# Value of time, schedule delay and reliability

## Estimation results of a Stated Choice experiment among Dutch commuters facing congestion

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***Abstract***

This paper presents empirical estimates of the traveller's valuation of travel time, scheduled delay and uncertainty derived from a large stated choice experiment among Dutch car commuters facing congestion. We have analysed and compared choice data obtained from two different type of experiments to investigate departure time, route and mode choice responses. The first, relatively simple, experiment consisting of four choice sets to estimate each of the parameter values resulted in rather reasonable estimates (with the highest value attached to late arrival). Important socio-economic characteristics explaining these findings include income and the presence of arrival and departure time restrictions. Similar findings in terms of VOT and VSDL estimates have been obtained when analyzing data from a second, more extensive, choice experiment based on current behaviour of the respondent. The estimated choice models suggest that commuters prefer the car over the public transport alternative. We find that it is unnecessary to add an additional cost for unreliability (or uncertainty) of travel when scheduling costs are fully specified in the model. The analysis also suggests that people's aversion to arriving early is increasing non-linearly as their schedule delay early time increases. Heterogeneity has been included into the estimations. The results again emphasize the importance of departure and arrival time restrictions and income, but also the length of the commuting trip length seems important.

# 1. Introduction

Road pricing may have different behavioural consequences depending on the structure of the scheme. Car drivers may decide to travel at other times, change mode or to car-pool. One of the ways to analyse the behavioural responses of individuals to pricing schemes is to conduct a stated choice experiment. Models are estimated on the choice data of respondents that incorporate the attributes of the alternatives as well as contextual effects (external factors) influencing choices. The resulting models are not used to predict demand but instead allow to find trade-offs between paying with traveling under preferred conditions (in terms of specific attributes, e.g. departure time or travel time) versus paying less or nothing with facing less attractive travel conditions. The preferences (and hence the bahvioural responses) of travelers can be determined including substitution rates between different parameters, which may be cost and time for instance. This enables to measure the value of time (VOT) of certain groups.

Traditionally, value of travel time is thought of being one of the largest cost components in cost benefit analysis of transportation projects, and the reduction of travel time is usually regarded as the main source of benefits that travelers receive from the improvement of a transport facility. However, when the seriousness of road congestion raises considerably, the reliability of travel time may be more important than the savings of travel time for the travelers, particularly when travelers have the schedule constraint. Several reliability related components, such as standard deviation of travel time, and schedule delay early and late, have been considered in mode or route choice modeling since the last decade. Numerous studies have shown the importance of these reliability factors in traveler's choice behavior, in some cases reliability becomes an even higher value than travel time savings.

Recently, several countries have investigated the issue of including reliability components into cost-benefit analysis of transport projects. Empirical studies towards the monetary value of time have shown a great deal of convergence (especially with respect to different trip purpose, different income groups, and different travel modes). The monetary value of reliability is less certain. This fact may be largely due to the lack of a common definition and accurate measurement of reliability. Moreover, the model specification of traveler's responses to changes in reliability shows some degrees of diversity amongst studies.

In this paper, we present outcomes from a stated choice experiment among Dutch car commuters facing congestion. Respondents were offered two different types of stated choice questions. The first four choice sets contained a simple choice structure of varying one single attribute and the cost term enabling us to estimate values of time, schedule delay (late and early) and uncertainty (or reliability) from the choices made by each individual. The second set of choice alternatives included more attributes that were varied in a systematic way and more choices that had to be made by the respondents (11 screens were shown). Besides estimating the values of time, schedule delay and uncertainty, the data also provides information on the behavioural responses to road pricing. Data from both types of questions is different in nature and hence requires a different type of analysis. We start with the more simple analysis of the interval estimates resulting from the first four choice sets. Next, we will analyse the second set of choice data by estimating different type of models. This allows us to compare estimates from both approaches.

The aim of this present study is twofold. First, we want to analyse choice behaviour and estimate important concepts such as the value of time and reliability for Dutch commuters. Second, we address the impact of the individual characteristics on these estimates. By interacting those trait variables with travel time and reliability related attributes, we are able to assess the estimates for different groups of travelers. These outcomes will be compared with results from literature.

The rest of the paper is organized as follows. Section 2 describes the choice experiment and the data used in our empirical assessment. Section 3 presents the results from the first part of the stated choice experiment, the point estimates. It includes a short statistical analysis searching for explaining variables. Section 4 discusses the theoretical framework of the discrete choice analysis applied to the stated choice data of the second choice set. The results of this analysis will be discussed in Section 5. Finally, Section 6 concludes.

## 2. Data sources and survey description

### 2.1 Data collection

The data used in this paper have been obtained by conducting a (interactive) computer based survey among Dutch commuters. The questionnaire can roughly be divided into three parts. First, we asked for some socio-economic characteristics of the respondent (such as education and income). In order to analyze the behavioral responses to road pricing we developed a stated choice experiment (two different types as previously described), which is the second part of the survey. And finally we asked for the opinion of the respondents on several carefully explained road pricing measures. The first and the second part have been answered by 1115 respondents, whereas the latter sample (opinion questions) consisted of 564 respondents. This paper will present outcomes of the analysis of the stated choice experiment.

The data collection was executed by a specialized firm (NIPO), who has a panel of over 50,000 respondents. Since the survey was aimed at respondents that use a car for their home to work journey and also face congestion on a regular basis, we selected working respondents, who drive to work by car two or more times per week, and who face congestion of 10 or more minutes for at least two times a week. This resulted in a total of about 6,800 possible respondents. An initial analysis revealed that a random sample would result in a relatively low number of women and lower income groups. Because the behavior of lower income people is important to analyze, it was decided to ‘over sample’ the lower income groups and create an equal number of respondents over the various income classes. The data were collected during three weeks in June 2004.

### 2.2 Survey

As previously explained, the survey started with some general questions asking for important explanatory variables of the respondent (such as income, gender and education). This provided us a profile of the Dutch commuter facing congestion. Our sample suggest that most commuters are men (76%) and relatively high educated (about 44% has a bachelor or higher degree). The characteristics of our data base have been compared with the general profile of the Dutch car driver facing congestion, in order to check representativeness. Research by Goudappel Coffeng (1997) suggests that about 75% of all drivers in congestion are men (almost equal to our findings). Our sample includes more respondents between the age of 26 and 35 (about 10%), whereas the share of persons older than 45 years is lower. Moreover, drivers in congestion tend to be higher educated (our sample includes more (8%) bachelors and masters and less junior secondary general) and have a higher income. The effect of the “over sampling” of lower income is clearly present. About 21% of the drivers in this sample has an income below €28.500, whereas only 8% drivers of the 1997 sample earned an income below the average of that time.

The second part of the survey consisted of a stated choice experiment. The choice experiment was set-up in such a way that the respondent can distribute 10 trips amongst four constructed alternatives. These alternatives are constructed based on answers of respondents about their current travel behavior. In total, respondents are presented with 15 (4 + 11) screens in the experiment.

The first four screens are simpler versions of the choice experiment in which we only change the road pricing fee and one other attribute (travel time, shift to earlier arrival time, shift to later arrival time and uncertainty in travel time). These choice questions have been designed in such a way that we can infer the interval estimates of individuals' value of time (VOT), value of schedule delay early (VSDE), value of schedule delay late (VSDL) and the value of uncertainty (or reliability, VUNC) from the allocation of 10 trips over four alternatives (see Section 3 and Appendix 1 for a more detailed explanation).

The second part of the experiment, from which we estimate the choice models, consists of 11 screens[2]. The design has 44 choice sets, but can be blocked into 4 sets of 11. Each respondent is assigned a block randomly, and the order of the 11 treatments in a block is randomized as well. The levels of attributes of the constructed alternatives are based on a fractional factorial design (orthogonal non-linear main effects design) using 4 levels for 13 of the attributes and 2 levels for two of the attributes. The attributes are based on current behavior of respondents in order to design alternatives as close to reality of the individual respondent as possible (see Appendix 2 for an example). Each of the attributes has a limited number of values (levels) and these levels are combined in a systematic way such that each attribute is independent of another. Each screen consists of 4 alternatives with separate attributes (alternative specific attributes, see Table 1). Three alternatives are car specific, the remaining alternative is always public transport (even in cases the respondent indicated that there is no public transport alternative available, the choice sets concern hypothesized situations). The first car alternative (A) is based on the preferred travel conditions of the respondent with a relatively high price. The other road possibilities (alternative B and C) have lower road pricing fees but in return the travel conditions (in terms of arrival time, travel time, uncertainty and trip length (C)) are less attractive.

