Commuters' Valuation of Travel Time Variability

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Commuters' valuation of travel time variability

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Abstract

The value given by commuters to the variability of travel times is empirically analysed using stated preference data from Barcelona (Spain). Respondents are asked to choose between alternatives that differ in terms of cost, average travel time, variability of travel times and departure time. Different specifications of a scheduling choice model are used to measure the influence of various socioeconomic characteristics. Our results show that travel time variability is valued on average 2.4 times more than travel time savings. Heterogeneity among commuters in terms of restrictions about the starting work time is shown to have significant effects on the value of travel time variability.

Keywords: travel time variability; value of time; commuting; stated preference.

1. Introduction

Although travel time savings are a key component of direct user benefits generated by investments in transport projects, their valuation using cost benefit analysis only takes into account the project's impact on average travel times, disregarding its consequences on time variability. This fact may result in projects that contribute to a reduction in the dispersion of travel times, without significantly reducing their average values, not being chosen when compared to others that have the opposite effects. For instance, a project that provides information in advance with respect to the trip conditions, may not have a significant impact on average travel times, but may be very useful to avoid unexpected delays in exceptional circumstances.

One of the reasons for the absence of travel time variability impacts from standard evaluation procedures is the relative lack of evidence about its precise economic value. Despite the fact that the transport economics literature has acknowledged its importance for a long time, the efforts devoted to the estimation of its value are much less common than those given to travel time savings, for which a large number of results exist for different countries, trip purposes and other characteristics. In the case of travel time variability, the difficulties associated with appropriately measuring its economic value explain why there is still a lack of knowledge about the influence of different socioeconomic attributes or trip characteristics. Given that trips have very diverse motives and characteristics, better understanding how such heterogeneity influences the values of variability of travel times is an unavoidable step for a better evaluation of transport policies.

Although some estimations from European contexts are available, most empirical analyses of the values of travel time variability for car commuters have been obtained in the US, while in Europe there has been a relatively larger interest in public transport users (particularly in the UK). In this paper we estimate the economic value of travel time variability by commuters in a European city (Barcelona) using stated preference data and analyse the role that individual characteristics and trip circumstances have on such value.

Our results are consistent with the approach found in most empirical literature regarding commuters' valuation of travel time variability. We find that variability is not valued *per se*, but due to the impact that it may have in provoking early or late arrivals. Therefore, its economic valuation depends on the values given to the magnitude of early or delayed arrivals. We find that delay time is valued at more than twice the savings of average travel times, although the precise value depends on working time flexibility.

The paper is structured as follows. In section 2 we discuss the different implications of alternative approaches used to estimate the value of travel time variability. Then, section 3 explains the stated preference experiment that we carry out to obtain the data and summarises the main characteristics of the sample. Our results are presented and discussed in section 4, while section 5 concludes. An appendix provides additional details about the design of the questionnaire.

2. Modelling travel time variability.

The concept of travel time variability refers to the commuter's inability to forecast how long his trip will last. Following Bates (2001), we define travel time as being variable when random factors may have an impact on the duration of the trip in such a way that actual arrival time does not coincide with the desired one. This definition implies that variations in the mean travel time that are predictable by the commuter cannot be considered as 'variable'.

Travel time variability is usually modelled in one of two ways, depending on the assumption made about the reasons why it is valued. If it is assumed that individuals merely dislike the possibility of being early, or late, so that travel time variability is valued *per se*, then it is enough to include in the individual's indirect utility function a measure of travel time variability together with the usual components of travel costs. Alternatively, it can be assumed that travel time variability is valued according to the consequences of being early or late. In this case its modelling should consider the consequences on the time restrictions of the individuals, such as early or late arrivals with respect to the desired arrival time. However, as it will be pointed out below, both interpretations are not mutually incompatible.

Small (1982) highlights the importance of modelling time-dependent demand functions in order to take into account changes in the scheduling of activities. He estimates a model for scheduling commuter trips that considers the costs associated with early and late arrivals plus a fixed cost for arriving late. Noland and Small (1995) extended that framework by explicitly considering variable travel times. This development is the basis of our empirical estimation and can be summarised as follows. Given an exogenously determined preferred arrival time at his destination, the commuter chooses a departure time in order to minimise a cost function that, as well as the costs generated by total travel time, includes those due to arriving earlier or later than desired. Such a function can be postulated as follows:

$$C_s = \alpha\ T + \beta\,(SDE) + \gamma\,(SDL) + \phi\, D_L \qquad (1)$$

where T is total travel time, SDE (schedule delay early) and SDL (schedule delay late) are respectively the time margins with which arrival takes place earlier or later than desired. If t_w is the (exogenously determined) desired arrival time and t_h is the chosen departure time, SDE can be expressed as Max (0, t_w-(t_h+T)), and SDL as Max(0, (t_h+T)-t_w). The dummy variable D_L, which would take a value of one if SDL>1, accounts for the extra cost of arriving late, irrespectively of how much.

