A meta-analysis of valuation of travel time reliability

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Table of contents

Summary

The reliability and scheduling delay of travel time attributes have been considered as important factors in traveler's decision making. Numerous studies have attempted to incorporate travel time reliability and scheduling delay early/late attributes into traveler's choice models since the last decade. However, there is still a wide-ranging debate on empirical valuations, and substantial differences of estimation values are shown among studies. Our aim in this study is to investigate several unresolved issues in the empirical valuation of reliability and scheduling delay early/late and estimate these effects by means of a multivariate statistical technique: meta-analysis. The main finding is that including all reliability and scheduling delay early/late attributes in choice model would lead to lower estimated values for these attributes. We also find that the stated preference data produce substantial lower values for the ratio between scheduling delay early/late and travel time coefficients and the possible explanation may be the misperception error together with the risk aversion attitude of travelers.

1 Introduction

Various factors are known to govern travel behavior. Along with the attribute of travel time, reliability of travel time has been regarded as an important component in individual's decision making of route choice or mode choice. Intuitively, the concept of 'reliability' suggests that an individual has to make his or her travel decision under uncertain circumstances with respect to travel time, and hence the nature of reliability can be described by the distribution of travel time (Bates, 2001).

A fair number of studies have attempted to incorporate travel time reliability attributes into travelers' choice models during the last decade. However, there is still a wide-ranging debate on reliability valuation, particularly in the way of modeling; and substantial differences of estimation values are shown among studies. No consensus has been achieved thus far, neither on point estimates nor on the methodological question of how to measure the value of reliability.

In this study we focus on the review of empirical estimates of reliability in travel time related attributes. We look not only at the valuation of travel time reliability itself, but also concern the valuation of scheduling delay variables. Our aim is to study the sources of variations in empirical estimates and to investigate the unresolved issues by means of meta-analysis, a quantitative method of literature surveys. By performing the meta-regression, the main difference in estimates can be explained in a systematic way. Thus, the merit of meta-analysis may serve as the guideline for future research in this area.

The paper is organized as follows. Section 2 considers the concepts of value of time, reliability, and scheduling cost. It also shows the most used empirical modeling approach in travel time reliability valuation. Section 3 discusses the main arguments and possible sources of variation in empirical works. Section 4 describes the data and shows the overview of empirical estimates in the context of various reliability indications such as the reliability ratio, scheduling delay early ratio and scheduling delay late ratio. The meta-regression results and discussions are presented in Section 5, and Section 6 concludes.

2 Theoretical framework

2.1 Concepts of reliability and scheduling delay

Since the concept of reliability can be regarded as the distribution of travel time, it appears that at least two dimensions of travel time have to be considered in modeling the effect of reliability—namely, its magnitude and frequency. One plausible indicator of reliability is the variance or standard deviation of travel time, which can be evaluated in practice to illustrate the loss of utility due to the amount of this value.

Along with the utility loss incurred by the unreliability in travel time, a traveler may also attach additional (dis-)utility to arriving at the destination before or after his preferred arrival time (PAT). Thus, the difference between actual arrival time and preferred arrival time may play a role in traveler's decision making. Following Small's paper (1982), this measurement of difference between PAT and actual arrival time is defined as schedule delay (SD). That is, $SD = PAT - [t_h + T(t_h)]$, where t_h is the departure time and the amount of travel time $T(t_h)$ depends on the chosen departure time. In general, people may value early and late arrivals differently according to the different consequences. Most research (Small 1982, Noland and Small 1995, Bates et al. 2001) evaluate SD as two separate terms, schedule delay early (SDE) and schedule delay late (SDL), which can be expressed as: $SDE = Max(0, PAT - [t_h + T(t_h)])$ and $SDL = Max(0, [t_h + T(t_h)] - PAT)$.

