, although no differences were observed between stated ranges with and without incentives. The experiment also validated the assumptions underlying the earlier theorems.

In relation to the third study aim, the disparity between perceived and actual travel time distributions was found to result in statistically significant differences in VOT – up to 17% – due to perceptions of lower travel times leading to higher VOTs. This has significant implications on VOT studies and the need to explore its stability based on perceptions.

Finally, the study examined the 'risk communicated' in the travel time ranges stated by an individual. From the experiment, the ranges stated under clear monetary incentives followed the predictions of Theorem 2 reasonably well. In addition, the study found that the Dhaka taxi drivers on average conveyed a risk of 77% when they stated travel time ranges.

Overall, this study concludes that controlling and eliciting perceptions are important behavioural components in explaining choices, and that a lack of control over perceptions may lead to radically different estimates over preferences. This study also found that stated ranges, when given with clear monetary incentives associated with accuracy, provide reliable predictions in the absence of knowing individuals' underlying incentives to accurately state travel times.

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APPENDIX A: PERCEIVED AND ACTUAL TRAVEL TIME DISTRIBUTIONS

Table A1: Comparison of perceived distributions elicited with incentives and no incentives (stated) with actual on Route 1

	Stated			Incentivised			Actual		
	Coef.	**Std. Err.**	**P**	**Coef.**	**Std. Err.**	**P**	**Coef.**	**Std. Err.**	**P**
μ									
Safe 1	12.718	0.167	0.000	12.564	0.185	0.000	16.044	0.155	0.000
Safe 2	13.391	0.385	0.000	13.174	0.358	0.000			
σ									
Safe 1	1.961	0.402	0.000	2.463	0.431	0.000	3.326	0.403	0.000
Safe 2	3.217	0.694	0.000	2.841	0.543	0.000			

Table A2: Comparison of perceived distributions elicited with incentives and no incentives (stated) with actual on Route 2

	Stated			Incentivised			Actual		
	Coef.	**Std. Err.**	**P**	**Coef.**	**Std. Err.**	**P**	**Coef.**	**Std. Err.**	**P**
μ									
Safe 1	16.192	0.242	0.000	17.526	0.207	0.000	21.354	0.282	0.000
Safe 2	16.565	0.505	0.000	17.913	0.332	0.000			
σ									
Safe 1	4.490	0.925	0.000	3.180	0.435	0.000	5.019	0.902	0.000
Safe 2	5.391	2.037	0.008	2.477	0.482	0.000			

APPENDIX B: ESTIMATION RESULTS OF RISK ATTITIDE AND VOT

Table B1: Estimation results of risk attitude and VOT based on perceptions elicited with no incentives (stated)

	Coef.	**Std. Err.**	**z**	**P>|z|**
Risk Attitude (r)				
rental_amount	0.0003	0.0001	2.1700	0.03
own	-0.2037	0.0910	-2.2400	0.03
Nhh	0.0058	0.0033	1.7300	0.08
_cons	0.0284	0.0135	2.0900	0.04
VOT *r				
Safe_Route1	-0.2180	0.0477	-4.5700	0.00
Safe_Route2	0.0562	0.0097	5.7800	0.00
Log Fechner (LNmu)				
_cons	-2.8801	0.1358	-21.2100	0.00

Table B2: Estimation results of risk attitude and VOT based on perceptions elicited with incentives

	Coef.	**Std. Err.**	**z**	**P>|z|**
Risk Attitude (r)				
rental_amount	0.0003	0.0001	2.6700	0.01
own	-0.2237	0.0832	-2.6900	0.01
Nhh	0.0066	0.0028	2.3200	0.02
_cons	0.0211	0.0116	1.8200	0.07
VOT *r				
Safe_Route1	-0.2012	0.0448	-4.4900	0.00
Safe_Route2	0.0016	0.0156	0.1000	0.92
Log Fechner (LNmu)				
_cons	-2.8811	0.1388	-20.7600	0.00

Table B3: Estimation results of risk attitude and VOT based on actual travel time distributions

	Coef.	**Std. Err.**	**z**	**P>|z|**
Risk Attitude (r)				
rental_amount	0.0003	0.0001	1.93	0.05
own	-0.1964	0.0997	-1.97	0.05
Nhh	0.0054	0.0033	1.64	0.10
_cons	0.0278	0.0124	2.24	0.03
VOT *r				
Safe_Route1	-0.1719	0.0377	-4.56	0.00
Safe_Route2	0.0137	0.0089	1.55	0.12
Log Fechner (LNmu)				
_cons	-2.8811	0.1388	-20.76	0.00