However, due to the existence of unexpected congestion, travel time (T) is variable, and it can be interpreted as a random term (variable) whose distribution can be assumed to depend on the chosen departure time (t_h). In that context the choice of departure time can be set in expected utility maximisation terms: the commuter maximises his expected utility and chooses a departure time that includes a 'headstart' time (Gaver, 1968), defined as the extra advance in departure time to take into account the effects of variable travel times. Using (1) and the explained decomposition of travel times, expected utility can be expressed as

$$E[U(t_h)] = \alpha\ E[T(t_h)] + \beta\ E[SDE(t_h)] + \gamma\ E[SDL(t_h)] + \phi\ P_L(t_h) \qquad (2)$$

As shown by Bates (2001), a common simplification of (2) assumes that the parameters that define the distribution of travel time variability are not time dependent, recurrent congestion is independent of departure time and there is no lateness penalty. In this case, taking departure time to be continuous, the standard deviation of T approximates the sum of the schedule delay early and late components of travel time at the optimal departure time t_h. Such simplification justifies the direct inclusion of the standard deviation of travel time in the utility function, leading to a model where choice depends on the mean and the standard deviation of travel times. This mean-variance model corresponds to the interpretation of travel time variability having an impact *per se* on the individual's utility, which would be captured by the coefficient of the standard deviation of travel time[1].

At the optimal departure time, the expected utility level can be expressed as a linear function of expected travel time, the expected margins of early or late arrival and the probability of arriving late (Noland and Small, 1995):

$$EU^* = \alpha\ (T) + \beta\ E(SDE) + \gamma\ E(SDL) + \theta\ P_L^* \qquad (3)$$

[1] Although "mean-variance" is the usual term for this model, in fact what this model considers is the effect of the standard deviation of travel time.

This expression can be used to postulate a choice model of route choice, where each alternative is characterized by different degrees of travel time variability and departure times. The choice process is based on an implicit valuation of average travel times, the possible delays or advances with respect to the desired arrival time, as well as of the fact of being late by itself. In order to obtain estimates of those values it is necessary to assume a distribution of variable travel times in each route[2].

There are a growing number of studies that empirically estimate the value given to travel time variability. Although work has been done for public and freight transport (see Bates (2001), Wardman (2001), Noland and Polak (2002) and de Jong et al.(2004)), most of the research effort has focused on the variability of travel times experienced by users of private cars.

Almost all empirical work has relied on data obtained with stated preference techniques. This can be explained by the difficulties associated with measuring travel time variability, both in real terms and in the way that it is perceived by transport users. The only papers that, to our knowledge, use revealed preference data are those by Lam and Small (2001) and Small et al. (2005). They observe route choices between an uncongested tolled route and an untolled one subject to delays in the SR91 corridor in Los Angeles, and build a variable that captures variability in travel times for each case.

Black and Towriss (1993), Senna (1994), Abdel-Aty et al.(1995) and Copley et al.(2002) estimate mean-variance models. The main result that is obtained from these models is the 'reliability ratio', that is, the marginal utility of a reduction of the standard deviation of travel time over that of average travel time. The papers by Noland et al.(1998) and Small et al.(1999), surveyed by Noland and Polak (2002), are the best examples of the schedule delay function approach. They are therefore able to estimate the values given to early and late arrivals, and compare them to that of in-vehicle travel time. We comment on some results of these papers in section 4, when discussing our estimation results.

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[2] An area where little research has been carried out is the analysis of factors that explain variability from the supply side. Ideally, an equilibrium model of supply and demand that takes into account variability from both sides should be specified. Noland et al. (1998) combine the results obtained in the estimation of a demand model with a simulation model of traffic conditions that allows for variability, making it possible to endogenously evaluate the impact of different transport policies on expected travel times and costs.

3. The stated preference experiment

Given the lack of available measurements of travel time variability in the context that we study, our empirical analysis uses data from a stated preference experiment. The choice experiment focuses on private car users, who are asked to choose between two alternative routes for their home-to-work trip. The design of our experiment follows that reported by Small et al.(1999) in their analysis of valuation of travel time variability in California. The origin of this type of analysis can be traced back to previous work by the same authors (Noland et al. 1998) and Black and Towriss (1993).