2.2 Modeling approaches

The earliest work to consider the effect of reliability in travel behavior originates from the mean-variance approach. Jackson and Jucker (1981) specified a model where a traveler can make the trade off between travel time and variance of travel time explicitly. Both of these two elements are included in a cost function that travelers seek to minimize it. A general form of this mean-variance approach is given by Eq (1).

$$Min\ C = E(T) + \lambda \cdot Var(T) \qquad (1)$$

The coefficient of variance of travel time λ can be seen as a measure for risk aversion. Instead of $Var(T)$ in Eq.(1), sometimes the standard deviation was used. This mean-variance approach, used effectively in the field of portfolio analysis in financial market, has its sounded theoretical backgrounds and can be applied easily in mode or route choice. Yet the weakness of this approach might be its disability in dealing with departure time choice behavior with scheduling constraints, which will be discussed in the next paragraph.

Proposed by Small (1982), the scheduling concept was first modeled in traveler's choice behavior and examined with empirical data. The general form of indirect utility function can be presented as,

$$U = \beta_T \cdot T + \beta_C \cdot C + \beta_E \cdot SDE + \beta_L \cdot SDL + \theta \cdot D_L, \quad (2)$$

To introduce the concept of uncertainty, Noland and Small (1995) extend the scheduling model from Eq.(2) by considering the probability distribution of travel time and adding an additional random component. The result is presented as Eq.(3)[1]. This choice problem under uncertainty is what is called *Maximum Expected Utility* (MEU) theory.

$$E(U) = \beta_T \cdot E(T) + \beta_C \cdot C + \beta_E \cdot E(SDE) + \beta_L \cdot E(SDL) + \theta \cdot P_L \quad (3)$$

The basic idea of Eq.(3) is that travel time reliability, regarded as a function of the standard deviation of travel time, may produce inconvenience in planning activities. Its effect should however, be made independent of scheduling concerns in the model. Note that the specification in Eq.(3) implies consideration of both the scheduling model and the mean-variance approach. Our main interest of analysis in this present paper will be the parameters of reliability, schedule delay early, and schedule delay late, all compared to the parameters of the travel time or cost term.

Once the model is estimated, one can derive the marginal rate of substitution between any pair of the attributes in the bundle. For example, the monetary value of travel time (VOT), an important economic indicator in transportation studies, is defined as the marginal substitution rate between travel time and costs and hence as the ratio of the respective coefficients (see Eq.(4)). Similarly, the values of schedule delay early, schedule delay late, and uncertainty can be derived.

$$VOT = \frac{\partial U / \partial T}{\partial U / \partial C} = \frac{\beta_T}{\beta_C} \quad (4)$$

One practical issue in the meta-analysis that will follow is that some studies do not include the cost related terms in their estimated model. To increase the number of observations in the database, we therefore decided to use the marginal rate of substitution between time and reliability for our variable of interest in meta-analysis. The marginal rate of substitution between travel time and reliability is the so-called *reliability ratio*, i.e., $RR = \beta_R / \beta_T$, defined by Black and Towriss (1993). To facilitate the empirical analysis of scheduling variables, we also define *schedule delay early ratio* and *schedule delay late ratio* as $SDER = \beta_{SDE} / \beta_T$ and $SDLR = \beta_{SDE} / \beta_T$. Another advantage of using the reliability or scheduling ratio in the analysis is to get rid of the transformation

[1] See Noland and Small (1995) for the modeling details.

problem because of the exchange rate conversion problems. Since the monetary values of reliability and scheduling variables are estimated based on the local currencies, and hence cannot be comparable with the original values. Using the free of unit ratio values will not be affected by the conversion procedure.

3 Issues in the valuation of reliability

3.1 Revealed versus stated preference

There are two major sources of preference data, revealed and stated preference, which both can be used to estimate discrete choice models. Traditionally, empirical studies of traveler's choice behavior rely on data from observing what people *actually* do, i.e., revealed preference (RP) data. However, recent studies favor data from people's choice under hypothetical situations, which we refer to as sated preference (SP) data. The inherent difference of *RP* and *SP* type data may lead to some perception problem for respondents and also the estimation in econometric model. Earlier studies (Ghosh, 2001; Yan, 2002) show that the median SP estimates of VOR and VOR are about half of the median RP estimates and the differences are statistically significant. Brownstone and Small (2003) mention that the difference between SP and RP is probably caused by the misperception of travel time in RP surveys, and people may exaggerate the amount of delay time due to the impatience with heavy traffic. Whether the SP method underestimates our targeted estimates in a systematic way will be left for the meta-analysis.