[2] See for a detailed description of the experiment: Amelsfort (2004).

*Table 1: Design of the second part of the SC experiment (11 screens)*

| Alternative | Attribute | Levels |
|---|---|---|
| A: car (pay) | Arrival time | 4 (-10, -5, PAT, +5)^ |
| | Travel time | 4 (85% of trip length free flow, 90%, 95% and 100%) |
| | Uncertainty | 4 (uncertainty margin * 0.2, 0.4, 0.6 and 0.8)^ |
| | Trip costs (fuel + charge) | 4 (charge depends on distance, distance*0.08, 0.1, 0.12, and 0.14) |
| B: car (change departure time) | Arrival time | 4 (-50, -30, -10, PAT,+10)^ |
| | Travel time | 4 (65% of trip length free flow, 70%, 75% and 80%) |
| | Uncertainty | 4 (uncertainty margin * 0.8, 1, 1.2 and 1.4)^ |
| | Trip costs | 4 (charge depends on distance, distance * 0.03, 0.04, 0.05, and 0.06) |
| C: car (change route) | Arrival time | 4 (-30, -20, -10, PAT)^ |
| | Travel time | 4 (55% of trip length free flow, 60%, 65% and 70%) |
| | Uncertainty | 4 (uncertainty margin * 0.6, 0.8, 1, and 1.2)^ |
| | Trip costs | 4 (charge depends on distance, distance * 0, 0.01, 0.02, and 0.03) |
| | Trip length | 2 (distance * 1.2, and 1.4) |
| D: public transport (change mode) | Arrival time | 4 (-30, -10, +10, +30 compared with PAT) |
| | Travel time | 2 (based on reported travel time with public transport if available (if not: 1.3 * mean car travel time), no change, and reported travel time * 1.2) |

*^ PAT = preferred arrival time, uncertainty margin = difference between reported mean travel time and free flow travel time*

## 3. Analysis of interval estimates

The value of time, value of schedule delay late and early, and value of uncertainty were derived from choices made by the respondents. The first part of the stated choice experiment consisted of four different choice moment (each with four different scenarios) with the objective to find individual estimates. This section outlines the contents of the scenarios presented to the respondents and the results of the analysis of the choice data.

### 3.1 The survey

Four different screens were designed to obtain the estimates (one for each variable), each offering four alternatives that differ in tolls, travel time, departure time and uncertainty (only in the screen for VUNC). The respondents were then asked to allocate ten (commuting) trips over these four different alternatives. The design of the alternatives for VOT, VSDE, VSDL and VUNC respectively has been created as follows.

The average VOT according to previous (Dutch) studies is about € 7.5 per hour (see Gunn, 2001 and AVV, 1998). Given this value, we have identified the following four intervals:

1. € 0 – 4
2. € 4 – 8
3. € 8 – 12
4. > € 12

In order to allocate responses to one of the above categories, the choice was offered to the respondent as presented in Table 2.

*Table 2: The first screen: four alternatives to estimate an individuals' VOT*

| | A (group 4) | B (group 3) | C (group 2) | D (group 1) |
|---|---|---|---|---|
| Departure time | $T_D$ | $T_D$ – 15 min. | $T_D$ – 30 min. | $T_D$ – 45 min. |
| Travel time | $T_f$ | $T_f$ + 15 min. | $T_f$ + 30 min. | $T_f$ + 45 min. |
| Arrival time | $T_A$ | $T_A$ | $T_A$ | $T_A$ |
| Toll | € 6 | € 3 | € 1 | € 0 |

The respondent was then asked to allocate ten trips over these four alternatives. If the respondent chooses alternative C over D, we can infer that he is willing to pay € 1 to save 15 minutes of travel time (implying a VOT of at least € 4 per hour). In order to calculate an interval estimate for an individual we do need a mean interval value. It is not plausible to assume that the exact values are the middle points of its interval (and this is not possible for the fourth interval). Therefore we hypothesize that there is an underlying statistical distribution that can be fitted to the actual aggregated trip allocation of the interval estimate questions and approximate the mean interval values based on this presumed distribution. We have chosen to use the Gamma distribution. In order to find the parameters of the best fitting Gamma distribution, we have applied the least square method (minimum difference between actual and simulated distribution). When the parameters have been estimated, it is possible to determine the mean interval values. Furthermore, it appeared that the distributions were (slightly) different for income; the mean interval value depends on the income of the respondent. Table 3 presents the mean average values for VOT, VSDE, VSDL and VUNC for the different income groups.

*Table 3: The mean average values for VOT, VSDE, VSDL and VUNC for the different income groups (€/hour).*

| Income (gross yearly) | VOT | | | | VSDE | | | | VSDL | | | | VUNC | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **0-4** | **4-8** | **8-12** | **>12** | **0-2** | **2-4** | **4-6** | **>6** | **0-8** | **8-16** | **16-24** | **>24** | **0-3** | **3-6** | **6-9** | **>9** |
| <28.500 € | 2.4 | 5.9 | 9.8 | 18.5 | 1.1 | 2.9 | 4.9 | 9.6 | 3.5 | 11.7 | 19.7 | 44.1 | 1.6 | 4.4 | 7.3 | 13.4 |
| 28.500-45.000 € | 2.4 | 5.9 | 9.8 | 18.1 | 1.1 | 2.9 | 4.9 | 9.5 | 3.4 | 11.6 | 19.6 | 40.2 | 1.6 | 4.4 | 7.3 | 13.1 |
| 45.000-68.000 € | 2.7 | 6.0 | 9.9 | 17.6 | 1.1 | 2.9 | 4.9 | 9.5 | 3.5 | 11.6 | 19.7 | 40.2 | 1.6 | 4.4 | 7.3 | 13.3 |
| >68.000 € | 2.7 | 6.0 | 9.9 | 17.9 | 1.1 | 2.9 | 4.9 | 9.5 | 3.2 | 11.6 | 19.6 | 38.9 | 1.6 | 4.4 | 7.3 | 12.9 |

It is now possible to determine the estimates for an individual's value of time as the weighted average of the intervals' expected values, where the weights are determined by the trips allocated to that interval by the respondent. For instance, when a respondent with an income of less than 28.500€ allocates 5 trips to B and 5 trips to C a VOT estimate of 7.8 results ((5*5.9+5*9.8)/10). The VSDE, VSDL and VUNC have been estimated in a similar way, only the interval values and attribute values were different (see Appendix 1 for the screens and interval values).

### 3.2 Results and statistical analysis

Table 4 shows the mean values for the various estimates. The mean value of time is about € 10, which is considerably higher than the average Dutch estimate of € 7.5. The interval estimate of the value of schedule delay early is considerably lower than the schedule delay late. This can be explained by the fact that people normally prefer to arrive earlier than late. The value of uncertainty has a mean value of 5.4, lower than the VOT.  The minimum and maximum values and the standard deviation indicate the considerable level of variation (in particular with the VSDL).

*Table 4: Descriptive statistics of interval estimates for VOT, VSDE, VSDL, and VUNC (€/hour)*

| | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| VOT | 1115 | 2.49 | 18.49 | 9.9109 | 5.03236 |
| VSDE | 1115 | 1.11 | 9.61 | 4.6566 | 2.83314 |
| VSDL | 1115 | 3.62 | 38.27 | 14.4829 | 11.84617 |
| VUNC | 1115 | 1.71 | 12.79 | 5.4033 | 3.32310 |

Since we also have information on socio-economic characteristics of the respondent, it is possible to analyze the impact of these variables. Literature indicates that income, for instance, is an important explaining variable. Higher income people tend to have a higher value of time. Table 5 shows the values we found for four different income categories. The results are somewhat ambiguous. The highest income group indeed has the highest VOT, but the high estimate for the lowest income group is more difficult to explain.