The geographical context where we carry out the empirical work is the Maresme corridor, north of Barcelona city, in Spain. The corridor is formed by two parallel routes (the untolled national road A-2 and the tolled highway C-32) which connect Barcelona with north-eastern suburbs and small towns. Both the national road and the motorway, which has been open to traffic since 1969, are frequently used by residents in the area and experience congestion at different times of the day. Although Barcelona's region is subject to substantial tourist traffic between Spain and France, almost all tourists use another motorway (AP-7) which provides much better links for long-distance trips. Besides having its own employment centres, the Maresme region has been subject to intense suburbanisation from Barcelona city, resulting in heavy commuter traffic through the corridor. Most of the population is therefore familiar with the choice between alternative routes characterised by different monetary costs, travel times and possible delays (due to accidents or heavy traffic resulting in unexpected congestion, for instance). By choosing this corridor for our analysis we minimise the impact of the main problem of stated preference surveys, namely that respondents not familiar with the type of hypothetical choices that they are asked to make may not properly assess the variables used to characterize the alternatives. On the other hand, it is possible that respondents to the survey try to justify their actual choices, or use the survey to complain against the existence of tolled routes (a long-standing political argument in some areas of Spain). In order to avoid the biases that may result from this, we use different methods, such as unlabelled alternatives to characterise each route, a random ordering of the questions in the choice set and a definition of monetary costs than never shows one alternative to be free.

We analyse route choices in the context of home-to-work commuting trips. Given the importance of being on time for these trips, variability in travel times is more relevant than in trips due to other reasons, such as leisure. The larger degree of homogeneity in the determinants of commuting trips makes it possible to focus on the role that socioeconomic characteristics of the commuter or trip constraints may have in explaining heterogeneity in the valuation of travel time variability.

As mentioned above, the choice set is composed of two routes, each one of them characterised in terms of monetary cost (vehicle operation costs plus the toll in the case of the motorway) average travel time (the time that would usually be required to drive from home to the workplace, which would be the result of free flow time plus the time due to recurrent congestion) and a measure of travel time variability due to unexpected congestion consisting of five equally likely travel times. As shown in the previous section, the schedule function approach assumes that the individual may modify his departure time in order to take possible delays into account. Thus, an additional variable that characterises the alternatives is the advance with which the commuter leaves home with respect to the required departure time if travel times were not subject to variability. The alternatives are therefore defined by four attributes: average travel time, variability in travel times, monetary cost and earlier than desired departure time. Small et al.(1999) discuss whether the full implications of choices characterised by four relatively complex characteristics can be correctly understood in a stated preference experiment. In their pilot survey they test two alternative ways of aggregating two variables into a single one. One way is to add departure time and the distribution of possible travel times into a distribution of possible arrival times to destination. The second option aggregates the average travel time and the departure time into a variable that defines departure in terms of minutes with respect to the desired arrival time to destination. They choose the first method, since the results of the pilot survey show that the latter specification is not correctly understood by most respondents, while the first one is. We also use our pilot survey for this purpose, and reach the same conclusion. Although Wardman (2001) argues that such aggregations of variables may result in individuals not interpreting in a correct way the information presented, the alternative risk is that too much information is used to characterise each alternative and the details about the variability of travel times are not fully taken into account. Therefore, our questionnaire mimics that of Small et al.(1999). An example of the choice presented for one scenario is shown in table 1.

(Table 1)

Details about the stated preference survey are provided in the appendix. The survey provided 259 valid questionnaires from individuals who use the corridor for their commuting trips, implying a response rate of 10%. Given that each sampled commuter reported choices in nine different scenarios, the number of available observations to estimate the choice model is 2331. Most (86%) respondents commute on a daily basis using the corridor, and 75% use the tolled motorway. Since this figure is very close to the actual motorway's share of total traffic (70%), we are confident that our results suffer no sampling bias[3]. Two thirds of respondents are men, with an average age of 40. A majority of respondents (63%) pay the full cost of their trips, while 29% declare that their employers pay all or part of them. A slight majority have no children (54%) and almost a quarter have two (18.9%) or more (5.5%).

The questionnaire includes two questions that allow the identification of different restrictions that individuals may face in their commuting trips. The first one is defined along the lines of Small et al.(1999) as the maximum delay with which commuters may arrive to their workplace without it having negative consequences on their wages or job position. The aim of this variable is to identify the effect of travel times being variable on the possibility of not only arriving late, but doing so too late. The second question asks if other activities, such as taking children to school or shopping, are carried out during commuting trips. It is expected that commuters that undertake such activities would place a higher value on travel times being less variable. Table 2 summarises the responses given to these questions.

(Table 2)

Table 3 shows the reported household gross monthly incomes and the education level of the main income providers. There is a high share of commuters belonging to households whose main income provider has a university degree. Even though self-reported household incomes are likely to be biased, the values reported are above those of the geographical area of reference. Moreover, more than ¾ of them have two or more occupied members, which is a large figure for Spanish standards. All this information identifies the sample as relatively well off.