3.2 Utility specification: reliability versus scheduling variables

UK studies, Arup 2002 and Bates et al. 2003, concluded that the value of reliability can be entirely explained by expected scheduling cost. Indeed, some empirical works (Noland, 1995; Small et al. 1999) obtained insignificant results in valuating the effect of reliability when including both of reliability and scheduling variables in the model. One plausible explanation could be that most empirical work does not distinguish between reliability and scheduling concepts very well in the context of questionnaire, and hence the respondents might mix up these two effects into one. Thus, the estimated scheduling costs usually also reflect the unreliability costs.

Though the concept of reliability and scheduling are closely related to each other, they should not be treated as identical. The idea is that apart from people's scheduling preference, they may have some additional disutility due to the inconvenience or anxiety caused by unreliability of travel time, even when the 'expected scheduling delay' cost is the same. Moreover, a great part of trips do not have strict scheduling constraints (e.g., shopping or leisure) and people may be indifferent as long as arriving at the destination within a certain range of arrival times. In such a case, the disutility may come from the inconvenience of planning due to the unreliability of travel time rather than scheduling considerations.

Another subtle but relevant point in utility specification issue is the inclusion of lateness variable, P_L in Eq. (3), which can be modeled as either the probability or the dummy of lateness. Similar to the argument of reliability versus scheduling variables, we can infer that the existence of lateness variable in the model may probably affect the estimates of reliability and scheduling variables in the same manner, and particularly for the scheduling delay late variable due to the closely relation between P_L and *SDL*.

One of our main purposes is to investigate this utility specification effect and to see what the extent of this influence is.

3.3 Types of choice set

It remains unclear whether the estimations of reliability or scheduling variables would be varied in different types of choice set. (e.g., route choice, mode choice, or the combination of departure time choice). Briefly speaking, the characteristics of choice problems are distinct in some points between 'within' mode choice (i.e., route choice) and 'between' mode choice (i.e., joint route and mode choice); whereas the departure time choice can be incorporated into any of these two type of choice models by explicitly indicating the departure and arrive time in the choice questions. Thus, the utility setup--the set of attributes included in the model--should be able to respond to these different features of choice problems.

Basically, if the underlying utility function is correctly specified to reveal traveler's actual choice behavior, the estimates of reliability and scheduling variables obtained from different choice set domains should be close to each other. However, some concerns may arise in practice. For example, since not all the alternatives are available to the respondents in the real mode choice problem, the observed behavior might not be the same as the hypothetical one. Thus, it is interesting to see whether there is substantial difference in valuation of the types of choice models.

3.4 Observed and unobserved heterogeneity

Numerous studies on the value of time (a summary study, Wardman 2001) have shown that a great deal of variations of estimated values is originated from trip and individual characteristics. In general, there are two ways to take these sources of variations into account in the modeling approach. One is to specify them as the observable variables in the model and the other is by randomizing the parameters or allowing more general correlated error structure form. While the former is referred to '*observed heterogeneity*', the later is regarded as '*unobserved heterogeneity*' in the literature (Brownstone and Small, 2003).

The observed heterogeneity in the estimates can be evaluated by incorporating the interaction terms of those trip or individual traits variables with travel time, reliability, or cost variables. Particularly, trip purposes and modes may be the most important factors that researchers are interested in. One of the aims of the present study is to examine these heterogeneity effects on the reliability and scheduling ratios estimates.

More recent studies have taken the unobserved heterogeneity into account, thanks to the advances in econometrics modeling techniques and computing power. In the literature (Hensher 2001, Greene and Hensher 2003), there are two considerations to accommodate the unobserved variability of preferences into the model: (a) allowing correlation structures of error terms (b) randomizing the parameters associated with each attribute. Nevertheless, it is less clear whether incorporating unobserved heterogeneity will lead to under- or overestimated values. Hensher (2001) suggested that the less restrictive choice model tends to produce higher estimates; while Ghosh (2001) showed that the most general model yielded the lowest estimates, which contradicts Hensher's results. Thus, it may be interesting to see whether there is substantial effect of accounting for unobserved heterogeneity on the reliability and scheduling ratios.

