Travellers' Attitudes to Travel Time Variability: Inter-Modal and Intra-Modal Analysis

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Synopsis

A major feature of any reliable transport system is a low level of unexpected travel time variability (TTV). The ability to identify travellers' attitudes to TTV and to ascribe monetary values to their preferences is crucial for the assessment of proposed schemes that might have reliability effects. Past research has not yet overcome the issue of whether the effects of TTV on travellers' behaviour are fully explained by their trip scheduling considerations. While there is evidence that this is the case for car users, it has been shown that railway users are also influenced by the inconvenience caused by TTV per se; for bus users there is hardly any evidence at all. There is in particular lack of discussion about the distribution of preferences among individuals. The current paper investigates the attitudes to TTV and scheduling considerations of car, rail and bus users, based on a survey held in the city of York, England. Multinomial Logit and Mixed Logit models for the choice of departure time are presented. These models account for both the inter-modal and the intra-modal dimensions of the variations in scheduling preferences among travellers. Different formulations of the Multinomial Logit model and different distributions of the Mixed Logit model coefficients are analysed. Some drawbacks of the different formulations are illustrated. It is shown that mean-variance formulations undervalue the effects of TTV; using mean-variance models in scheme appraisal might prevent an important source of benefit from revealing itself, and should therefore be strictly avoided. The models demonstrate that travellers of all modes penalise early arrival to their destination at a similar level as they penalise the mean travel time, but the penalty on late arrival is much higher. Car and bus users differ from each other mainly in their attitudes to lateness, whereas rail users place much higher penalties on all the examined variables. In addition, it is shown that the use of normally-distributed coefficients in a Mixed Logit model results in irrational monetary values. Triangularly-distributed coefficients lead to more reasonable estimates, although the occurrence of some extreme values should be still treated with suspicion. Recommended ranges of the willingness to pay of car, bus and rail travellers are derived.

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INTRODUCTION

A major feature of any reliable transport system is a low level of unexpected travel time variability (TTV). The reduction of TTV is increasingly becoming an objective in itself in many transport projects, independently of the traditional objective of reducing the mean travel time (MTT). To enable the promotion of schemes that aim at reducing TTV, the economic benefit that they bring should be revealed; this benefit has not been conventionally included in the common practice of project appraisal. The current paper presents an attempt to estimate monetary values that can be used in an economic assessment to capture the effects of TTV on travellers, based on the concept of willingness to pay (WTP). Particular attention is given here to variations among travellers in their attitudes of TTV: variations between the users of different modes are examined through separate models, and variations within the population of users of each mode are analysed by using random coefficients.

We are interested in understanding the effect of TTV on decisions made by travellers in their morning commuting journey. Unless mentioned otherwise, TTV variables discussed here are measured as the standard deviation of travel times. Our definition of TTV includes day-to-day variations caused by factors that are unpredictable to a rational traveller; namely, the residual, random TTV element that remains after subtracting some components that can be expected. This is similar to the definition of *ambient variability* discussed by Fowkes and Watson (1989) and also accords with the discussion by Bates et al (2001). For instance, our definition of TTV <u>does not include</u> variability caused by systematic changes in demand, roadside activity, weather conditions or daylight throughout the analysis period, the week or the year. Our definition <u>does include</u> the variability caused by random fluctuations in these factors. It also <u>includes</u> variation caused by the daily-changing traffic composition, in terms of drivers' human characteristics, personal preferences and driving styles. Our definition <u>does include</u> the effect of accidents, incidents and road works. For public transport passengers in particular, TTV as defined here <u>includes</u> variability caused by cancellation or delay of a service (due to either workforce or traffic problems), and due to change of the vehicle type used for a specific service.

The following section reviews existing research that converts the effects of TTV into monetary terms. The subsequent section presents Multinomial Logit models where TTV is considered either directly or indirectly, and compares their performance. In the section that follows, error components are introduced to the models, to allow for intra-modal taste heterogeneity, and difficulties in replicating the distribution of the WTP are discussed. In the final section, some conclusions are drawn.

ATTITUDES TO TTV IN AN ECONOMIC CONTEXT: EXISTING LITERATURE

The economic significance of TTV was initially discussed theoretically by Knight (1974). Knight shows that since travellers' surplus is a convex function of travel time, different values of surplus derive from different travel time distributions, even when they have the same mean. Bates et al (1987) present another theoretical analysis, showing that the concern that travellers feel about TTV reduces the savings from improved traffic conditions.

Empirical attempts to model travellers' attitudes to TTV have been reported in literature starting from the late 1960's; two modelling approaches can be identified. The first approach claims that travellers see TTV per se as a source of inconvenience, similarly to the way they treat the mean travel time (MTT); this concept is commonly referred to as *the mean-variance approach*. Mean-variance models use utility or cost functions that deal with TTV directly, often using a variable that stands for the standard variation of the journey time (Jackson and Jucker, 1982; Polak, 1987a, b; Black and Towriss, 1993; Senna, 1994a, b).