*Table 5: The average values of the VOT, the VSDE, the VSDL, and the VUNC for the different income groups (€/hour)*

| | VOT | VSDE | VSDL | VUNC |
|---|---|---|---|---|
| <28.500 € | 9.9 | 4.6 | 18.6 | 5.8 |
| 28.500-45.000 € | 9.2 | 4.3 | 14.9 | 5.0 |
| 45.000-68.000 € | 9.8 | 4.7 | 13.6 | 5.3 |
| >68.000 € | 10.5 | 5.0 | 12.6 | 5.2 |

The effect of income and other possibly important explaining variables have been tested statistically. We have conducted a regression analysis with the interval estimates as the dependent variable. Table 6 shows the results for the four regressions. Despite the low overall fit of the models, the significance and sign of the coefficients give a tentative indication of the impact of the various variables. When we first again look at income, the previous conclusion for VOT is confirmed: the impact is not significant (at the 10% level). The effect of income is significant at this level for the VSDE and the VSDL (with a negative coefficient) of the respondents. Income and education may be correlated here. A possible explanation for the negative impact of education and income on VSDL is that lower educated people usually have jobs with less flexible working hours. Since our survey included a question on working time restriction (do you have to be at your work at a certain time?), we can test the impact of this constraint. Table 6 indeed shows that the VSDL is (significantly) higher for people with an arrival time restriction. The VUNC is also higher for people with a restriction (either departure or arrival time), suggesting that these value less uncertainty.

When we look at the results for VSDE, gender has a significant impact, with females having a higher VSDE than male respondents. Having a departure time restriction or not (can you depart at any time or not?) is very significant (at the 1% level), flexible commuters tend to have a lower value of schedule delay early. Income, education and travel cost compensation also have an impact. The impact of this latter variable (higher VOT and VSDE for respondents that are fully compensated) may be explained by their higher willingness to pay for time gains.

*Table 6: Regression results for VOT, VSDE, VSDL and VUNC*

| | VOT | | VSDE | | VSDL | | VUNC | |
|---|---|---|---|---|---|---|---|---|
| | B | Sig. | B | Sig. | B | Sig. | B | Sig. |
| Constant | 9.42 | .000 | 4.46 | .000 | 25.09 | .000 | 7.068 | .000 |
| Gender (dummy)* | .632 | .111 | .405 | .076 | -.702 | .492 | .187 | .507 |
| Education | -.171 | .096 | .-.103 | .083 | -.779 | .003 | -.166 | .023 |
| Gross yearly inc. | 8.9E-02 | .106 | 6.4E-02 | .044 | -.251 | .077 | -2.27E-02 | .562 |
| Arr. time restr. (dummy)** | -.539 | .094 | -.182 | .326 | -3.948 | .000 | -.419 | .067 |
| Dep. Time restr (dummy)*** | -.554 | .098 | -.640 | .001 | -3.007 | .001 | -.523 | .028 |
| Cost comp1 (dummy)**** | -.749 | .130 | -.124 | .664 | 1.998 | .120 | .113 | .748 |
| Cost comp2 (dummy)**** | -.624 | .055 | -.403 | .032 | -.533 | .525 | -8.23E-02 | .722 |
| Working hours a week | 4.1E-02 | .740 | 7.44E-02 | .292 | .194 | .540 | -5.68E-02 | .516 |
| R square | .015 | | .026 | | .068 | | .019 | |

* Female =1; **having no arrival time restriction =1; *** having no departure time restriction =1.
**** Cost comp1: respondents receive no compensation from employer, cost comp2: respondents are partly compensated, cost comp3 are fully compensated by employer.

# 4. Theoretical framework and modeling approach of the stated choice experiment data

## 4.1 Discrete choice models

Discrete choice models are the methodological tools widely used in analyzing individual traveler's choice behavior (Ben-Akiva and Lerman, 1987). Most models used in practice are based on the random utility theory (RUT), which assumes that individual's preference/taste can be described by a deterministic (systematic) part of utility, $V_{ij}$, and a stochastic component, $\varepsilon_{ij}$. The random utility specification in the case of respondent *i* choosing among *J* alternatives is expressed in Eq. (1).

$$U\left(choice\ j\ for\ individual\ i\right) = U_{ij} = V_{ij} + \varepsilon_{ij}, \quad j = 1,...,J. \qquad (1)$$

The systematic component is assumed to be the part of utility contributed by attributes that can be observed by researchers, while the random component is the part of utility contributed by attributes unobserved by researchers. The observed part of systematic utility $V_{ij}$ is a function of attributes in the alternative and characteristics of the decision maker. A linear in parameters function, which is specified by a vector of the decision maker's taste $\beta$, can be denoted as $\mathrm{V}_{ij} = \sum_{k=1}^{K} \beta_i X_{ik}$ (Ben-Akiva and Lerman, 1987). Utility maximization theory assumes that individual chooses the alternative that yields the highest utility level. This leads to the following random utility model:

$$\Pr ob\,[U_{ij} > U_{il}] = \Pr ob[(\varepsilon_{il} - \varepsilon_{ij}) < (V_{ij} - V_{il})] \quad \text{for all } j \neq l \tag{2}$$

The empirical specification of $V_{ij}$ is crucial to modeling individual's choice behavior due to the fact that the utility function not only reflects individual's decision making process given the socio-economic environment, but also determines the predictive capability of the choice model. In the later subsection, we will discuss the empirical specification of the utility function in more detail.

In making the choice model operational, the random terms (unobserved by the analysts), play also a crucial role. Different assumptions on the joint distribution of random terms in the utility function result in different models. The most extensively used model in transportation studies is the Multinomial Logit (MNL) model, which assumes that the random terms are independently and identically distributed according to extreme value type I distribution. Under these assumptions, the choice probability for respondent i to choose alternative j becomes:

$$\Pr ob[Y_i = j] = \frac{\exp(V_{ij})}{\sum_{l=1}^{J} \exp(V_{ij})} \qquad \text{where} \quad \mathrm{V}_{ij} = \sum_{k=1}^{K} \beta_i X_{ik} \tag{3}$$

This model can be solved by using maximum likelihood estimation method. The log likelihood function is given as:

$$\log L = \sum_{i=1}^{n} \sum_{j=1}^{J} d_{ij} \log \Pr ob[Y_i = j] \tag{4}$$

In this present study, the dependent variable used is the choice proportions allocated among four alternatives. Thus, $d_{ij}$ is defined as the choice proportion distributed by the respondent *i* to alternative *j* in each choice profile, and we have $\sum_j d_{ij} = 1$ under each choice profile (Greene, 2003).

### 4.2 Choice model specification

As well as travel time and travel cost elements, the scheduling (trip timing) preference is also found to be one of the important determinants of commuters' travel behavior. A utility function with explicitly scheduling delay costs specification (Small, 1982; Henderson and Plank 1984;

Wilson 1989; Chin 1990, etc.) has been tested extensively in modeling travelers' route/mode and departure time choices.

Small (1982) introduced the schedule delay (SD) variable to measure the difference between traveler's actual arrival time and preferred arrival time (PAT). Since people may value early and late arrivals differently due to their different consequences, the SD variable can be evaluated as two separate terms, schedule delay early (SDE) and schedule delay late (SDL). SDE is defined as the amount of time arriving earlier at the destination than the PAT, while SDL is the amount of time arriving later than PAT. This gives the relationship in the indirect utility function as follows:

$$U = \beta_T \cdot T + \beta_C \cdot C + \beta_E \cdot SDE + \beta_L \cdot SDL + \theta \cdot D_L , \tag{5}$$

where T denotes the travel time and C gives the travel cost. SDE is defined as Max(0, PAT - actual arrival time), SDL is defined as Max(0, actual arrival time - PAT), and $D_L$ is the lateness dummy, which is equal to 1 when $SDL \geq 0$ and 0 otherwise. The coefficients of $\beta$ and $\gamma$ measure the costs of being early and late, while $\theta$ represents a fixed penalty of late arrival. Since T, SDE and SDL are disutilities, the coefficients are assumed to be negative. Small's (1982) empirical finding is that $|\beta_L| > |\beta_T| > |\beta_E|$, which means that people prefer early arrival to additional travel time, and prefer additional travel time to late arrival.