(Table 3)

4. Model estimation and results.

We specify the route choice decision process with a logit model. Under random utility theory assumptions, the deterministic component of the indirect utility function for individual i when choosing alternative j is based on the schedule delay function discussed in section 2, and can be expressed as

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[3] In order to take into account potential sampling biases, all the reported models have been reestimated with the WESML estimator (Manski and Lerman, 1977). The results –which are available from the authors- showed that there were not significant differences between the estimated coefficients in the weighting and unweighting options.

$$V_{ij} = V(T_{ij}, SDL_{ij}, SDE_{ij}, P_{Lij}, M_{ij}) = \beta_T E(T_{ij}) + \beta_L E(SDL_{ij}) + \beta_E E(SDE_{ij}) + \beta_P P_{Lij} + \beta_M M_{ij} \quad (5)$$

where T_{ij}, SDL_{ij} and SDE_{ij} are defined as in (1) and M_{ij} is the monetary cost of the alternative. The expectation operator $E(\cdot)$ is applied to the five scenarios that characterize each alternative, whose design is explained in the appendix. $E(T_{ij})$, the average travel time, is easily calculated. However, $E(SDL_{ij})$ and $E(SDE_{ij})$ only take into account the cases in which a late or early arrival takes place, respectively. As shown by Small et al. (1999), it is variability in travel times that generates the values of those variables. Thus, the costs due to the existence of variability can be captured through the costs of expected early or late arrival times. The more variable travel times, the larger the values of those expected values. Finally, P_{Lij} captures the additional impact on utility of the probability of arriving late, independently of the magnitude of the delay. It is empirically defined as the proportion of times in which a late arrival would take place.

We use a binomial logit specification to estimate the empirical discrete choice models, where the dependent variable takes the value 1 when the tolled motorway alternative is chosen. All explanatory variables are expressed as the difference between their values in the motorway and the national road. The specification strategy followed focuses first on the selection between the mean-variance and the schedule delay function approaches to the modelling of travel time variability. The results[4] of following each approach are shown in models 1 to 3 (table 4).

(Table 4)

We initially estimate a broad specification that incorporates all the variables that capture the impact of travel variability according to both approaches: schedule delay early, schedule delay late and the standard deviation of travel times (model 1)[5]. The cost and travel time coefficients take the expected signs and are statistically significant, but only one of the variability measures (SDL) is marginally significant.

Model 2 corresponds to the mean-variance approach, where only the standard deviation of travel time captures the effect of variability. This model allows for the calculation of the reliability ratio between the coefficients of the standard deviation and the average travel time. We estimate a value of 0.98, in line with the literature. Although Black and Towriss (1993) found a value of just 0.55 for trips to and from work by car and a value of 0.70 for all types of trips in their sample, more recent work has estimated ratios above unity: Noland et al.(1998) find a value of

4 All the reported models have been estimated with

[5] The variable P_L that captures the probability of late arrival is omitted since its coefficient is not significantly different from zero in any of the preliminary estimations. Given the way in which they are defined, the variables SDL and P_L are strongly correlated, and their estimation is therefore difficult.

1.27 for commuting trips in Los Angeles, and Copley et al.(2002) obtain a ratio of 1.3 in a model estimated with Manchester data. According to Bates (2001), a typical value for the reliability ratio would be 1.1.

Model 3 captures the effects of travel time variability only through the early or late scheduled delays. The estimates of the cost and travel time coefficients are very stable with respect to the previous models, while statistically significant estimates are now obtained for both SDE and SDL. As expected, and in line with Noland et al.(1998) and Small et al.(1999), the results of this model show that more importance is attached to delay than to travel time, which in turn is more valued than early arrival time[6].

Model 1 clearly shows that it is not possible to simultaneously use both approaches to capture the impact of travel time variability on the choice process. We therefore need to choose between model 2 and model 3. Applying a likelihood ratio test to the alternative exclusion of the standard deviation or the SDE and SDL variables yields clear results[7] in favour of model 3. Therefore, similarly to what was found by Noland et al.(1998) and Small et al.(1999, 2005), our estimations offer evidence favourable to the schedule function approach when analysing the role played by variable travel times.

The estimates of the cost and time variables in the previous models are robust with respect to the alternative specifications. This stability makes it possible to deal with one frequent problem in stated preference experiments, such as whether respondents correctly understand the choices they are asked to make. One way of evaluating *ex post* the magnitude of this problem is to analyse the coherence of the estimation results, which can be done by computing the price and travel time demand elasticities. Elasticity values correspond to aggregate values for the whole sample, computed by simulation of price or time increases as arc-elasticities. We obtain elasticities of -0.26 and -0.48, respectively, which are close to what could be expected in a corridor with relatively congested traffic[8].

A key issue when analysing the valuation of travel time variability is the existence of heterogeneity among commuters. Such heterogeneity may be captured by different socioeconomic and trip characteristics, and may affect choice in two ways: it can have an

[6] Small et al.(1999) suggest the inclusion of a quadratic term for SDL and SDE, with the aim of capturing non linear effects. However, in our case such specification did not provide results significantly different from the ones reported.