The alternative approach gives evidence that the entire cost attributed to TTV can be captured indirectly, by modelling travellers' earliness and lateness considerations when choosing at what time to depart for their journey; this is sometimes called *the scheduling approach* (but should not be confused with the term *scheduling* as used in the context of public transport operations). The scheduling approach is based on the concept that if travel times vary from day to day, arriving always at the destination exactly at the desired time is unfeasible. Travellers can react to TTV by choosing to move their departure from home backward or forward, and by doing this, to change their chance of arriving too early or too late; the scheduling approach claims that this choice is the main manifestation of their attitudes to TTV.

The idea that TTV causes travellers to change their departure time is introduced by Gaver (1968). Gaver and subsequently Knight (1974) ascribe a penalty to late or early arrivals to the destination, and define a *safety margin* that travellers allow on their departure time, seeking optimal trade-off between the penalties. Hall (1983) develops a safety margin model in which travellers delay their departure from the origin as much as they can, as long as their risk of being late does not exceed a certain limit. Pells (1987a, b) expands the discussion about the differences between values of time at home, at work when arriving early and at work when arriving late. Pells develops two choice models for evaluating the value of slack time and the value of lateness.

It should be noted that scheduling models are identified by both the variables they incorporate and the type of choice they try to predict, while mean-variance models are defined only on the basis of the included variables. In principle, a mean-variance formulation can be used for modelling various choices, including scheduling choices. The main point in the distinction between the two approaches is the issue of whether or not the cost attributed to TTV can be adequately accounted for by the attitudes towards early or late arrival.

Several authors examine the predictive power of both mean-variance and scheduling models; they develop a scheduling model, and check whether there is a pure nuisance related to TTV itself by examining the significance of an explicit TTV variable. Noland et al (1998) build a choice model with typical scheduling variables, such as the MTT, average lateness to the destination, average earliness and probability of late arrival; they show that a TTV variable does not result in a much more powerful model. Small et al (1999) compare between two versions of a mean-variance model, with and without a set of scheduling variables. The TTV variable is found significant only when scheduling costs are not explicitly accounted for, and the authors strictly conclude that “in models with a fully specified set of scheduling costs, it is unnecessary to add an additional cost for unreliability”. The model created by Bates et al (2001) is the only one that rejects these findings: they state that a TTV variable has some contribution on top of the explanatory power of scheduling considerations.

Bates et al (2001) note that empirically, the sum of the earliness and lateness components in a utility function in a scheduling model can often be approximated by a single component expressing the standard deviation of travel times. Although this insight only holds under certain conditions, this might suggest that the costs captured in mean-variance formulations are in fact indirect estimates of scheduling considerations. Noland and Polak (2002) show that in a special case, where there is no lateness penalty and changing the choice of departure time does not cause a change in recurrent congestion, the scheduling and mean-variance approaches are equivalent.

Among the findings of different research works, the big majority agrees that scheduling models give a better understanding of the cost of TTV. But in common practical, non-academic use, mean-variance models are repeatedly preferred (TRL, 2004; Atkins, 1997; and others). Scheduling models are seldom used due to the difficulty in obtaining the input data they require, that includes information about the distribution of arrival patterns of travellers to their destinations. The unpopularity of scheduling models also stems from difficulties in their implementation, which normally necessitates the use of simulation. Mean-variance models are easier to apply, since they only oblige to obtain estimates of traffic data such as the MTT and TTV.

Only few of the relevant works take account of the heterogeneous nature of travellers’ behaviour. Polak (1987a, b) brings theoretical background for the treatment of risk aversion or risk proneness; several formulations of utility functions that take this into consideration are presented but not calibrated. Senna (1994a, b) continues this discussion and calibrates mean-variance models for travellers with different conceptions of risk. De Jong et al (2004) and Hess et al (2004) present models for the choice of mode and time of day, which use a Mixed Logit formulation. These models make an important contribution by allowing for a distribution of individual attitudes to the extent of earliness and lateness. However, the discussed lateness and earliness depend only on the MTT; the survey on which the models are based does not present distributions of journey times, and therefore, the effects of TTV cannot be captured even if scheduling variables are included. None of the other works known to us, which consider taste variations across the population of travellers, is a departure time choice model or a model that analyses the effect of TTV.