The model proposed by Noland and Small in 1995 extended Small's 1982 trip scheduling model (see Eq.(5)) by considering the probability distribution of travel time and adding an additional random component depicting the uncertainty effect that is apart from the scheduling constraint. The result is presented as Eq.(6), this is called *Maximum Expected Utility* (MEU) theory.

$$E(U) = \beta_T \cdot E(T) + \beta_C \cdot C + \beta_E \cdot E(SDE) + \beta_L \cdot E(SDL) + \theta \cdot P_L \tag{6}$$

where $E(T)$ is the expected travel time, $E(SDE)$ is the expected schedule delay early, $E(SDL)$ is the expected schedule delay late, and $P_L \equiv E(D_L)$ is the lateness probability.

Once the model is estimated, one can derive the marginal rate of substitution between any pair of the attributes in the bundle. Obtaining such measures is a common objective in the use of discrete choice models. 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.(7)).

$$VOT = \frac{\partial U / \partial T}{\partial U / \partial C} = \frac{\beta_T}{\beta_C} \quad (7)$$

Similarly, the values of schedule delay early, schedule delay late, and uncertainty can be derived.

## 5. Estimation results of stated choice experiment data

Having covered the basics of maximum likelihood estimation of the utility parameters of the MNL choice model in the previous section, we now discuss the various results that have been obtained as a consequence of the application of such a procedure onto our data. We have estimated various specifications of this choice model, we only present those estimates that are best interpretable. First, the basic model is outlined including the resulting estimates of VOT, VSDE, VSDL and VUNC. After this we include heterogeneity into the estimation of the models.

### 5.1 Multinomial logit model (MNL)

As a starting point, we analyze respondents' overall tradeoffs for mean travel time, uncertainty of travel time, and travel cost. This is similar to the 'mean-variance' modeling approach proposed by Jackson and Jucker (1981) where travelers were supposed to make a trade off between mean travel time and variance of travel time. This gives the estimates of how people evaluate travel time and uncertainty with respect to the monetary cost. The generic indirect utility functions of car ($V_C$) and public transport modes ($V_{PT}$) are given in Equation (8).

$$\begin{aligned} V_{CAR} &= \beta_C C + \beta_T E[T] + \beta_{UNC} UNC + EDT + VEDT + VVEDT \\ V_{PT} &= ASC_{PT} + \beta_C C + \beta_T E[T] + \beta_{UNC} UNC + EDT + VEDT + VVEDT \end{aligned} \quad (8)$$

where C is the travel cost (in our experiment consisting of both fuel and toll costs), E[T] is the mean travel time, and UNC is the amount of uncertainty travel time[3]. $ASC_{PT}$ is the alternative specific constant of public transport. The idea of adding an ASC for public transport is to capture the effect of respondents' difference in preferences for car or public transport. Since our experiment also involves different departure time conditions implied by different mode/routes alternatives. We, therefore, specify a set of dummy variables, EDT, VEDT, and VVEDT, to

[3] The mean travel time is defined as the mean value of minimum and maximum total travel time in the choice experiment, while uncertainty is the difference between maximum and minimum total travel time.

explain the utility difference incurred by chosen different departure time slots. EDT denotes the dummy for 'early departure' and is equal to 1 when the departure time is 30 to 60 minutes earlier than the respondent's preferred departure time (PDT); VEDT is the dummy of 'very early departure' and is equal to 1 when the departure time is 60-90 minutes earlier than the PDT; and VVEDT gives the 'very very early departure' dummy and is 1 when the departure time is more than 90 minutes earlier than the PDT.

Next, we estimate a more complete model incorporating the scheduling variables based on Eq.(7). This model illustrates that the individual accounts for the following attributes in their decision making: travel cost, C; mean travel time E[T]; expected schedule delay early, E[SDE]; expected schedule delay late, E[SDL]; probability of arriving later than the preferred arrival time, $P_L$[4]; and amount of uncertainty travel time UNC. The generic indirect utility functions of car ($V_C$) and public transport modes ($V_{PT}$) are given as

$$V_{CAR} = \beta_C C + \beta_T E[T] + \beta_{SDE} E[SDE] + \beta_{SDL} E[SDL] + \beta_{P_L} P_L + \beta_{UNC} UNC + EDT + VEDT + VVEDT$$

$$V_{PT} = ASC_{PT} + \beta_C C + \beta_T E[T] + \beta_{SDE} E[SDE] + \beta_{SDL} E[SDL] + \beta_{P_L} P_L + EDT + VEDT + VVEDT \quad (9)$$

Uncertainty of travel time is also included in this model, however, one it is likely that this is of less relevance since most of the uncertainty effects are captured by E(SDE), E(SDL), and $P_L$.

The first two columns of Table 7 show the MNL estimates of the mean-variance modeling and the trip scheduling modeling approach. The unit of all time-related attributes is in minutes and travel cost is in Euros. A general finding obtained from these two models is the negative public transport ASC and negative coefficients of EDT, VEDT, and VVEDT dummies. Because ASC represents individuals' taste of choosing that alternatives, the negative ASC for public transport indicates that respondents prefer car to public transport when the attributes are the same for these two modes. This phenomenon may be explained by the fact that our survey respondents are all car users, thus it is naturally intuitive that car alternatives are more favored as a consequence. The negative values of early departure dummies show that commuters acquire some disutility when shifting their departure time to a less preferred condition, and this disutility increases as departure time is shifting to the earlier side.

[4] The computation of E[SDE], E[SDL], and $P_L$ is given in Appendix 3.

When comparing these first two model estimations, we see that uncertainty is only significant in model 1. In model 2, with the scheduling consideration, uncertainty is not important anymore. This result suggests that uncertainty may be explained by the scheduling constraints. Small et al. (1999) obtained a similar result for the estimate of standard deviation of travel time in the scheduling specification utility function. The authors argue that when the scheduling costs are fully specified in a model, it is unnecessary to add an additional cost for unreliability (uncertainty) of travel.

Based on the specification in equation (9), we extend our analysis and investigate the mode specific effects by interacting the travel time and scheduling variables with a public transport dummy. This leads to the following specification:

$$\begin{aligned} V = {} & \beta_C C + \beta_T E[T] + \beta_{SDE} E[SDE] + \beta_{SDL} E[SDL] + \beta_{P_L} P_L + \beta_{UNC} UNC + EDT + VEDT + VVEDT \\ & + \beta_{PT} * PT * E[T] + \beta_{PSDE} * PT * E[SDE] + \beta_{PSDL} * PT * E[SDL] \end{aligned} \qquad (10)$$

where $PT = 1$ if the alternative is public transport, and zero otherwise.

The aim is to analyze whether respondents evaluate the attributes of public transport and road transport with different values. By checking the significance of coefficients of these interaction terms, we can examine whether the valuation of public transport significantly differs from road transport. The results of model 3 (Table 7) indeed show that there is a difference in the disutility attributed to travel time and schedule delay.

Finally, we considered nonlinear effects of scheduling variables, such as *E[SDE]* and *E[SDL]*, by including the quadratic terms of these variables in our indirect utility function (model 4 and 5). The coefficient of this quadratic term of SDE is negative and significant, indicating the non-linear effect. It indicates that people's aversion to arriving early is increasing non-linearly as their schedule delay early time increases. Based on Model 4, the public transport interaction terms are included in Model 5.