3.5 Different measurement in attributes

There are various measurements of reliability in empirical assessments, such as standard deviation, coefficient of variation, difference between 90^{th} and medium of travel time etc. This lack of consensus on how to characterize the reliability by a common variable creates some problem in comparison of empirical estimates and this issue will be discussed in more detail in Section 5.2.

In addition to the wide range of reliability measurements, travel time is also evaluated at different grounds, such as mean or medium travel time, free flow time, congested time, and medium delay time, etc. Since the value of time is the denominator of reliability ratio, these different measurements in travel time may have influence on our variable of interest. However, if we want to classify each travel time measurement into different categories, we would have very few observations in some certain measurements. In order to solve this problem, we select some of the conceptually similar measurements, e.g., 'congested travel time', 'medium travel time savings' and 'mean delay', then place them into a same group called 'congested travel time (denoted as VOT_CT)'. In the following analyses, this group will be compared to the other one 'uncongested travel time', which is the combination of 'travel time' and 'free flow travel time' measurements.

4 Methodology

4.1 Data and sampling

To search the empirical estimates for reliability and scheduling variables, we started from the EconLit database, transportation research journals and the google search engine, including published papers, reports, and working papers.[2] A recent review study of travel time reliability from RAND Europe (2004) serves as a good reference for collecting the reliability estimates. We computed the reliability and scheduling ratios following the procedure we explained in the end of Section 2.3. However, we excluded some estimates, which used diverging definitions of reliability and cannot be made comparable to other estimates (e.g., Koning and Axhausen 2002[3]). The overall studies and computed ratios are shown in Table 1.

Table 1 Overview of studies with empirical estimates

Authors	Study type	Year of Publication	VOR ratio (RR)		VSDE ratio (SDER)		VSDL ratio (SDLR)	
			obs	mean	obs	mean	obs	Mean
Small	RP	1982	-	-	2	0,667	2	2,139
Hendrickson and Plank	RP	1976	-	-	2	0.362	2	11.564
Wilson	RP	1989	-	-	4	4,742	4	5,888
Lam and Small	RP	2001	26	1,179	6	0.456	4	0.762
Small et al.	SP	1999	3	2,515	4	1.190	4	5.010-
Ghosh (Dissertation)	SP&RP	2001	5	0,986	-	-	-	-
J. Yan (Dissertation)	SP&RP	2002	30	1,082	-	-	-	-
Noland (Dissertation)	SP	1995	3	0,536	4	0,872	4	1,813
Koskenoja (Dissertation)	SP	1996	7	0,378	7	0,507	5	1,396
Bates et al.	SP	2001	-	-	1	0,442	1	0,897
Hensher	SP	2001	6	0,574	-	-	-	-
A. de Palma et al.	SP	2003	-	-	12	0,655	12	1,494
G. de Jong et al.	SP	2003	-	-	9	1.059	9	1.422

[2] Since our variables of interest is the reliability ratio, scheduling ratios, we only considered empirical studies that include the valuation of either both of travel time and reliability or both of travel time and scheduling variables

[3] Koning and Axhausen used two separate variables 'duration of delay' and 'probability of delay' to present the effect of reliability.

Cascetta and Papola	RP	2003	-	-	5	2,301	5	4,392
Rietveld et al.	SP	2001	1	1.40[4]	-	-	-	-
Daly et al.	SP	2005	-	-	26	0.886	26	1.440

4.2 Correction of reliability estimates

As we mentioned in the section 3.5, there are various measurements of reliability and these different uses of reliability measurement certainly create some problem in comparison (see Table 2).