Most of the models cited above focus on car users’ behaviour. An intermodal comparison between values of TTV is derived by Black and Towriss (1993) from their mean-variance models of car, bus and train users; scheduling considerations or departure time choice are not explicitly addressed. Only few works that concentrate on public transport users’ attitudes to TTV are found in literature. For rail travellers, the only research is described by Cook et al (1999) and further analysed by Bates et al (2001); they develop a model for the choice of railway service and departure time. For bus users, Pells (1987a, b) introduces innovative ideas regarding scheduling behaviour, but does not use within a single cost function the entire set of scheduling variables that have been recently proved necessary. Part of the data used in the current paper for inter-modal analysis is also used by Hollander (2005) for a separate discussion of bus users' attitudes to TTV.

TTV has behavioural effects not only on departure time choice. It has been shown that TTV influences mode choice (Prashker, 1979; Hendrickson and Plank, 1984; Bhat and Sardesai, 2005; and others), route choice (Abdel-Aty et al, 1995; Liu et al 2004), the combined choice of route and departure time (Lam, 2000) or a combination of route, time and mode (Lam and Small, 2001). However, all these models but a few (Lam and Small, 2001; Bhat and Sardesai, 2005) do not prove that a monetary value can be attributed to the effect of TTV; as aforementioned, the interest in attitudes to TTV in the current context is mainly for an economic analysis. In addition, it has been repeatedly claimed that the influence of TTV on mode, route or other decisions is secondary to its influence on scheduling choices, for users of all modes (Hendrickson and Plank, 1984; Mahmassani and Stephan, 1988; Noland and Small, 1995; Bates et al, 2001).

Features of the main reviewed works are summarised in table 1. We conclude this review by noting that it is still unanswered whether the scheduling approach can satisfactorily explain travellers' reaction to TTV. While for modelling the effect on car users there seems to be evidence for the sufficiency of scheduling variables, the evidence for rail users is to the contrary, and for bus users there is hardly any evidence at all. None of the reviewed models compared the preferences of users of different modes at the same time and place, using the same survey method. It is thus unknown if differences between their conclusions stem from truly different behavioural patterns of the users of different modes. There is also need to further examine the heterogeneity of attitudes to TTV among travellers.

MEAN-VARIANCE VERSUS SCHEDULING APPROACH

The presented models are based on data collected in an SP survey, carried out in the city of York, England, from November 2004 to February 2005. The survey is an extension of the bus-user survey described in Hollander (2005), and follows the same methodology. After removing some invalid responses, the sample included 244 bus users, 290 car users and, unfortunately, only 20 rail users. Each respondent answered nine questions of a similar structure; each question included a choice between two alternatives defined by their cost, departure time, MTT and TTV. MTT and TTV were not stated explicitly, but through a graphical display of a pattern consisted of five daily travel times. For a description of the full survey methodology, see Hollander (2005). Due to the small number of respondents that commute by rail, the forthcoming analysis treats the model for rail users with great caution; it is primarily judged by common sense and not by measures of statistical performance (such as t-test). While the model presented here for rail users is obviously not as applicable as the models for car and bus, we still find that there is great interest in presenting a comparative analysis of the results for all three modes.

The survey data were used to estimate mode-specific Multinomial Logit models, using the Alogit 4.1 software package. During the attempts to reach models that show the best statistical performance, the contribution of typical variables of both scheduling and mean-variance formulations was examined. For all three modes it was found that a direct TTV variable remains significant while the scheduling variables are not included, but does not improve the power of the model once the lateness and earliness variables are introduced. For car users, this result is similar to the findings of Noland et al (1998) and Small et al (1999). For rail users, this contradicts the conclusions of Bates et al (2001). This also confirms that a scheduling formulation is equally applicable to bus users, which have not been discussed separately in this context so far. The final models are presented in table 2. Results of the t-test appear in brackets.

Another finding that holds similarly to the users of all three modes is that the penalty on earliness is very similar to the penalty on the journey time itself. After trying several possible combinations of the MTT and the mean earliness variables, it was decided to choose the simplest formulation, where the sum of MTT and the mean earliness is included as a single variable; other significant variables are the cost and the mean lateness. *We denote the mean travel time and earliness variable by **MTE**, and the mean lateness by **ML***. Any addition to this simple formulation did not result in any significant improvement of the explanatory power of the model.