[7] Testing model 2 against model 1 provides a LR statistic of 15.22 (5% critical value=5.99). However, the test of model 3 against model 1 shows a LR value of 0.28 (5% critical value=3.84), so that the null cannot be rejected.

influence on the absolute preference for the alternatives or it may modify the relative valuation of the attributes that characterize each alternative. In the first case, the characteristic is included in the utility function as an additional explanatory variable, and therefore has a direct impact on the constant term. In the second case, it interacts with the attributes that characterize the alternatives and therefore modifies the estimated slope coefficients.

When including in the model the socioeconomic variables that capture individual heterogeneity, equation (5) may be rewritten as:

$$V_{ij} = \alpha_j + \beta_{iT} T_j + \beta_{iL} SDL_j + \beta_{iE} SDE_j + \beta_{iP} P_{lj} + \beta_{iM} M_j + \gamma Z_i \quad (6)$$

where Z_i are the characteristics that modify the constant term, and the coefficients' estimates may include interactions with other attributes. The decision about which variables are directly included in the indirect utility function and which are used to segment the sample is up to a certain point arbitrary. Ideally, an equation should be specified for each type of individual (whereby heterogeneity would influence both the constant and the variables' coefficients) and the equality of coefficients across types of individuals would be tested. However, the number of available observations makes such strategy unfeasible. Therefore, a priori assumptions were required based on literature results and some preliminary estimations.

According to the available information from the questionnaire, the socioeconomic variables that enter the equation modifying the constant term are the age and gender of the commuter, and the number of children in the household. Regarding income levels, we tested alternative specifications where this variable modified the slope of the time and cost coefficients. Household income could be approximated in three ways: self-reported income, educational level and job category. However, none of the three alternatives led to significant results when used to segment the time or cost variables. This result may be due to the fact the sample is drawn from a population of relatively high incomes and educational levels. Additionally, the coefficients of the time and variability measures were segmented according to the following trip characteristics: restrictions regarding arrival times to the workplace, the length of the trip and whether additional activities (such as shopping or carrying children to school) were carried out during the trip. The most significant and interesting results were obtained when segmenting according to the restrictions on arrival time to work reported by the commuters (as summarised in table 2). After some preliminary estimations, we differentiate between commuters that can start working at any time and those that have a fixed entry time, further distinguishing according to their maximum allowed delay, with a threshold of 10 minutes.

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[8] The authors have estimated short and long run price elasticities of -0.21 and -0.33 for the same corridor

Table 5 presents the results for the selected specification. Lack of reply by some respondents to some of these questions reduces our sample size to 2133 choices. Model 4 shows that the estimation is robust, since the coefficients of the time and cost variables are very stable with respect to those in model 3. All the coefficients of the socioeconomic variables are shown to be significant and with the expected signs. Estimation results show that men and commuters with more children are more likely to choose the tolled alternative. Since age is included non-linearly it has an increasing influence on the probability of choosing the more expensive alternative until the commuter is 47 years old[9].

The segmentation according to arrival time restriction for both SDL and SDE variables proves to be clearly significant. According to model 4, having a maximum allowed delay of 10 minutes or less implies valuing each minute late almost 2.4 times more than what commuters with higher allowed delays or flexible entry times do. Early arrival time is only valued when individuals have a fixed entry time; for those with no fixed entry time its value is not significantly different from zero. No significant results were obtained when attempting to obtain different estimates for the cost or average travel time coefficients.

(Table 5)

An interesting feature of discrete choice models is that they make it possible to obtain values given to travel time savings as the ratio between estimated coefficients for time and monetary cost. From model 4 results, a value of travel time savings of 14.1 €/hour is obtained. Although this value may be regarded as a relatively high estimate, two issues should be borne in mind. First, average travel time includes a component of time spent in congestion, which is usually valued at a higher rate than time spent in free flow situations. Besides, this is an estimate corresponding to daily commuter trips of individuals with relatively high incomes and educational levels[10].

It is also possible to obtain estimates of the values of savings in early or late arrival times, as these are the ways in which the consequences of variability of travel times are captured. When

using aggregate data (Asensio and Matas, 2005).

[9] Given that the model includes more than one dummy variable, the constant term can not be properly interpreted due to a subidentification problem, unless some a priori constraints are imposed on the coefficients of the dummy variables.

[10] The estimated value of travel time savings is 77% of the wage rate, as reported in Catalonia's Wage Structure Survey. This result is relatively large, but note that 52% individuals in the sample have higher education, while the corresponding figure for the whole Spanish population is 22.4%. In Spain

no trip characteristics are taken into account (as in model 3), late arrival time is valued at 34.4 €/hour, a value 2.3 times over that of travel time, while savings in early arrival time are valued at just 7 €/hour, or 0.48 times the value given to travel time. These results are similar to the findings of other authors, such as Small (1982), who obtains ratios of 2.41 and 0.61, or Noland et al. (1998), whose model without extra penalty for late arrival shows ratios of 2.18 and 0.75, respectively.

