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THE COST OF TRAVEL TIME VARIABILITY FOR AIR AND CAR TRAVELLERS

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de Vrije Universiteit Amsterdam,
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door

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This thesis concludes four years of research as a PhD student at the Department of Spatial Economics at the VU University Amsterdam. My interest in Spatial and Transport Economics was triggered by the lectures of Henri de Groot who offered me the possibility to do research at the CPB for a while. After finishing the STREEM master I wrote my thesis which was patiently supervised by Piet Rietveld, and concluded that doing research is fascinating and allows for creativity. A conclusion that is still valid now.

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I was lucky, I feel blessed.

Paul, 17 November 2011
1 Introduction

1.1 Motivation and relevance for policy

Passenger transport is at the heart of economic activity because it enables people to trade their ideas, skills, labour and goods for money (Small and Verhoef, 2007). Therefore a reliable transport system is important since it enables this trade.

Engineers and economists have recognised that vulnerability of transport networks and fluctuations in travel demand result in variation in travel times, and many studies have developed equilibrium models to study the effects of unreliable transport systems (see for overviews with an engineering perspective: Jenelius et al., 2006; Immers et al., 2004; Tu, 2008; Liu, 2008; Li, 2009; Knoop, 2009; Li et al., 2010). These models can be static, meaning that the dynamic choice of the traveller is ignored, or dynamic, where travellers can choose their optimal departure time from home and it is recognised that travellers anticipate variations in travel times. For example, Clark and Watling (2005) use a static network equilibrium model to study the effect of variable demand and Emmerink et al. (1998a; 1998b) study the impact of information on user cost using a static model with the standard deviation of travel times as a proxy for the cost of travel time uncertainty. Noland (1997) and Noland et al. (1998) study travel decisions using a departure time choice framework and find that travel time variability increases travel costs substantially. Arnott et al. (1999) study the cost of travel time variability in a dynamic bottleneck model, where demand and supply are variable.

Transport economists are interested in the user cost that is due to travel time variability and naturally ask the question how much we are willing to pay to improve the reliability of transport networks. More than 40 years ago Gaver (1968) was probably the first to show that travellers anticipate to fluctuations in travel times and show that they use the concept of buffer times in order to minimise the effects of variable travel times.
Travel time variability makes travel decisions complex in reality, and is not easy to model, and it is therefore that only recently it has been proposed to include travel time variability in policy evaluation of transport infrastructure appraisal (SACTRA, 1999; RAND Europe, 2004; Hamer et al., 2005; Eliasson, 2008,2009; OECD/ITF, 2010). There has been an increasing demand for research on travel time reliability, leading to a large number of studies on the subject, because preliminary research suggest that the benefits of improving the reliability of transport systems may be substantial (see for recent overviews for example: Tseng, 2008; Eliasson, 2009; Li et al., 2010a; Hjorth, 2011). Although most up-to-date research suggests that the major user benefit of infrastructure investments is still the gain in average travel time, previous research already showed that the user benefits of improvements in reliability may be substantial (Koskenoja, 1996; Small et al., 1999; Bates et al., 2001; Tseng, 2008; RAND Europe, 2004; Peer et al., 2010; Franklin and Karlström, 2009; Fosgerau and Karlström, 2010). For example, SACTRA (1999) showed for the UK, that the benefits of improved travel time variability in infrastructure may add 5-50% to user benefits.

In order to do cost-benefit analysis (CBAs), analysts typically need economic behavioural models that are supported by empirical evidence. This thesis contributes both in the area of the specification of behavioural models and the estimation of the preference parameters of these models.

This thesis develops dynamic behavioural models and applies these models using observed travel time data. It also provides some simplified application rules that may offer policy practitioners (such as governments) shortcuts when calculating the user benefits of reductions in travel time variability, without the need of using departure time choice models.

1.2 The cost of travel time variability

Travel time variability means that travel times are random, and therefore for a given departure time the arrival time at the (intermediate) destination is random. The complementary definition of travel time variability is travel time reliability, meaning that

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1 For an overview of countries that consider implementing reliability benefits in CBAs see: http://bca.transportationeconomics.org/benefits/travel-time-reliability/reliabilityandbca.
more reliable travel times imply a lower variation in arrival times. This study uses reliability to describe a transport system, and variability to describe the randomness in travel times. Other authors suggest using travel time uncertainty to describe randomness in travel times (Noland and Small, 1995; Li et al., 2010). However, there is a subtle difference between travel time variability and travel time uncertainty. If travel time is uncertain, the probabilities of travel times are strictly speaking unknown, but if travel time is variable the probabilities of travel times are known by the traveller. Through this study, it is assumed that travellers know the travel time distribution, and that is why this study refers to the randomness of travel times as travel time variability.

In order to estimate the cost of travel time variability, previous research used proxy’s for the variability of travel times in the utility or cost function of the traveller (see for overviews: Noland and Polak, 2002; Hollander, 2006; Van Lint et al., 2008; Börjesson et al., 2011). The first approach used in the literature is the mean-dispersion approach, where some measure of dispersion of travel times is included in the cost function that travellers seek to minimise. For example, Jackson and Jucker (1981) and Senna (1994) propose to include the standard deviation or the variance of travel times in the user cost function. Lam and Small (2001) and Small et al. (2005) use the percentile differences of the travel time distribution to describe travel time variability. Usually the 50th-80th or 50th-90th percentile difference is used. The value of reliability is then the reduction in travel cost for a marginal reduction in the measure of dispersion. The mean-dispersion approach has advantages for empirical application and estimation of the user cost of travel time variability, because it uses a reduced form cost function for the dynamic choice of the traveller. However, it has been criticised for two reasons. First, it does not capture the behavioural responses to travel time variability, because the dynamic nature of the choice of departure time or connection is not included. Second, they usually assume implicitly that the (standardised) travel time distribution is equal over time of day.