Table 1: Summary of models with TTV variables

Source	Approach	Formulation	Calibrated?	Attitudes to risk?	Market segmentation?	Calculation of costs or benefits?
Gaver (1968)	Scheduling	Cost minimisation	No	No	No	No
Knight (1974)	Scheduling	Utility maximisation	No	No	No	No, but the idea is introduced
Jackson and Jucker (1982), Black and Towriss (1993)	Mean-variance	Utility maximisation	Yes	No	No	No
Hall (1983)	Scheduling	Joint minimisation of time and risk	No	No	No	No
Pells (1987a, b)	Scheduling	Utility maximisation	Yes	No	Yes	Yes
Polak (1987a, b)	Scheduling	Utility maximisation	No	Yes	No	No
Senna (1994a, b)	Mean-variance	Utility maximisation	Yes	Yes	Yes	Yes
Noland and Small (1995)	Scheduling	Cost minimisation	Partially	No	No	Yes
Noland et al (1998)	Scheduling + mean-variance	Cost minimisation	Yes	No	No	Yes
Small et al (1999)	Scheduling + mean-variance	Utility maximisation	Yes	No	Yes	No
Cook et al (1999), Bates et al (2001)	Scheduling + mean-variance	Utility maximisation	Yes	No	No	Yes

Table 2: Scheduling models

		Car	Bus	Rail
Coefficients	Cost	-0.6996 (-18.1)	-1.375 (-14.2)	-0.1739 (-3.4)
	MTE	-0.05209 (-10.0)	-0.07173 (-11.5)	-0.03229 (-3.2)
	ML	-0.2315 (-5.6)	-0.1974 (-4.1)	-0.1147 (-1.3)
Likelihood	Initial	-1985	-1534	-124
	Final	-1726	-1369	-116
WTP	MTE	7.4	5.2	18.6
	ML	33.1	14.4	66.0

The WTP is calculated as the ratio of the MTE or ML coefficients to the cost coefficient. Expectedly, the WTP among car users is higher than among bus users. It can be observed, however, that the relative sensitivity of car users to late arrival is much higher: while the difference between car and bus users in their value of MTE is 42%, the difference in the value of ML is 130%. The monetary values of MTE and ML for rail user are at least twice higher than for car users; this might seem unusual if compared to results from other countries (see, for instance, De Jong et al, 2004, where the WTP among car users is higher than among rail users). Nevertheless, a high level of WTP among rail users is consistent with the findings of recent works that bring inter-modal evaluation of the value of time for travellers in the United Kingdom (Wardman, 2004; TRL, 2004). The sensitivity to late arrival is apparently not strictly proportional to the WTP: car users are the most averse to lateness, as they penalise every minute of ML equally to 4.5 minutes of MTE. Rail users will pay for a reduction of one minute in ML the same as for 3.5 minutes of MTE, and for bus users this ratio is 2.8.

It was mentioned above that mean-variance models are very common in practice despite some evidence to their inferiority. It is therefore interesting to examine what might be the consequences of the popularity of the more convenient approach. To check this, another model was estimated for each mode, including cost, MTT and TTV variables, similarly to most mean-variance models. The results are presented in table 3.

Table 3: Mean-variance models

		Car	Bus	Rail
Coefficients	Cost	-0.5966 -(15.5)	-1.179 -(12.1)	-0.1634 -(2.6)
	MTT	-0.05612 -(10.4)	-0.08208 -(12.3)	-0.0352 -(3.2)
	TTV	-0.005768 -(0.4)	-0.007792 -(0.5)	-0.005758 -(0.2)
Likelihood	Initial	-1985	-1534	-124
	Final	-1729	-1359	-116
WTP	MTT	9.4	7.0	21.5
	TTV	1.0	0.7	3.5

Apparently, the mean-variance models have the same final likelihood as the scheduling models; this might be another reason for their common use. However, it comes across that the statistical performance of the TTV variables is very poor, which is in itself a sufficient motivation for not using these models for the analysis of reliability effects. The derived values of MTT are higher than in the scheduling models; a possible way to interpret this is that some cost that is unexplained by TTV is attributed in the mean-variance models to the MTT, in the absence of the scheduling variables that truly capture this cost.

Comparing the value of TTV as implied by the mean-variance models to the values of MTE and ML from the scheduling models is not easy, since there is no straightforward way to convert a minute of TTV to lateness and earliness; this varies from one situation to another. Nevertheless, it can be shown that mathematically, in most journeys made by a rational traveller, the ML is likely to be around an average level of 20% of TTV (and is always greater than 0 but smaller than the TTV). The mean earliness, which is penalised in the scheduling model at the same level as MTT, is likely to be a number at the same order of magnitude of the TTV (and is always between 0 to 3 times the TTV). Since there is normally some trade-off between earliness and lateness, one of these numbers is normally at the high side of the mentioned feasible range. Bearing all this in mind, it is clear that if the cost associated with TTV in a specific journey is computed using both models, the values derived from the mean-variance models will almost always imply a much lower cost than the values of earliness and lateness in the scheduling models. For instance, if a car traveller departs from home at 8:00 in order to arrive at work at 8:30, and in five successive days arrives at 8:27, 8:25, 8:34, 8:29 and 8:30 – the MTT is 29.0 minutes, the TTV is 3.4, the mean lateness is 0.8 and the mean earliness is 1.8; according to the scheduling model, the cost of MTT is £2.15 and the indirect cost of TTV is £0.40, whereas according to the mean-variance model, the cost of MTT £2.73 is and the direct cost of TTV is £0.03. In other realistic situations we get different costs, but the cost of TTV is always much lower when the mean-variance model is used. Since the scheduling variables perform much better statistically, we conclude that the mean-variance models underestimate the true cost of TTV. The total cost calculated using a mean-variance model is not necessarily undervalued, but the part of it that is a result of TTV is distorted. In the appraisal of a scheme aimed at reducing TTV, using a mean-variance model is thus very likely to be misleading.