*Table 7: Estimation results of the basic models for SCE data*

| Explanatory variables | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| ASC of public transport alternative<br>A_PT | -1.0851***<br>(-22.317) | -0.7824***<br>(-15.040) | -0.7919***<br>(-7.877) | -0.7896***<br>(-15.158) | -0.7678***<br>(-8.374) |
| Travel cost<br>C | -0.0944***<br>(-16.635) | -0.0938***<br>(-16.520) | -0.0952***<br>(-16.619) | -0.0934***<br>(-16.440) | -0.0945***<br>(-16.500) |
| Mean travel time E[T]<br>E[T] | -0.0134***<br>(-11.011) | -0.0132***<br>(-9.131) | -0.0126***<br>(-8.455) | -0.0133***<br>(-9.125) | -0.0126***<br>(-8.460) |

| | | | | | |
|---|---|---|---|---|---|
| E[T]*Public transport dummy | | | -0.0021** | | -0.0020** |
| E[T]*PT | | | (-2.207) | | (-2.120) |
| Expected schedule delay early | | -0.0189*** | -0.0196*** | -0.0051 | |
| E[SDE] | | (-8.754) | (-8.865) | (-0.744) | |
| Expected schedule delay early squared | | | | -0.0003** | -0.0004*** |
| $E[(SDE)^2]$ | | | | (-2.109) | (-8.950) |
| E[SDE]*Public transport dummy | | | 0.0090** | | |
| E[SDE]*PT | | | (2.286) | | |
| Expected schedule delay early squared*public transport dummy | | | | | 0.0002** |
| $E[(SDE)^2]$*PT | | | | | (2.234) |
| Expected schedule delay late | | -0.0233*** | -0.0261*** | -0.0273*** | -0.0267*** |
| E[SDL] | | (-9.639) | (-9.451) | (-5.665) | (-9.831) |
| Expected schedule delay late squared | | | | 0.0001 | |
| $E[(SDL)^2]$ | | | | (0.921) | |
| E[SDL]*Public transport dummy | | | 0.0103** | | 0.0096 |
| E[SDL]*PT | | | (2.545) | | (2.628) |
| Probability of late arrival (later than PAT) | | -0.1001** | -0.0800 | 0.0173 | 0.0469 |
| $P_L$ | | (-2.066) | (-1.624) | (0.242) | (1.082) |
| Uncertainty | -0.0069*** | 0.0018 | 0.0015 | 0.0016 | 0.0018 |
| UNC | (-5.430) | (1.258) | (0.983) | (1.116) | (1.148) |
| Dummy for departing 30-59 min earlier than preferred departure time (PDT) | -0.0896*** | -0.1124** | -0.1160** | -0.1314*** | -0.1520*** |
| EDT | (-3.192) | (-2.477) | (-2.537) | (-2.827) | (-3.503) |
| Dummy for departing 60-89 min earlier than PDT | -0.6259*** | -0.5390*** | -0.5484*** | -0.5426*** | -0.5695*** |
| VEDT | (-14.199) | (-6.708) | (-6.790) | (-6.747) | (-7.243) |
| Dummy for departing more than 90 min PDT | -0.9908*** | -0.9704*** | -0.9646*** | -0.9850*** | -1.0020 |
| VVEDT | (-9.303) | (-6.694) | (-6.605) | (-6.785) | (-6.974) |
| Log likelihood | -15557.44 | -15422.50 | -15416.37 | -15419.90 | -15414.25 |
| R-sqrd Adjusted | 0.08484 | 0.09270 | 0.09299 | 0.09281 | 0.09311 |

Note: t-statistics are shown in parenthesis. Significant is indicated by ***, **, and *, referring to significance at 99%, 95%, and 90% level, respectively.

The resulting parameter values (VOT, VSDE, VSDL and VUNC) from these models are summarized in Table 8. The generic VOT values around € 8.5 seem reasonable and in between the results from Dutch literature and the (mean) interval estimates presented in Section 3. Similar results are found for the VSDL.

When we move to the estimations of scheduling specification in Model 2, we find a large value of schedule delay early compared with the previous interval estimates. This may be due to the non-linear effect of the SDE variable. We have seen that inclusion of the quadratic terms of SDE (model 4) leads to a coefficient of $E[(SDE)^2]$ that is significantly negative. Because expected SDE appears as a quadratic term in the utility function, the marginal cost of SDE rises with SDE. Consequently, the VSDE is within a reasonable range when the expected schedule delay early time is within 20 minutes. This finding is plausible, since similar results are also obtained in previous studies (Hendrickson and Plank, 1984; Small et al. 1999), these are also in line with our interval estimates.

From the estimated coefficients of the interaction terms in Model 3 and Model 5, we note that that the valuations of travel time and scheduling attributes in public transport are significantly different from those in car transport. The values of time, derived from Model 3 and 5, are significantly higher for public transport than for road transport. Jiang and Morikawa (2004) analyzed the variation of value of travel time theoretically and they concluded that value of travel time savings is higher for a slower mode if the marginal utility decreases with travel time. As public transport is designed as a slower mode in our choice experiment and marginal utility is likely to decrease when travel time rises, our finding confirms what theory suggests. Another possible explanation is that public transport is generally less preferred, people are willing to pay relatively more to reduce public transport travel time than time spent in a car. For the values of scheduling variables, road transport has higher estimates than public transport. This may be explained by the fact that uncertainty in road transport is captured in the scheduling costs and not important anymore when these terms are included in the models. Public transport travel time may then become relatively more reliable.

*Table 8: Monetary values of time and other time attributes of Model 1-5* (Unit: euro/hour)

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| VOT generic | 8.52 | 8.47 | - | 8.51 | - |
| VOT for car | - | - | 7.95** | - | 7.98** |
| VOT for public transport | - | - | 9.27** | - | 9.25** |
| VSDE generic | - | 12.07 | - | | - |
| At SDE=10 min | | | | 4.06 | |
| At SDE=20 min | | | | 8.11 | |
| At SDE=30 min | | | | 12.17 | |
| VSDE for car | - | | 12.35** | - | |
| At SDE=10 min | | | | | 5.60** |
| At SDE=20 min | | | | | 11.20** |
| At SDE=30 min | | | | | 16.80** |
| VSDE for public transport | - | | 6.67** | - | |
| At SDE=10 min | | | | | 2.42** |
| At SDE=20 min | | | | | 4.85** |
| At SDE=30 min | | | | | 7.27** |
| VSDL generic | - | 14.88 | - | 17.54 | - |
| VSDL for car | - | - | 16.44** | - | 16.95** |
| VSDL for public transport | - | - | 9.92** | - | 10.87** |
| VUNC generic | 4.40 | - | - | - | - |

All monetary values given in this table are of the significance levels within 95% interval, whereas ** is the indication to show the difference between car and public transport is of 95% significant interval.

**5.2 Observed heterogeneity: multinomial logit model with a set of covariates**

In this section, we elaborate our analysis by interacting the travel time and scheduling related attributes with behavioral indicators, such as restriction of work starting time and restriction of home departure time, and with some socioeconomics indicators, such as gender, income, education, and travel cost compensation. The characteristics of our database on these variables can be found in Appendix 6. Our starting point is based on the scheduling specification in Model 2 (i.e., Eq.(9)).

**5.2.1 Behavioral indicators: effects of departure and arrival time restrictions**

Intuitively, individual's flexibility of arrival time at work and departure time from home will have some impact on the valuations of travel time and scheduling costs. Numerous empirical studies have confirmed that the work starting time flexibility has significant impact on the schedule delay estimates (e.g. Small 1982; Small et al. 1999). Most studies focused on arrival time restrictions, less studies explicitly addressed the impact of departure time flexibility on schedule delay costs. Our data contains information on the flexibility to adjust the arrival time at work and we know whether respondents can freely choose their departure time or not (they are constrained by personal or household circumstances). This enables us to investigate the effects caused by these imposed restrictions on the estimates. Therefore we specify the interaction terms for these restriction dummies with time and scheduling attributes, and analyze the significance of the effects.

*Table 9: Monetary values implied by Model 10 (shown in appendix 3) (euro/hour)*

| | VOT | VSDE | VSDL | Penalty (later or earlier than restr.) |
|---|---|---|---|---|
| No restriction [a] | 8.06 | 9.84 | 11.54 | - |
| Late arrival time at work restriction | 7.14 | 12.67* | 15.66** | 6.42*** |
| Early departure time from home restriction | 9.88 | 18.35*** | 11.45 | 1.46 |
| Late departure time from home restriction | 12.86*** | 7.78 | 10.78 | 2.98** |

***, **, and *, indicate that the difference between one particular group and reference group are significant at 99%, 95%, and 90% levels, respectively.

[a] No restriction on departure and arrival time is taken as the reference group for comparison.

[b] Although VOT is negative in this group, it is only significant within 90% confidence interval but not within 95% confidence interval.

Table 9 gives the monetary values of time and values schedule delay variables (the underlying MNL models can be found in Appendix 4). People with restricted starting times at work have higher VSDE and VSDL and they also incur a penalty for arriving later than the restricted time. For the restrictions of individuals' commuting departure time, the effects are different between early and late departure constraints. Commuters tend to have a higher VSDE when it is impossible to change their departure time to an earlier time slot. Commuters that cannot change departure time to a later moment are having a higher VOT.