Table 2 Different definitions of reliability used in empirical estimations

Reliability definitions	Notation	# obs	Min	Max	Mean
Standard deviation of travel time	STD	7	0.548	3.222	1.794
Coefficient of variation of travel time	CV	9	0.131	0.576	0.332
Difference between 90th and 50th travel time	90DMP	29	0.483	1.714	1.072
Difference between 80th and 50th travel time	80DMP	19	0.968	1.952	1.469
Uncertainty	UNC	6	0.541	1.461	0.750
Incident	INC	11	0.380	0.441	0.421

If we estimate the utility function as Eq (3) for a given set of observations, the estimated coefficient of standard deviation, denoted as STD, and estimated coefficient of coefficient of variation, denoted as CV, cannot be equal, i.e., $\beta_1 \neq \beta_2$ in Eq.(5). The ideal way to correct these coefficients based on different measurements is to go back to the original survey data, and then estimate the model again by using a standard definition of reliability. However, this is not feasible in our case. The second best way to adjust these coefficients is by looking at the relationship between those different measurements then correct the coefficients according to these transformed relationships.

$$U = \alpha \cdot E(T) + \beta_1 \cdot (STD) + ... = \alpha \cdot E(T) + \beta_2 \cdot (CV) + ... \qquad (5)$$

Take STD and CV for example (see Eq (5)), we know in advance that there exists a relationship between STD and CV, that is, $CV = SDT / (mean\ travel\ time)$. Thus, we can infer that $\beta_2 = \beta_1 \times (mean\ travel\ time)$.

Next, we can investigate the relations between standard deviation (STD), difference between 90th and medium travel time (90DMP), and difference between 80th and medium travel time (80DMP) under three types of distributions. In the case of uniform distribution, we can derive the analytical solutions for the relations between STD, 90DMP and 80DMP. This shows that the values of 90DMP and 80DMP are just the scale of standard deviation. Thus, assuming that travel time follows uniform distribution, we can correct the estimated coefficient of 90DMP to standard deviation, based on the calculated ratio. A

[4] Reliability in Rietveld et al. is defined as ‘reduction a 50% probability of 15 minutes delay to zero’. The estimate shown in Table 1 has already been converted into the one defined by standard deviation of travel time.

similar situation holds also for triangular distributions. For the normal distribution, since the analytical solution is difficult to implement, we used simulations to infer these ratios.

In the case of uncertainty time (UNC), it is possible to derive the transformation ratios between UNC and STD if we presume that uncertainty time equals the range of upper and lower bounds in the uniform and triangular distributions. All the "transformation ratios" between these variables are listed in Table 3 for these three distributions.

From Table 3 we found out that the values of transformation ratios of the normal distribution are located in between the values of uniform and triangle distributions. Therefore, we decided to choose the transformation ratios for the normal distribution as our "corrected reference". We therefore hypothesize that the distribution of travel time is normally distributed, and then correct the reliability estimates to make them to be comparable.

This correction approach described above can be used in correcting estimates between STD, CV, 90DMP, 80DMP, and UNC. Unfortunately, we cannot proceed the same exercise to the case of 'incident'. Thus, we will drop those reliability estimates associated with 'incident' variable from our formal meta-analysis.

Table 3 Transformation ratios between STD and 80/90DMP under various distributions

	Uniform distr.	**Normal distr.**	**Triangular distr.**
STD	1,000	1,000	1,000
90DMP	1,384	1,283	0,993
80DMP	1,038	0,843	0,661
UNC	3.464	-	4.899

4.3 Overview of empirical estimates

A starting point of meta-analysis is to compare the means of estimates, which are computed from various treatments of categories. The conditional means of RR, SDER, and SDLR on those potential variation factors discussed in the previous section are given in Table 4. Serving as the preliminary stage of meta-analysis, these conditional means give a rough idea about how these factors affect the variables that we are interested in. As we can see from Table 4, these conditional means vary significantly in several within-group comparisons such as data type, travel time measurement, and utility specification etc. Some findings in Table 4 are confirmed with our expectation, for instance, including both reliability and scheduling variables induce lower estimates on both variables. Intuitively, using different travel time measurements also has some impact on SDER and SDLR.

In the next section, we will explore the data more profoundly in the meta-regression.