THE DISTRIBUTION OF ATTITDES TO TTV

Attaching a single set of monetary values to all users of the same mode is clearly a simplified representation of the way travellers actually behave. Accounting for the heterogeneity of preferences among travellers is likely to enable more powerful decision-making based on the analysed data. This section describes the attempts to convert the Multinomial Logit scheduling models presented above to Mixed Logit models, where error components are introduced to allow for taste variations among travellers. The theory of Mixed Logit modelling is well-documented in literature and is therefore not reviewed here; for a useful overall description of the Mixed Logit model, the reader is referred to Hensher and Greene (2003), Bhat (2001) and Batley et al (2001).

The use of simulated likelihood methods, through software packages such as Alogit and Biogeme, makes the estimation of Mixed Logit models an easier task than ever before. However, some recent studies have found evidence that traditional statistics, such as maximum likelihood and t-test, tend to indicate a good fit between the Mixed Logit model and the input data even when the actual fit is not satisfactory (Sørensen, 2003; Hess et al, 2005; Hollander, 2005). A particular problem relates to travellers' WTP, derived from Mixed Logit models: the distribution of values tends to ascribe values with the wrong sign to a certain share of the population (Hess et al, 2005; Hollander, 2005). An easy way to avoid this difficulty is still unavailable, and it is hence important to make a careful logical judgement of the validity of any result. Experience with Mixed Logit models also suggests that trying several alternative distributions of the coefficients, prior to choosing the preferable model, is a recommended practice.

Three versions of a model where variation of the coefficients among travellers is allowed were estimated for each mode, using Alogit 4.1. The models are presented in table 4; the variables used in these models are the same as in the scheduling models discussed earlier in this paper. It was found that introducing error components of the cost and ML improves all three models; but allowing for variation of the MTE coefficient did not seem to contribute much. Note that values of the t-test for rail users are lower than what is normally accepted, as a result of the relatively small number of rail users in the input data. They are presented to enable inter-modal comparison; as mentioned above, we generally tend to accept coefficient values if they behave rationally and are consistent with our expectations. A further discussion of the validity of the rail model is brought later in the paper.

The first version attempted of a Mixed Logit formulation used normally-distributed coefficients; we denote this by model 1. The estimation results reveal that for all three modes and for both the cost and ML variables, the error component is bigger than the mean (in absolute values). Although the mean coefficient is negative, the outcome is a distribution that straddles zero. The distributions of the WTP were obtained through simulation. First, individual choice models for 10,000 (ten thousands) users of each mode were drawn from the distributions of the coefficients. Then, monetary values of MTE and ML were calculated in each individual model, and the distribution of values was analysed; it is presented in figure 1. It should be noted that not all resulting values can be seen in the diagram. When the WTP is calculated, the cost coefficient is used as the denominator; since the distribution of this coefficient includes some values very close to zero, the distributions of values of MTE and ML include some extremely big (in absolute values) negative numbers. Statistical properties of the range of values of MTE and ML are shown in table 5.

Table 4: Mixed Logit scheduling models

Coefficient	Normal (model 1)	Triangular (model 2)	Triangular with ML coefficient bounded (model 3)
Cost – mean	car: -8.135 (-2.4) bus: -6.617 (-5.1) rail: -6.596 (-0.6)	car: -10.940 (-1.9) bus: -5.457 (-3.9) rail: -1.388 (-0.6)	car: -5.720 (-4.2) bus: -3.844 (-6.5) rail: -3.935 (-0.5)
Cost – Error comp.	car: 8.576 (2.2) bus: 6.699 (4.0) rail: 10.000 (0.6)	car: 8.136 (1.9) bus: 3.761 (2.9) rail: 1.653 (0.6)	car: 4.741 (3.8) bus: 3.109 (4.5) rail: 5.062 (0.5)
MTE	car: -0.3035 (-2.6) bus: -0.2107 (-5.8) rail: -0.3894 (-0.6)	car: -0.4901 (1.9) bus: -0.2146 (-4.0) rail: -0.1422 (-0.6)	car: -0.2373 (4.4) bus: -0.1421 (-6.9) rail: -0.3754 (-0.5)
ML – mean	car: -1.965 (-2.3) bus: -1.028 (-4.1) rail: -5.139 (-0.6)	car: -3.140 (-1.8) bus: -0.9863 (-3.1) rail: -1.171 (-0.6)	car: -1.357 (-3.8) bus: -0.5485 (-4.6) rail: -3.291 (-0.5)
ML – error comp.	car: 4.151 (1.8) bus: 2.455 (2.8) rail: 4.215 (0.6)	car: 17.49 (1.2) bus: 6.172 (2.6) rail: 2.203 (0.5)	car: 1.357 (3.8) bus: 0.5485 (4.6) rail: 3.291 (0.5)
Final likelihood	car: -1586 bus: -1276 rail: -108	car: -1607 bus: -1294 rail: -113	car: -1619 bus: -1301 rail: -111