### 5.2.2 Travel environment and socioeconomic indicators

Literature has shown that values of time and schedule delay vary with travel environment and socioeconomic variables such as trip length, income, and gender (Small et al., 1999; Lam and Small, 2001). In this subsection we investigate the effects of trip length, income, gender, education, and travel cost compensation by the employer on our estimates of interest. The estimation results can be found in Appendix 5, while the summarized monetary values are given in Table 10.

These results are plausible since they are consistent with the variations on our estimates in the analysis of interval estimates. Moreover, most of the findings are in line with literature, such as positive trip length effect on values of time (Gunn, 2001); positive income effects on values of time (Small et al, 1999) and positive female effects on schedule delay cost (Lam and Small, 2001). Particularly, we also find that scheduling costs are lower for respondents with a higher income and a higher educational level. This may be explained by the fact that higher educated people intend (with a higher income) have higher classified jobs, which generally have less restricted working times.

*Table 10: Monetary values implied by Model 11 to 15 (euro/hour)*

| | VOT | VSDE | VSDL |
|---|---|---|---|
| Trip length 30 km or less [a] | 6.31 | 14.82 | 19.80 |
| Trip length 30-60 km | 6.20 | 9.47*** | 11.23*** |
| Trip length 60 km or more | 10.78*** | 11.18* | 9.18*** |
| Household yearly income 28,500 or less [a] | 4.88 | 14.29 | 18.74 |
| Household yearly income 28,500-45,000 | 6.08 | 11.30 | 16.79 |
| Household yearly income 45,000-68,000 | 12.31*** | 9.75** | 10.56*** |
| Household yearly income 68,000 or more | 10.10*** | 12.41 | 12.02*** |
| Male [a] | 8.10 | 10.43 | 15.30 |

| | | | |
|---|---|---|---|
| Female | 10.26** | 17.36*** | 14.74 |
| Lower education (HAVO or less) [a] | 8.50 | 11.29 | 17.24 |
| Higher education (HBO or above) | 8.50 | 11.29 | 12.32** |
| No travel cost compensation [a] | -2.31[b] | 10.94 | 15.77 |
| Partial travel cost compensation | 7.34*** | 8.68 | 11.17 |
| Fully travel cost compensation | 10.15*** | 13.12 | 13.25 |

***, **, and *, indicate that the difference between one particular group and reference group are significant at 99%, 95%, and 90% levels, respectively.

[a] This is taken as the reference group for comparison.

[b] Although VOT is negative for this group, the coefficient is significant different from zero within 90% confidence interval but not within 95% confidence interval.

## 6. Concluding remarks

This paper presented the outcomes of a large SP experiment among Dutch commuters facing congestion. The aim was to find trade-offs between paying with traveling under attractive conditions (in terms of arrival time, travel time, etc.) versus paying less (or nothing) with facing less attractive travel conditions in terms of departure time, route length and mode. We have estimated choice models to infer values of important issues in transport economics (such as the value of time) and to determine behavioral responses to transport pricing.

The survey consisted of two types of experiments. The first experiment was relatively simple, we offered each respondent four car alternatives in one choice set and asked them to allocate 10 trips. For each type of parameter value we wanted to estimate (VOT, VSDE, VSDL, and VUNC), we developed a different choice set (alternatives only differed on toll, travel time and arrival time (early or late, with departure times changed accordingly)). The allocations of trips, together with the mean interval value (determined by assuming an underlying statistical (Gamma) distribution) resulted in interval estimates for the various parameter values. In line with other empirical results we found that VSDL has the highest value (a mean value of €14), followed by the VOT (about €10). However, this latter value is higher than the generally used value for the total Dutch population. Commuters tend to have minor problems with arriving too early and uncertain travel times. Reliability is also valued less high. Important socio-economic characteristics explaining these findings include income (VSDL, lower income groups tend to have a higher VSDL) and the presence of arrival and departure time restrictions. Inflexible commuters generally have a higher value of time, schedule delay and uncertainty.

The second experiment was more extended and consisted of 11 choice sets, and again respondents were asked to allocate 10 trips over four alternatives. It was a labeled experiment in which the alternatives consisted of different attributes (15 in total), which were based on current behaviour of each individual. Each attribute had either 2 or 4 different levels. The alternatives contained more attributes and various (systematically varying) levels. We have estimated various choice models by using the choice proportions set-up in which travel time is included as the mean travel time (and not the minimum). The results indicate that these respondents prefer car over the public transport alternative. When we include scheduling costs into the estimations uncertainty becomes insignificant. This has also been found by others and suggests that it is unnecessary to add an additional cost for unreliability (or uncertainty) of travel when scheduling costs are fully specified. Nonlinear effects of scheduling variables have also been addressed in our model estimations. The analysis indicates that people's aversion to arriving early is increasing non-linearly as their schedule delay early time increases.

The resulting parameter values for VOT and VSDL seem rather plausible and comparable to the interval estimates. Only model 1 resulted in a significant estimate of uncertainty, but the derived VUNC seems reasonable. The generic VSDE estimates for car and public transport were rather high. This may be explained by the non-linear effect of the SDE variable. The VSDE decreases (to a more reasonable value) when the expected schedule delay early time is within 20 minutes. Note that that the valuations of travel time and scheduling attributes in public transport are significantly different from those in car transport. The higher values of time for public transport can be explained however.

We have also included personal variables in the utility functions to include heterogeneity into the analysis. It is found that the presence of departure or arrival time restrictions is important for the parameter values (confirming the results find with the interval estimates). People with restricted starting times at work have higher VSDE and VSDL and they also incur a penalty for arriving later than the restricted time. For the restrictions of individuals' commuting departure time, the effects are different between early and late departure constraints.

Trip length seems to have an impact, especially on the VSDE and VSDL. Respondents making longer commuting trips generally attach a lower value to arriving earlier or later than the preferred time. The VSDL is lower for people with a higher income, this is similar to what we have found for the interval estimates. Travel cost compensation only seems to have impact on the VOT, with fully compensated commuters generally having higher values of time.

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## *Appendix 1: Scenarios to obtain VSDL, VSDE and VUNC interval estimates*

Literature suggests that the **VSDE** is about half of the VOT. Therefore, we defined the following 4 intervals:

1. € 0 – 2
2. € 2 – 4
3. € 4 – 6
4. > € 6

| | A (group 4) | B (group 3) | C (group 2) | D (group 1) |
|---|---|---|---|---|
| Departure time | $T_D$ | $T_D$ – 15 min. | $T_D$ – 30 min. | $T_D$ – 45 min. |
| Travel time | $T_f$ | $T_f$ | $T_f$ | $T_f$ |
| Arrival time | $T_A$ | $T_A$ – 15 min. | $T_A$ – 30 min. | $T_A$ – 45 min. |
| Toll | € 3 | € 1.50 | € 0.50 | € 0 |

According to the literature **VSDL** is about twice the VOT. Therefore, we defined the following 4 intervals:

1. € 0 – 8
2. € 8 – 16
3. € 16 – 24
4. > € 24

| | A (group 4) | B (group 3) | C (group 2) | D (group 1) |
|---|---|---|---|---|
| Departure time | $T_D$ | $T_D$ + 10 min. | $T_D$ + 20 min. | $T_D$ + 30 min. |
| Travel time | $T_f$ | $T_f$ | $T_f$ | $T_f$ |
| Arrival time | $T_A$ | $T_A$ + 10 min. | $T_A$ + 20 min. | $T_A$ + 30 min. |
| Toll | € 8 | € 4 | € 1.33 | € 0 |

We have defined, rather arbitrarily, the following intervals for the **VUNC**:

1. € 0 – 3
2. € 3 – 6
3. € 6 – 9
4. > € 9

| | A (group 4) | B (group 3) | C (group 2) | D (group 1) |
|---|---|---|---|---|
| Departure time | $T_D$ – 30 min. | $T_D$ – 30 min. | $T_D$ – 30 min. | $T_D$ – 30 min. |
| Min. travel time | $T_f$ + 30 min. | $T_f$ + 5 min. | $T_f$ + 0 min. | $T_f$ |
| Max. travel time | $T_f$ + 30 min. | $T_f$ + 35 min. | $T_f$ + 40 min. | $T_f$ + 55 min. |
| Min. arrival time | $T_A$ | $T_A$ – 15 min. | $T_A$ – 30 min. | $T_A$ – 45 min. |
| Max. arrival time | $T_A$ | $T_A$ + 5 min. | $T_A$ + 10 min. | $T_A$ + 15 min. |
| Tol | € 6 | € 3 | € 1 | € 0 |