Table 4 Conditional means for various categories of studies

	VOR ratio (RR) studies (n=69)		VSDE ratio (SDER) studies (n=73)		VSDL ratio (SDLR) studies (n=69)	
Groups	n	Mean	n	Mean	n	Mean
Data Types						
Revealed preference	47	1.320	13	1.198**	11	2.662*
Stated preference	22	1.312	60	0.834**	58	1.708*
Choice types						
Between mode choice	-	-	37	1.119***	38	1.824
Within choice mode	-	-	36	0.672***	31	1.904
Mode specific estimate						
Private transport	-	-	49	0.838	46	1.877
Public transport	-	-	24	1.022	23	1.826
Trip purpose						
Commute	-	-	45	0.772**	41	2.026
Others	-	-	28	1.102**	28	1.617
Unobserved Heterogeneity						
Not account for	60	1.256*	33	0.723**	28	2.115
Unobserved hetero.	9	1.726*	40	1.044**	41	1.686
Travel time measurements						
Uncongested travel time	39	1.295	58	0.996***	56	2.026*
Congested travel time	30	1.348	15	0.522***	13	1.146*
Utility specification I						
No scheduling/reliability variable	54	1.473***	58	0.994***	59	1.971
Including scheduling / reliability variable	15	0.760***	15	0.528***	10	1.205
Utility specification II						
No lateness variable	61	1.386**	49	0.915	47	1.749
Including lateness variable	8	.0.796**	24	0.864	22	2.096

Note: The statistical test (t-test) is concerned with the comparison of means within each group. Significance is indicated by ***, **, and *, referring to significance at the 1%, 5%, and 10% levels.

5.0 Empirical results of meta-regression

To explain the variation in reliability and scheduling ratios in a systematical way, we employ the meta-regression technique to meet our purpose. In brief, meta-regression is based on the following relation (Stanley and Jarrell, 1989):

$$y = f(p, x, r, t, l) + \varepsilon \quad (6)$$

where y is an effect size observed in a series of studies, p is the specific causes, x is moderator variables affecting the cause-effect relationship, and r, t, and l are moderator variables representing differences in research designs, time-periods considered, and locations covered by the initial studies.

In the context of the current analysis, we have three distinct series of effect sizes—reliability ratios, scheduling delay early ratios, and scheduling delay late ratios, as the dependent variables in our OLS regression model. We specify the explanatory variables as the possible causes of variation, and with this specification we basically aim to investigate the effects that we have discussed in the previous section in a multivariate setting. We also consider the location dummy and time trend to explain the spatial and temporal difference respectively. The results of regression are reported in the following.

Table 5 Results of meta-regression (basic OLS) of RR, SDER, and SDLR

Categories	Variables	RR	SDER	SDLR
Fixed effect	Constant	3.386	1.846***	2.309*
		(1.32)	(4.24)	(1.75)
Data type	SP	-0.108	-0.904***	-2.139***
		(-0.30)	(-4.51)	(-3.40)
Choice type	BETWEEN	-	0.076	0.275
		-	(0.27)	(0.33)
Unobserved heterogeneity	HET	-0.138	-0.300	-1.456*
		(-0.45)	(-1.22)	(-1.99)
Mode specific estimate	PUBLIC	-1.053	-0.270*	-0.496
		(-1.46)	(-1.93)	(-1.18)
Trip purpose	Commuting	-	-0.037	0.694*
		-	(-0.26)	(1.67)
Travel time measurement	VOT_CT	0.186	-0.786***	-1.779**
		(0.88)	(-3.46)	(-2.49)
Location effect	US	-1.230	-0.410	0.677
		(-2.90)	(-1.22)	(0.65)
Time trend	YEAR	-0.033	0.015	0.091*
		(-0.38)	(0.99)	(1.91)
Utility Specification I	SCHEDULE / RELIABILITY	-0.659**	-0.377	-2.524***
		(-2.10)	(-1.64)	(-3.37)
Utility Specification II	LATENESS	0.037	0.013	-0.128
		(0.11)	(0.10)	(-0.29)
R-squared		0.3205	0.4450	0.3636
Adj R-squared		0.2299	0.3555	0.2538
Probability value F-test		0.0021	0.0000	0.0019
Number of observations		69	73	69

Note: Significance is indicated by ***, **, and *, referring to significance at the 1%, 5%, and 10% levels, respectively, with t-values in parentheses.