Figure 1 and table 5 clarify that the share of negative coefficient values, and the division by numbers close to zero, distort the estimates of the WTP to an extent that makes them most unreliable. The hierarchy between the three modes, as appears in the diagrams, makes good sense; but the estimates of the standard deviation are far too high, and it is clear that the mean values are mainly influenced by an excessive amount of flawed extreme values.

The main cause for the problems of model 1 is the unbounded nature of the normal distribution. Model 2 was introduced as an attempt to tackle this difficulty by using the triangular distribution. The triangular distribution tends to have a milder spread than the normal, and its linearity makes it very easy to implement (for other properties of the triangular distribution, see Hensher and Greene, 2003; and Hollander, 2005). Note that in order to accord with common definitions of the parameters of a triangular distribution, the error components of the triangular models described in table 4 stand for the spread of the distribution, and not the standard deviation.

The distributions of the monetary values of MTE and ML were computed using simulation, as described above for model 1. The results are presented in figure 2 and table 6. The values of MTE are much more reasonable than in model 1, as the negative tail for car and bus users has disappeared. Extreme negative values of MTE for 1.3% of rail users still exist outside the displayed range; although this cannot be accepted theoretically, the small amount of such values makes it tolerable from a practical perspective. Unfortunately, the distribution of monetary values of ML is not substantially different from the respective distribution in model 1. We do not deem the possibility of some negative values of ML irrational, since travellers with flexible start time at work might prefer to arrive slightly later than the time officially stated as their desired arrival time; but the extent to which the distribution of values of ML spreads out in both directions seems unlikely.

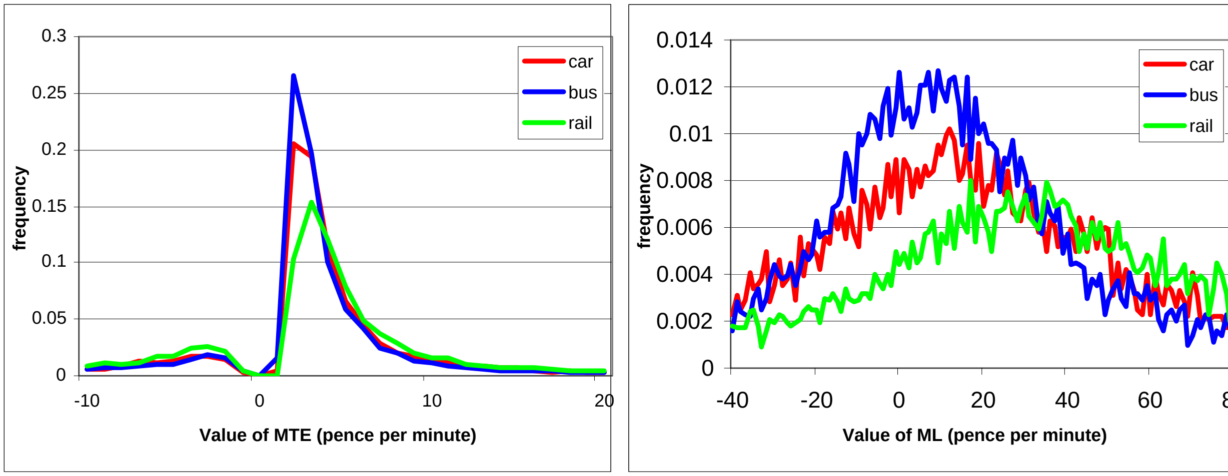

Figure 1: Distribution of the WTP in model 1

Table 5: Statistics of the WTP in model 1

	Car		Bus		Rail	
	Value of MTE	Value of ML	Value of MTE	Value of ML	Value of MTE	Value of ML
Mean	3.4	43.8	5.1	27.0	84.2	900.9
Standard deviation	1758.3	30486.6	194.8	2742.0	7179.7	112126.9
Percentage of negative values	18.1%	38.7%	16.2%	39.8%	25.6%	31.6%