## *Appendix 2: Example of one screen (with 4 alternatives) of the second part of the SC-experiment as presented to the respondent (levels are indicative)*

| **Alternative A** | **Alternative B** | **Alternative C** | **Alternative D** |
|---|---|---|---|
| Mode of transport: car | Mode of transport: car | Mode of transport: car | Mode of transport: public transport |
| Trip length : 35 km | Trip length: 35 km | Trip length: 49 km | Trip length: 35 km |
| Travel costs: € 8.10 of which:<br>– fuel: €3.20<br>– charge: €4.90 | Travel costs: € 4.60 of which:<br>– fuel: €3.20<br>– charge: €1.40 | Travel costs: € 6.20 of which:<br>– fuel: €4.20<br>– charge: €2.00 | Price of a ticket: € 3.18 |
| Departure time: 08.10 | Departure time: 08.25 | Departure time: 08.00 | Departure time: 07.25 |
| Total travel time between 40 and 50 minutes of which:<br>– free flow: 25 min.<br>– minimum time in congestion: 15 min.<br>– maximum time in congestion: 25 min. | Total travel time between 50 and 60 minutes of which:<br>– free flow: 25 min.<br>– minimum time in congestion: 25 min.<br>– maximum time in congestion: 35 min. | Total travel time between 55 and 65 minutes of which:<br>– free flow: 40 min.<br>– minimum time in congestion: 15 min.<br>– maximum time in congestion: 25 min. | Total travel time: 72 minutes |
| Arrival time is hence between: 8.50 and 9.00 | Arrival time is hence between: 9.15 and 9.25 | Arrival time is hence between: 8.55 and 9.05 | Arrival time: 08.37 |
| Number of trips ….. | Number of trips …. | Number of trips … | Number of trips … |

## *Appendix 3: Computation of E[SDE] and E[SDL]*

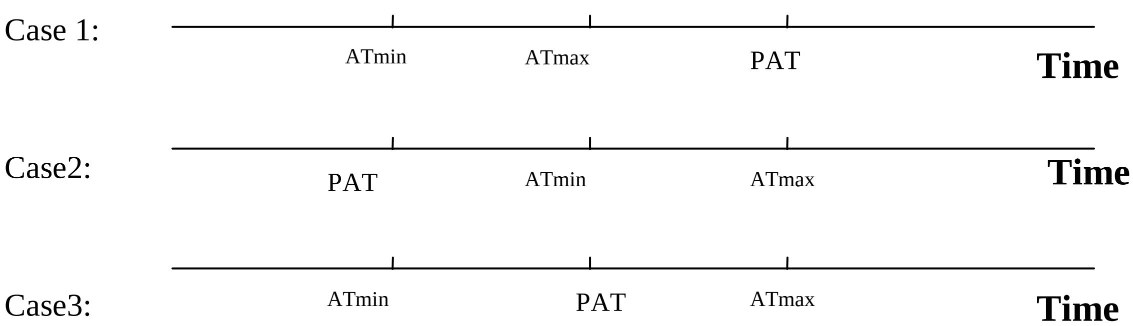
SDE is defined to be positive for early arrivals and zero otherwise; while SDL is positive for late arrivals and zero otherwise. $P_L$ represents probability of arriving later than preferred arrival time.

$$SDE(AT) = \max\{PAT - AT, 0\}$$

$$SDL(AT) = \max\{AT - PAT, 0\}$$

$$P_L = \Pr ob(AT > PAT)$$

where AT denotes the arrival time and PAT is the preferred arrival time.
To compute the E[SDE], E[SDL], and $P_L$ we can distinguish the following three cases:




where ATmin is the earliest arrival time and ATmax is the latest arrival time

**Case 1:** $AT\max \leq PAT$

$$E[SDE] = PAT - \frac{1}{2}(AT\min + AT\max)$$

$$E[SDL] = 0$$

$$P_L = 0$$

**Case 2:** $AT\min \geq PAT$

$$E[SDE] = 0$$

$$E[SDL] = \frac{1}{2}(AT\min + AT\max) - PAT$$

$$P_L = 1$$

**Case 3:** $AT\min < PAT \ \& \ AT\max > PAT$

$$E[SDE] = \frac{1}{2}(PAT - AT\min) * (1 - P_L)$$

$$E[SDL] = \frac{1}{2}(AT\max - PAT) * P_L$$

$$P_L = \frac{AT\max - PAT}{AT\max - AT\min}$$

## *Appendix 4: Estimation results of scheduling restriction effects based on Model 2*

| Explanatory variables | Model 6 | Model 7 | Model 8 | Model 9 | Model 10 |
|---|---|---|---|---|---|
| ASC of public transport alternative | -0.7841*** | -0.7848*** | -0.7783*** | -0.7826*** | -0.7871*** |
| | (-15.065) | (-15.061) | (-14.966) | (-15.047) | (-15.103) |
| Travel cost C | -0.0936*** | -0.0937*** | -0.0932*** | -0.0941*** | -0.0938*** |
| | (-16.446) | (-16.441) | (-16.401) | (-16.565) | (-16.430) |
| E[T] | -0.0129*** | -0.0136*** | -0.0125*** | -0.0125*** | -0.0126*** |
| | (-8.842) | (-8.541) | (-8.490) | (-8.542) | (-7.787) |
| E[T]*arriving later than work restr. | | 0.0009 | | | 0.0014 |
| | | (0.675) | | | (1.110) |
| E[T]*departing earlier than home restr. | | | -0.0051*** | | -0.0029 |
| | | | (-2.693) | | (-1.296) |
| E[T]*departing later than home restr. | | | | -0.0058*** | -0.0075*** |
| | | | | (-3.137) | (-3.787) |
| E[SDE] | -0.0187*** | -0.0166*** | -0.0170*** | -0.0193*** | -0.0154*** |
| | (-8.666) | (-6.469) | (-7.748) | (-8.728) | (-5.854) |
| E[SDE]*arriving later than work restr. | | -0.0040 | | | -0.0044* |
| | | (-1.576) | | | (-1.738) |
| E[SDE]*departing earlier than home restr. | | | -0.0145*** | | -0.0133*** |
| | | | (-3.708) | | (-3.330) |
| E[SDE]*departing later than home restr. | | | | 0.0027 | 0.0032 |
| | | | | (0.729) | (0.861) |
| E[SDL] | -0.0215*** | -0.0180*** | -0.0238*** | -0.0228*** | -0.0180*** |
| | (-8.804) | (-6.247) | (-9.505) | (-9.167) | (-6.072) |
| E[SDL]*arriving later than work restr. | | -0.0104*** | | | -0.0064** |
| | | (-3.305) | | | (-1.995) |
| E[SDL]*departing earlier than home restr. | | | 0.0032 | | 0.0001 |
| | | | (0.715) | | (0.030) |
| E[SDL]*departing later than home restr. | | | | -0.0037 | 0.0012 |
| | | | | (-0.771) | (0.263) |
| Probability of late arrival (later than PAT) | -0.1023** | -0.0945* | -0.1034** | -0.1001** | -0.1015** |
| | (-2.109) | (-1.948) | (-2.133) | (-2.065) | (-2.089) |
| Uncertainty | 0.0016 | 0.0017 | 0.0018 | 0.0018 | 0.0015 |
| | (1.171) | (1.183) | (1.312) | (1.254) | (1.090) |
| Dummy for arriving later than work restr. | -0.6299*** | | | | -0.6025*** |
| | (-6.219) | | | | (-5.773) |
| Dummy for departing earlier than home restr. | -0.3132*** | | | | -0.1345 |
| | (-4.391) | | | | (-1.457) |
| Dummy for departing later than home restr. | -0.1845* | | | | -0.2793** |
| | (-1.701) | | | | (-2.358) |
| Dummy for departing 30-59 min earlier than PDT | -0.1096** | -0.1121** | -0.1095** | -0.1113** | -0.1067** |
| | (-2.412) | (-2.469) | (-2.414) | (-2.452) | (-2.354) |
| Dummy for departing 60-89 min earlier than PDT | -0.5356*** | -0.5359*** | -0.5424*** | -0.5356*** | -0.5283*** |
| | (-6.657) | (-6.664) | (-6.751) | (-6.667) | (-6.565) |
| Dummy for departing more than 90 min PDT | -0.9763*** | -0.9665*** | -0.9917*** | -0.9670*** | -0.9665*** |
| | (-6.719) | (-6.663) | (-6.819) | (-6.668) | (-6.635) |
| Log likelihood | -15389.61 | -15416.98 | -15402.10 | -15415.86 | -15369.30 |
| R-sqrd Adjusted | 0.09456 | 0.09295 | 0.09383 | 0.09302 | 0.09554 |

Note: t-statistics are shown in parenthesis. Significant is indicated by ***, **, and *, referring to significance at 99%, 95%, and 90% level, respectively.