Table 5 shows the results of the meta-regressions of RR, SDER, and SDLR. The included sets of explanatory variables are aimed to investigate those sources of variation discussed in Section 3. These results will be explained in the following subsections.

5.1 Data types

The results in Table 5 indicate that the use of the SP method has no significant effect on RR estimates in our meta-regression; whereas Brownstone and Small (2003) concluded that SP underestimated VOT and VOR substantially. A possible explanation for this phenomenon is that the SP may underestimate both VOT and VOR in a systematic but equal-proportional way. As a result, this downward bias effect is cancelled out by taking the ratio of these two.

Different from the case of RR, the results obtained from SDER and SDLR show that SP has a highly significant negative effect. The result is quite robust since the conditional means of SDER and SDLR also show the same pattern that SP has lower estimates. One possible explanation for this phenomenon may be the existence of misperception of the amount of schedule delay and the risk aversion behaviour of travellers. The idea is following.

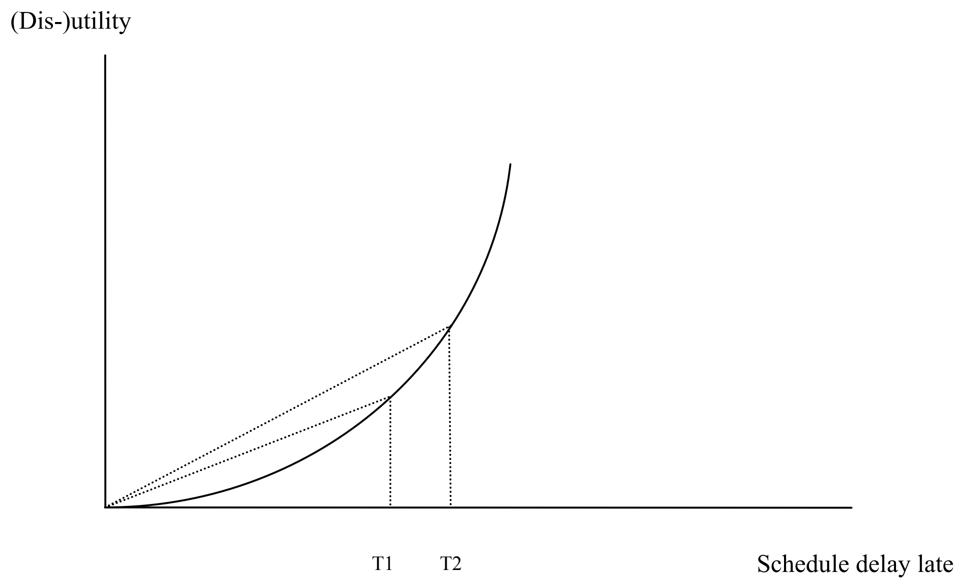

Figure 1 The shape of utility function with respect to schedule delay late variable

If a traveller is risk adverse to SDL, then we can expect that the shape of the utility function is convex with respect to SDL (see Figure 1). When a traveller experiences an actual amount of schedule delay late T1, but perceives it as T2, then he may evaluate the value of schedule delay late at T2 instead of the true value T1. From the figure we know that the slope is steeper at T2 than at T1. Thus, the value of schedule delay late may be overestimated under the RP data. Similarly, the value of SDE can be explained in the same manner.

In such a case, if the level of risk aversion is more in schedule delay variables than in travel time, then we can infer that this overestimation of VSDE and VSDL is stronger than of VOT. As a consequence, the difference in risk aversion to schedule delay and travel time may help us to understand why RP could overestimate the ratio of schedule delay.

5.2 Utility specification

Here the utility specification means whether the reliability/scheduling variables and lateness dummy are included in estimated model in studies. In the analysis of the reliability ratio, the explanatory dummies 'SCHEDULE' and 'LATENESS' denote the inclusion of scheduling variables and lateness variables in the same estimation model, respectively. Whereas with the analyses of schedule delay ratios, we use the explanatory dummy 'RELIABILTY' to indicate the existence of reliability variables in the same estimation model.