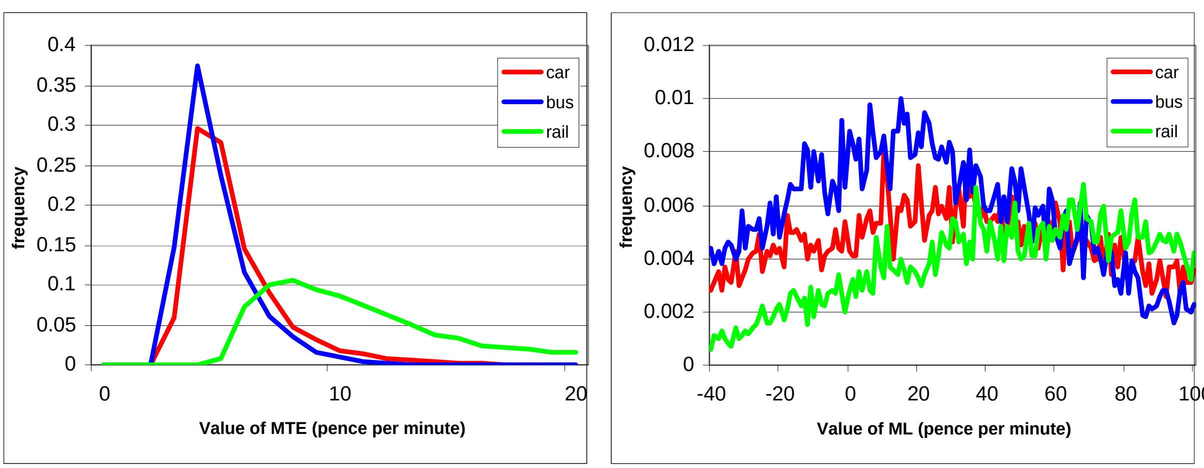

Figure 2: Distribution of the WTP in model 2

Table 6: Statistics of the WTP in model 2

	Car		Bus		Rail	
	Value of MTE	Value of ML	Value of MTE	Value of ML	Value of MTE	Value of ML
Mean	5.0	32.3	4.0	19.4	13.9	107.1
Standard deviation	2	79.4	1.5	54.1	290.8	2969.7
Percentage of negative values	0.0%	33.3%	0.0%	35.9%	1.3%	12.1%

Model 3 is launched as an attempt to deal with the problem of negative monetary values of ML. Triangular distribution was used again, and the MTE error component was not changed, as it produced satisfactory results in model 2. However, the mean and spread of the ML coefficient were obliged to be equal; this ensures that all resulting values of ML have the same sign. The distributions of the monetary values of MTE and ML, obtained from model 3, are presented in figure 3 and table 7. It can be seen that for car and bus users, there are no negative values for the monetary values of either MTE or ML. The other statistics for car and bus users make good sense; we therefore recognize model 3 as the most credible for these modes.

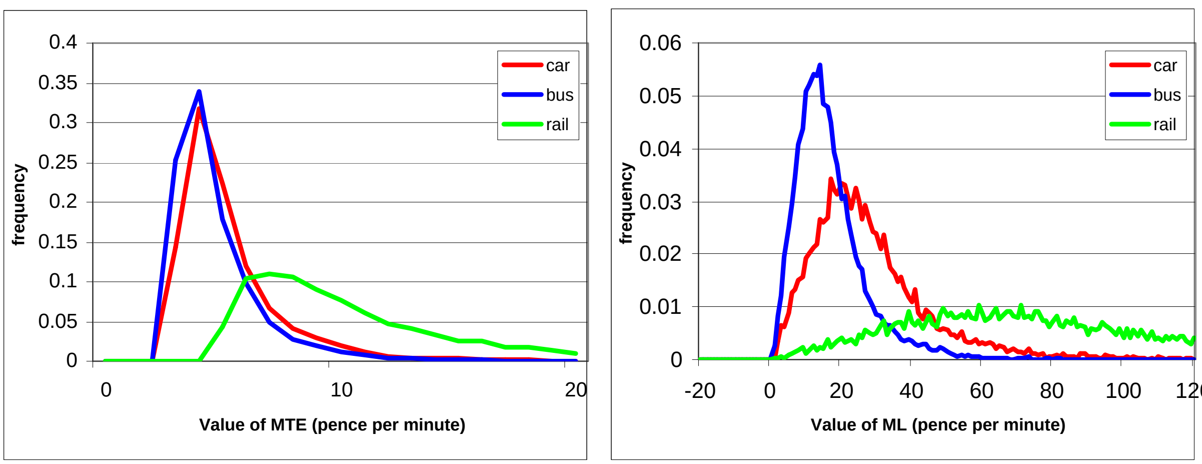

Figure 3: Distribution of the WTP in model 3

Table 7: Statistics of the WTP in model 3

	Car		Bus		Rail	
	Value of MTE	Value of ML	Value of MTE	Value of ML	Value of MTE	Value of ML
Mean	4.9	27.7	4.2	16.4	35.7	286.3
Standard deviation	2.4	18.7	1.9	10.5	1620.1	12323.9
Percentage of negative values	0.0%	0.0%	0.0%	0.0%	2.3%	2.3%