(Table 6)

Trip restrictions in the form of maximum allowed delay at the workplace imply very different valuations of savings of late and early arrival times. Delay time is valued by commuters with low delay allowances at 3.6 times their valuation of travel time, while the figure for those with more flexibility is just 1.5. On the other hand, only those commuters with fixed work starting times give a positive value to savings in early arrival times, almost two thirds of their valuation of time spent travelling. These results stress the need of taking into account individual and trip characteristics when valuing travel time variability.

5. Conclusions

In this paper new estimations of the value given to the variability of travel times by commuters in a metropolitan environment have been provided. This issue is of particular relevance for the more precise evaluation of policies that may impact on travel times, given that the empirical analysis carried out shows that the value placed on time variability is well above that of average travel time. Our results show that individuals value travel time variability because of the consequences of being early or late with respect to the desired arrival time. Consistently with this result, the value of time variability highly depends on the time restrictions faced by the individual. In particular, restrictions related to work starting times (entry flexibility and maximum allowed delays) have been shown to have very significant impacts on such valuations: While the estimated value of average travel time savings is 14.1 €/h, the value of late arrival reaches 51.4 €/h for those commuters who cannot be more than 10 minutes late. Those with more flexible start times value delays at 21.1 €/h. Savings on early arrival time are only relevant for those with fixed entry times, who value them at 9€/h.

The high value given to travel time variability has implications for transport policy, both in terms of decision making with respect to new investment in infrastructure and optimal pricing

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completing three years of higher education yields gross wages 40% above the national average, while five years increase that figure up to 80%.

of its use. Cost-Benefit Analysis should include valuations of the impact on travel time variability as an additional issue in order to improve the results of project evaluation. Moreover, any policy aimed at setting charges for the use of congested infrastructures should take into account the valuation of variability in travel times, as well as the observed heterogeneity in such valuation according to the trip characteristics.

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References

Asensio, J. and A. Matas (2005), *Elasticidad del tráfico en las autopistas de peaje en contextos urbanos,* Ministerio de Fomento, Madrid.

Abdel-Aty, M., R. Kitamura and P.P. Jovanis (1995). Travel time variability on route choice using repeated measurement stated preference data. *Transportation Research Record,* 1493, 39-45.

Bates, J. (2001) Reliability – The missing model variable, in D. Hensher (ed.*) Travel behaviour research: the leading edge*, Elsevier, Amsterdam., 527-546.

Bates, J., J.W. Polak, P. Jones and A. Cook (2001). The valuation of reliability for personal travel, *Transportation Research Part E*, 37, 191-229.

Black, I. G. and J. G. Towriss (1993). *Demand effects of travel time reliability*, Centre for Logistics and Transportation, Cranfield Institute of Technology.

Copley, G., P. Murphy and D. Pearce (2002) *Understanding and valuing journey time variability,* European Transport Conference, Cambridge.

De Jong, G., E. Kroes, R.Plasmeijer, P. Sanders and P. Warffemius (2004), *The value of reliability*, European Transport Conference, Strasbourg.

Gaver, D. P. (1968). Headstar strategies for combating congestion. *Transportation Science*, 2, 172-181.

Lam, C. L. and K. A. Small (2001). The value of time and reliability: measurement from a value pricing experiment. *Transportation Research Part E* 37, 231-251.

Louvière, J., D. Hensher and J. Swait (2000) *Stated choice methods: analysis and applications*, Cambridge University Press

Manski, C. F. and S. R. Lerman (1977) The estimation of choice probabilities from choice based samples, *Econometrica*, 45, 8, 1977-1988.

Noland, R. B. and K. A. Small (1995). Travel time uncertainty, departure time choice and the cost of morning commutes. *Transportation Research Record*, 1493, 150-158.

Noland, R.B., K.A. Small, P.M. Koskenoja and X. Chu (1998), Simulating travel reliability, *Regional Science and Urban Economics*, 28, 535-564.

Noland R. B. and J. W. Polak (2002). Travel time variability: a review of theoretical and empirical issues. *Transport Reviews*, 22 (1) 39-54.

Senna, L. (1994) The influence of travel time variability on the value of time, *Transportation* 21, 203-228.

Small, K. A. (1982). The scheduling of consumer activities: work trips. *American Economic Review* 72, 467-479.

Small, K. A., R. Noland and X. Chu (1999) *Valuation of travel-time savings and predictability in congested conditions for highway user-cost estimation*, NCHRP Report 431, Transportation Research Board, Washington, DC.

Small, K.A, C. Winston and J. Yan (2005), *Uncovering the distribution of motorists' preferences for travel time and reliability,* Econometrica, 73 (4) 1367-1382.

Wardman, M. (2001) A review of British evidence on time and service quality valuations, *Transportation Research E*, 37, 107-128.