## *Appendix 5: Estimation results of trip length, income, gender, education, and cost compensation effects*

| Explanatory variables | Model 11 | | Model 12 | | Model 13 | | Model 14 | | Model 15 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Est. b | t-stats. | Est. b | t-stats. | Est. b | t-stats. | Est. b | t-stats. | Est. b | t-stats. |
| ASC of public transport alternative | -0.8491*** | (-15.569) | -0.7811*** | (-15.019) | -0.7779*** | (-14.929) | -0.7789*** | (-14.969) | -0.8268*** | (-15.759) |
| Travel cost C | -0.1060*** | (-16.550) | -0.0970*** | (-16.971) | -0.0918*** | (-16.101) | -0.0940*** | (-16.523) | -0.1097*** | (-18.620) |
| E[T] | -0.0111*** | (-5.700) | -0.0079*** | (-4.336) | -0.0124*** | (-8.274) | -0.0133*** | (-8.648) | 0.0042* | (1.798) |
| E[T]*Trip length L2 (30-60 km) | 0.0002 | (0.095) | | | | | | | | |
| E[T]*Trip length L3 (>60 km) | -0.0079*** | (-3.832) | | | | | | | | |
| E[T]*Income2 (household inc. €28,500-45,000) | | | -0.0019 | (-1.081) | | | | | | |
| E[T]*Income3 (household inc. €45,000-68,000) | | | -0.0120*** | (-6.570) | | | | | | |
| E[T]*Income4 (household inc. >€68,000) | | | -0.0084*** | (-4.978) | | | | | | |
| E[T]*Female | | | | | -0.0033** | (-1.995) | | | | |
| E[T]*Higher education (HBO and above) | | | | | | | -0.0001 | (-0.074) | | |
| E[T]*Fully compensation of travel cost | | | | | | | | | -0.0176*** | (-7.540) |
| E[T]*Partial compensation of travel cost | | | | | | | | | -0.0228*** | (-9.893) |
| E[SDE] | -0.0262*** | (-9.417) | -0.0231*** | (-7.939) | -0.0160*** | (-7.050) | -0.0177*** | (-7.324) | -0.0200*** | (-5.157) |
| E[SDE]*Trip length L2 (30-60 km) | 0.0094*** | (3.227) | | | | | | | | |
| E[SDE]*Trip length L3 (>60 km) | 0.0064* | (1.784) | | | | | | | | |
| E[SDE]*Income2 (household inc. €28,500-45,000) | | | 0.0048 | (1.464) | | | | | | |
| E[SDE]*Income3 (household inc. €45,000-68,000) | | | 0.0073** | (2.172) | | | | | | |
| E[SDE]*Income4 (household inc. >€68,000) | | | 0.0030 | (1.210) | | | | | | |
| E[SDE]*Female | | | | | -0.0106*** | (-3.500) | | | | |
| E[SDE]*Higher education (HBO and above) | | | | | | | -0.0032 | (-1.2429) | | |
| E[SDE]*Fully compensation of travel cost | | | | | | | | | 0.0041 | (1.047) |
| E[SDE]*Partial compensation of travel cost | | | | | | | | | -0.0040 | (-0.993) |
| E[SDL] | -0.0350*** | (-9.630) | 0.0303*** | (-8.158) | -0.0234*** | (-9.172) | -0.0270*** | (-9.473) | -0.0288*** | (-5.824) |
| E[SDL]*Trip length L2 (30-60 km) | 0.0151*** | (3.797) | | | | | | | | |
| E[SDL]*Trip length L3 (>60 km) | 0.0187*** | (4.408) | | | | | | | | |
| E[SDL]*Income2 (household inc. €28,500-45,000) | | | 0.0032 | (0.718) | | | | | | |
| E[SDL]*Income3 (household inc. €45,000-68,000) | | | 0.0132*** | (2.937) | | | | | | |
| E[SDL]*Income4 (household inc. >€68,000) | | | 0.0109*** | (2.711) | | | | | | |
| E[SDL]*Female | | | | | 0.0008 | (0.222) | | | | |
| E[SDL]*Higher education (HBO and above) | | | | | | | 0.0077** | (2.448) | | |
| E[SDL]*Fully compensation of travel cost | | | | | | | | | 0.0084 | (1.610) |
| E[SDL]*Partial compensation of travel cost | | | | | | | | | 0.0046 | (0.896) |
| Probability of late arrival (later than PAT) | -0.0917* | (-1.876) | -0.1015** | (-2.092) | -0.0979** | (-2.020) | -0.0991** | (-2.045) | -0.1078** | (-2.217) |
| Uncertainty | 0.0009 | (0.666) | 0.0020 | (1.436) | 0.0017 | (1.240) | 0.0019 | (1.365) | 0.0014 | (0.986) |
| Dummy for departing 30-59 min earlier than PDT | -0.1036** | (-2.251) | -0.1089** | (-2.399) | -0.1087** | (-2.393) | -0.1113** | (-2.452) | -0.1233*** | (-2.709) |
| Dummy for departing 60-89 min earlier than PDT | -0.4641*** | (-5.649) | -0.5333*** | (-6.636) | -0.5552*** | (-6.893) | -0.5321*** | (-6.621) | -0.5270*** | (-6.541) |
| Dummy for departing more than 90 min PDT | -0.7577*** | (-5.097) | -0.9508*** | (-6.548) | -1.0106*** | (-6.946) | -0.9633 | (-6.640) | -0.8890*** | (-6.112) |
| Log likelihood | -15391.99 | | -15386.86 | | -15408.35 | | -15415.59 | | -15358.25 | |
| R-sqrd Adjusted | 0.09435 | | 0.09458 | | 0.09346 | | 0.09303 | | 0.09633 | |

Note: t-statistics are shown in parenthesis. Significant is indicated by ***, **, and *, referring to significance at 99%, 95%, and 90% level, respectively

## *Appendix 6: Explanation and population share of explanatory (dummy) variables of data set (N=1115)*

| **Categories** | **Definitions and population share** |
|---|---|
| Gender | Male = 1 if male (76.23%)<br>Female = 1 if female (23.77%) |
| Education | Lower education = 1 if senior general secondary (HAVO/VWO) or below (55.25%)<br>Higher education = 1 if Bachelor (HBO/WO) or above (44.75) |
| Income | Income 1 = 1 if household gross yearly income is less than 28,500 euros (20.72%)<br>Income 2 = 1 if household gross yearly income is 28,500 – 45,000 euros (26.73%)<br>Income 3 = 1 if household gross yearly income is 45,000 – 68,000 euros (26.10%)<br>Income 4 = 1 if household gross yearly income is more than 68,000 euros (26.46%) |
| Trip length | Trip length L1 = 1 if the usual commuting distance is less than 30 km (35.16%)<br>Trip length L2 = 1 if the usual commuting distance is 30 - 60 km (36.95%)<br>Trip length L3 = 1 if the usual commuting distance is more than 60 km (27.89%) |
| Late arrival time restriction | Late arrival time restriction =1 if commuters cannot arrival at work later than certain time (54.71%) |
| Early departure time restriction | Early departure time restriction =1 if commuters cannot depart from home earlier than certain time (15.07%) |
| Late departure time restriction | Late departure time restriction = 1 if commuters cannot depart from home later than certain time (14.44%) |