The results for rail users are still not convincing. We remind that although the model was forced to give the same sign to all ML coefficients by presetting the mean and standard deviation to be equal, such restriction was not used for the cost coefficient. Imposing boundaries on the range of coefficient values is done at the risk of not letting the estimation procedure reveal the true boundaries, and since only negative cost coefficient values were obtained for car and bus users anyway, interfering with the results did not seem necessary. However, in the model for rail users, the spread of the cost coefficient is still slightly bigger than the mean, and the result is that within the distribution of the coefficient there are some values very close to zero, both positive and negative. When the monetary values of MTE and ML are calculated, this leads to some very big (positive and negative) numbers that cannot be accepted.

Note the bounding the cost coefficient of rail users the same way we used for the ML coefficients will not solve the problem of too many extreme values, as some very small numbers will still be used as the denominator. In the absence of more accurate information about the true spread of the cost coefficient for rail users, we try fix it at 80% of the mean. 80% is approximately the ratio of the cost error component to the mean cost coefficient in model 3 for both car and bus users, and it is assumed that this can be an acceptable estimate for this ratio in the rail model. The corrected model, model 4, is presented in table 8, together with the best models for car and bus users. The t-test of model 4 gives higher values than the three other models of rail users, and we thus consider this the best model for rail users that can be reached within the scope of this study. The final models for all three modes do not lead to any negative monetary values. We remind that all final models use triangular distribution for the cost and ML coefficients.

Table 8: Final Mixed Logit models

		Car (model 3)	Bus (model 3)	Rail (model 4)
Coefficients	Cost – mean	-5.720 (-4.2)	-3.844 (-6.5)	-0.4938 (-1.5)
	Cost – spread	4.741 (3.8)	3.109 (4.5)	0.3950 (1.5)
	MTE	-0.2373 (-4.4)	-0.1421 (-6.9)	-0.05677 (-1.8)
	ML – mean	-1.357 (-3.8)	-0.5485 (-4.6)	-0.3793 (-1.3)
	ML – spread	-1.357 (3.8)	0.5485 (4.6)	0.3793 (1.3)
Value of MTE (pence per minute)	Mean	4.9	4.3	13.2
	Standard deviation	2.4	2.0	6.1
	Minimum	2.3	2.1	6.4
	Maximum	23.0	17.8	54.4
Value of ML (pence per minute)	Mean	27.8	16.5	88.3
	Standard deviation	18.6	10.8	57.9
	Minimum	0.4	0.1	1.7
	Maximum	205.6	103.4	542.8

Examining the WTP, as implied by the final models, discloses that users of different modes differ from each other in their attitudes to late arrival much more than in the attitudes to the mean travel time and earliness. The range of monetary values that car users would be willing to pay to reduce their MTE is slightly higher than what bus users would pay, but the difference in the amount of money they would pay to reduce ML is substantially bigger. Rail users are significantly more sensitive to any of the time elements, but their sensitivity to late arrival is exceptionally high. As we discovered in an early stage, when an error component of MTE was found insignificant, there is a big variation within the users of each mode in the attitudes to late arrival, whereas the intra-modal range of different values of MTE is somewhat narrower.

CONCLUSION

The analysis presented here dealt with the attitudes of car, bus and rail travellers to the effects of TTV. We find that the penalty that users of all three modes place on every additional minute of travel time is not significantly different from the penalty on a minute of early arrival. Late arrival is treated by travellers of all modes much more severely, although the ratio of the lateness penalty to the other penalties is much higher for rail users than for car and bus users. Car users value the mean travel time or earliness only slightly more than bus users, but the cost that the former ascribe to late arrival is much higher than the latter.

An inevitable conclusion from the modelling effort described here is that some common compromises, that make the modeller's life easier, might significantly reduce the credibility of the results. Such compromise is the use of mean-variance models, which are easy to implement since they do not rely on disaggregate information about the distribution of preferred arrival times, but seem to seriously underestimate the impact of TTV. Using mean-variance models in scheme appraisal might prevent an important source of benefit from revealing itself, and should therefore be strictly avoided. Another frequently-used practice that we find inappropriate is the use of normal distribution for the coefficients in a Mixed Logit model; the resulting range of monetary values is far from replicating a sound behaviour. The triangular distribution yields more plausible estimates of the WTP, although the occurrence of extreme values among these estimates should be carefully investigated all the same.

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