The result of including both reliability and schedule variables suggests that there is a significant negative effect on RR estimates as well as on SDER and SDLR estimates. Apparently, the concept of reliability and scheduling delay are not easy to be distinguished and statistically they are positively correlated with each other. Consequently, this negative effect on estimates between each other can be expected if the design of questionnaire was not well specified with respect to these two terms.

The insignificant coefficient of the 'LATENESS' dummy indicates that the inclusion of the lateness variable in the indirect utility does not have sizeable bias on the RR, SDER, nor SDER estimates. Since the specification of lateness dummy in Eq.(3) is to capture individual's additional disutility associated with the fact of being later than his preferred arrival time, we expect that this dummy has no influence on reliability estimates. The meta-regression result is consistent with the general expectation.

5.3 Types of choice set

From Table 5, we find that the between mode choice type does not produce estimates differently from what within mode choice does. As we have discussed in Section 3.3, if researchers can correctly model the choice behavior answered (or observed) from the travelers, the resulting reliability or scheduling estimates should not be too different in different types of choice questions.

5.4 Observed and unobserved heterogeneity

Commuting trip is usually considered to be the one with more scheduling concern. Thus, it is natural to anticipate some positive effect of commuting on the scheduling ratios estimates. Our meta-analysis confirms this idea that travelers have significant higher values on the schedule delay late ratio. As for the effect of trip modes, it is not clear that whether there is any substantial difference between car and public transport on the reliability and scheduling ratios.

The results from conditional means and meta-regressions do not provide any strong evidence on the effect of accounting for unobserved heterogeneity. Actually, with different degrees of complexity and different types of specification of accommodating the unobserved heterogeneity into the model, the result is probably mixed. Whether the consideration of unobserved heterogeneity has certain effects on empirical estimates requires further information on modeling details and a richer database.

5.5 Different measurement attributes

In the investigation of different measurements of travel time, we find out that there is a negative effect if the value of time is evaluated during congested periods. The effect is highly significant for SDER and SDLR. This result corresponds to our anticipation since the congested value of time is higher in general, and hence the computed ratios should have small values.

6.0 Conclusions

Since the last decade, reliability and scheduling delay of travel time are considered as important factors in traveler's decision making. Many researchers have attempted to model the reliability and scheduling delay attributes into traveler's choice model. As a result, a wide range of estimated values is produced owing to the different data types or methodologies used in the valuation. Our aim in the present paper is to analyze the explanatory factors that systematically affect our variables of interest—reliability ratio (RR), scheduling delay early ratio (SDER), and scheduling delay late ratio (SDLR) by means of the multivariate statistical technique: meta-analysis.

We start by correcting the reliability estimates that were evaluated under different measurements, i.e. coefficient of variation, standard deviation, difference between 90^{th} and medium, and difference between 80^{th} and medium of travel time. After making these reliability estimates comparable, we use several multivariate regression models to further explore the sources of variations among empirical estimations in RR, SDER, and SDLR. Explanatory variables included in our meta-analysis are the type preference data, the choice type, the trip mode, different VOT unit measurements, the inclusion of schedule and reliability attributes, and the inclusion of lateness attributes.

We find that, as expected, the inclusion of both reliability and scheduling attributes (SDE, SDL) would lead to lower estimated values for both attributes. Regarding the types of data, a striking finding is that the SP data may produce lower values for SDER and SDLR than the RP data. The misperception error of the magnitude together with the risk aversion attitude associated with schedule delay late/early variables may be one of the possible explanations. Still, to obtain more robust evidence for the understating problem of SP we need more empirical studies to confirm.

It remains unclear that whether accounting for unobserved heterogeneity has significant influence on RR, SDER, and SDLR estimates in our meta-analysis. Nevertheless, we believe that accounting for unobserved behavior heterogeneity, e.g. nested correlations among choice alternatives, more general error structure forms, or unobserved random effects in individuals (randomizing the parameters associated with some attributes) etc., in a more sophisticated manner will result in more accurate estimates and this is what future researches should head to.

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