Appendix A. The stated preference questionnaire.

This appendix provides details about the design of the stated preference survey used to obtain the data needed to estimate the different models. A pilot survey was followed by the main survey, both carried out during the fourth quarter of 2005. Commuters were contacted at different petrol stations in the national road and tolled motorway, where after some screening questions an envelope containing the survey and an introductory letter with instructions was distributed. Commuters were asked to complete the survey at home and return it by mail with pre-stamped envelopes that were provided.

Besides a socioeconomic questionnaire, the survey consisted of a set of nine choice questions. Each choice was formed by two alternatives, characterized by four variables: average travel time, variability of travel time, early departure time and monetary cost. For each variable, three possible values are considered. However, in order to reduce the number of possible scenarios that would result from the combination of all the variables' levels, the values of the monetary cost and average travel time variables were defined in difference terms. Costs and travel times are also related by the fact that in every choice scenario presented in the questionnaire, the quickest alternative is also the most expensive. In this way, besides avoiding dominance problems, choices are made more similar to the actual ones faced by commuters in their daily trips.

The three values that each variable may take are defined as follows. Average travel times and monetary costs were calculated by simulation of trip characteristics from the Maresme area to Barcelona's city centre under standard travel time conditions at peak times. The values thus obtained of the difference of travel time and cost between each route were used to define the central level, which was then modified upwards and downwards to calculate the other two required levels. The construction of the variable that captures the variability of travel time is based on the methodology of Small et al.(1999). Following Black and Towriss (1993), the distributions of variable travel times are presented as five possible travel times which are equally likely to occur[11]. Each possible distribution of variable travel times is summarised by a set of five coefficients which, once multiplied by the average travel time of the alternative, yield the five possible travel times. The three possible distributions capturing different degrees of variability can then be combined with each average travel time. In the case of departure times, one value is that which would result in punctual arrival if there was no variability of travel times, while the other two imply departing 5 and 8 minutes earlier, respectively.

The full factorial of a stated preference experiment designed in this way has 3^6 scenarios which can be reduced to a fractional factorial of 18 scenarios (Louvière et al, 2000). However, that is still a large number to guarantee that no fatigue effects appear. Therefore, two groups of questionnaires of 9 scenarios each were created and each surveyed commuter was randomly given a questionnaire of one group. Table A1 shows the levels of all variables used in the choices for each group. Although, as previously explained, the differences between alternatives in terms of average travel times and monetary costs only take three possible values, absolute values were used in the presentation of the characteristics of each alternative to avoid complexity.

[11] See Bates et al.(2001) for a discussion of the difficulties associated with the presentation of variability of travel times in stated preference questionnaires.

Table 1. Example of choice question

Please, choose **OPTION A** or **OPTION B**

OPTION -A-	OPTION -B-
Average travel time: 40 minutes You have the same probabilities of arriving: 10 minutes before your desired arrival time 6 minutes before your desired arrival time At the desired arrival time 5 minutes after your desired arrival time 18 minutes after your desired arrival time The cost of the trip is 2.75 euros	Average travel time: 46 minutes You have the same probability of arriving: 20 minutes before your desired arrival time 15 minutes before your desired arrival time 8 minutes before your desired arrival time 2 minutes after your desired arrival time 13 minutes after your desired arrival time The cost of the trip is 1.25 euros
A ☐	**B** ☐

Table 2. Restrictions during commuting trips

Maximum possible delay of arrival at workplace without penalty

	cases	%
Less than 5 minutes	58	22.4
5 to 9 minutes	47	18.2
10 to 14 minutes	33	12.7
15 to 19 minutes	8	3.1
20 or more minutes	32	12.4
No fixed entry time	59	22.8
No answer	22	8.5
Total	259	100.0

Other activities during the trip

	cases	%
Yes	107	41.3
No	125	48.3
No answer	27	10.4
Total	259	100.0

Table 3. Sample characteristics: education and income

Education level of main income provider

Categories:	cases	%
Primary	15	5.8
Secondary (compulsory)	24	9.3
Secondary (post-compulsory)	37	14.3
Professional (basic)	14	5.4
Professional (higher)	30	11.6
University (diploma)	50	19.3
University (B.A. or more)	87	33.6
No answer	2	0.8
Total	259	100

Household gross monthly income

Euros:	cases	%
Under 1000	7	2.7
1001-1500	28	10.8
1501-2000	34	13.1
2001-2500	42	16.2
2501-3000	35	13.5
3001-4000	38	14.7
4001-5000	23	8.9
5001-7000	15	5.8
7001-9000	5	1.9
Over 9000	14	5.4
No answer	18	7.0
Total	259	100

Table 4. Estimation results. Models 1 to 3.

	Model 1		Model 2		Model 3	
Variable	Coefficient	t Stat	Coefficient	t Stat	Coefficient	t Stat
Constant (motorway=1)	-0.8291	-4.698	-0.8663	-5.006	-0.8169	-4.664
Cost	-0.3932	-4.592	-0.4042	-4.747	-0.3905	-4.571
Travel time	-0.0970	-7.778	-0.1023	-8.565	-0.0954	-7.891
SDL	-0.1770	-1.950			-0.2234	-10.367
SDE	-0.0266	-0.680			-0.0459	-3.350
Standard deviation	-0.0239	-0.527	-0.1002	-9.720		
Observations	2331		2331		2331	
Obs. with road choice	1273		1273		1273	
Obs. with motorway choice	1058		1058		1058	
Regression St. Error	0.473		0.475		0.473	
Residual sum of squares	520.597		523.922		520.651	
Log likelihood	-1486.93		-1494.54		-1487.07	
Schwarz criterion	1.296		1.296		1.293	
Mc Fadden R-squared	0.074		0.069		0.074	

Table 5. Estimation results. Model 4.

Variable	Coefficient	t Stat
Constant (motorway=1)	1.9246	3.109
Cost	-0.4121	-4.530
Travel time	-0.0969	-7.507
SDL * delay<10 min.	-0.3534	-9.980
SDL * delay ≥ 10 min.	-0.1452	-3.995
SDL * no fixed entry time	-0.1445	-3.571
SDE * fixed entry time	-0.0617	-3.690
SDE * no fixed entry time	-0.0015	-0.053
Gender (male=1)	0.3722	3.691
Age	-0.1432	-4.873
Age squared	0.0015	4.471
Number of children under 16	0.2079	4.049
Observations	2133	
Obs with road choice	1152	
Obs with motorway choice	981	
Regression St. Error	0.4662	
Residual sum of squares	461.077	
Log likelihood	-1471.621	
Schwarz criterion	1.2866	
McFadden R-squared	0.099	

Table 6. Values of average travel times and travel time variability (€/hour)

Value of average travel time	14.1
Value of delayed arrival time	
Fixed start time (possible delay up to 10 min.)	51.4
Fixed start time (possible delay of more than 10 min.)	21.1
No fixed start time	21.0
Value of early arrival time	
Fixed entry time	9.0
No fixed entry time	not significant
Coefficients ratios w.r.t. average travel time	
Value of delayed arrival time	
Fixed start time (possible delay up to 10 min.)	3.6
Fixed start time (possible delay of more than 10 min.)	1.5
No fixed start time	1.5
Value of early arrival time	
Fixed entry time	0.6

Table A1. Scenarios used in the questionnaires.

First group	**Option**	**Cost**	**Average time**	**Early departure**	**Distribution of possible travel times**				
Scenario 1	A	3,25	40	8	36	38	40	42	46
	B	2,5	46	5	39	42	46	50	60
Scenario 2	A	2,75	45	5	41	43	45	47	52
	B	1,25	55	5	50	52	55	58	63
Scenario 3	A	3,25	45	5	38	41	45	49	59
	B	2,5	55	8	47	51	55	59	72
Scenario 4	A	3,25	35	5	26	30	35	39	51
	B	2,5	50	8	45	48	50	53	58
Scenario 5	A	2,75	35	0	32	33	35	37	40
	B	1,25	50	8	43	46	50	54	65
Scenario 6	A	2,75	40	5	34	37	40	43	52
	B	1,25	46	5	35	39	46	52	67
Scenario 7	A	4	35	0	30	32	35	38	46
	B	2	50	5	45	48	50	53	58
Scenario 8	A	4	40	5	30	34	40	45	58
	B	2	46	0	39	42	46	50	60
Scenario 9	A	4	45	0	34	38	45	50	65
	B	2	55	5	47	51	55	59	72
Second group	**Option**	**Cost**	**Average time**	**Early departure**	**Distribution of possible travel times**				
Scenario 1	A	4	35	5	32	33	35	37	40
	B	2	50	0	38	43	50	56	73
Scenario 2	A	2,75	40	0	30	34	40	45	58
	B	1,25	46	8	35	39	46	52	67
Scenario 3	A	3,25	40	0	36	38	40	42	46
	B	2,5	46	0	41	44	46	48	53
Scenario 4	A	3,25	45	0	38	41	45	49	59
	B	2,5	55	0	41	47	55	62	80
Scenario 5	A	2,75	45	8	34	38	45	50	65
	B	1,25	55	0	50	52	55	58	63
Scenario 6	A	3,25	35	8	26	30	35	39	51
	B	2,5	50	5	38	43	50	56	73
Scenario 7	A	4	45	8	41	43	45	47	52
	B	2	55	8	41	47	55	62	80
Scenario 8	A	2,75	35	8	30	32	35	38	46
	B	1,25	50	0	43	46	50	54	65
Scenario 9	A	4	40	8	34	37	40	43	52
	B	2	46	8	41	44	46	48	53