In departure time choice models, an explicit treatment of trip timing is usually included using the concept of schedule delay, which was introduced by Vickrey (1969)

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2 Not knowing probabilities may result in additional disutility or cost because of travel time variability. This is known as uncertainty aversion (Wakker, 2010).
and Small (1982). This concept assumes that travellers compare the cost (or disutility) of an arrival time to the cost of arriving at the preferred arrival time. In order to deal with travel time variability, the scheduling model of Small (1982) was extended by Noland and Small (1995). They show, amongst others, that anticipation to travel time variability plays an important role: a higher variability of travel times results in earlier departure times (Noland and Small, 1995; Fosgerau and Karlström, 2010; Fosgerau and Engelson, 2010). The scheduling approach is employed in this thesis because it is more intuitive from a behavioural perspective than the mean-dispersion approach, and assumes that there is a cost of arriving earlier or later than the preferred arrival time at the destination. This means that travellers are not primarily concerned by statistical measures like the standard deviation (or percentile differences), but dislike travel time variability primarily because as a result they can arrive too early or too late. Of course, travellers can anticipate to some extent to variable travel times by choosing their departure time optimally.

Mean-dispersion models may not model variable arrival times explicitly, but may still be taken as a reduced-form representation of scheduling cost that arise or grow when travel times become more variable. Fosgerau and Karlström (2010) showed analytically how the mean-standard deviation approach and the scheduling approach are related. For a travel time distribution that does not change over the day, the optimal expected user cost is linear in the standard deviation of travel times, with the exact relation depending on the shape of the standardised travel time distribution. This result does not hold for a scheduled service (such as an aeroplane, train or bus), because the choice of departure is then restricted by the timetable and therefore travellers cannot freely choose their departure times.

Tseng and Verhoef (2008) extended the scheduling model of Noland and Small (1995) by allowing also for a cost when travellers shift their departure times. They showed that the model better describes the choices made by respondents in a stated choice experiment. Their model was used by Fosgerau and Engelson (2010) and extended by Engelson and Fosgerau (2011) to analyse departure time decisions of travellers, who show that with linear marginal utilities of being at the origin or at the destination, the optimal expected user cost is a linear function of the variance of travel times and is
independent of the shape of the distribution of travel times. This result also holds for scheduled services, which is an attractive feature of the model.

Although scheduling models are hardly implemented in transport models, these are now widely accepted in the academic literature as the best candidate to model the behavioural response to travel time variability, since they capture the dynamic decision of the traveller appropriately and also are supported by a large number of empirical studies. Therefore, this study will use extensions of the Noland and Small (1995) scheduling model (Chapters 2, 3 and 4) to describe passengers’ behaviour when travel times are variable.

1.3 Objective and structure of the thesis

The main research question of this thesis is:

“How can the cost of travel time variability for car and air travellers be determined?”

This study is limited to personal travel, and focuses on the travel behaviour of travellers making an air trip (Chapters 2 and 3) and car trips of morning commuters (Chapters IV and V). Table 1.1 shows the steps needed to determine the cost of travel time variability, and indicates how the different chapters in this study are related to these steps. It implies that all chapters start with a micro-economic behavioural model that includes the dynamic choice of departure time or connection by travellers, accounting for travel time variability (step 1). The behavioural models in Chapters 2 and 5 are validated using stated preference data, applying advanced discrete choice estimation techniques (step 2).3 These chapters develop a stated-preference survey to collect data about the preferences of travellers. In Chapter 2, 3 and 5, these preference parameters are used to model the dynamic departure time decision of travellers, given the observed exogenous distribution of travel times (step 3). This step gives estimates of the cost of travel time variability and analyses how large the share of the cost of travel time variability is in the total expected user cost.

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3 For an accessible introduction into these techniques, see e.g. Train (2003).
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<tr>
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<th>Air travellers</th>
<th>Car travellers</th>
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<td><strong>Table 1.1 — Structure of the thesis.</strong></td>
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The cost is determined assuming that travellers behave optimally, meaning that they choose their optimal departure time or connection given the prevailing travel time distribution. The study estimates travel time distributions using nonparametric estimation techniques. Therefore, it is not needed to assume any particular parametric form, as is done in earlier research (Noland and Small, 1995; Bates et al. 2001). Step 3 is elaborated in more detail in Chapters 2, 3 and 5. Not unimportantly, step 3 also provides simplified application rules that may be useful for shortcuts in applied policy evaluation analysis.

### 1.4 Contributions to the existing academic literature

This study makes a number of contributions to the research on travel time variability. The first part (Chapters 2 and 3) studies the cost of travel time variability for air travellers. Chapter 2 develops a behavioural model for air travellers going to the airport, estimates the parameters of this model and calculates the cost of access travel time variability. As far as we know this Chapter is the first to study these issues in detail.

The scheduling choice of these travellers is different from the commuters’ choice because the cost of missing a flight is likely to be high and therefore the behavioural model takes into account the cost of missing a flight. First, the determinants of the preferred arrival times at airports are analysed using regression analysis. Second, the willingness to pay (WTP) for reductions in access travel time, early and late arrival time at the airport, and the probability to miss a flight are estimated, using data from a stated choice experiment.

Third, a model is developed to calculate the cost of variable travel times for representative air travellers going by car, taking into account travel time cost, scheduling cost and the cost of missing a flight, using empirical travel time data. In this model, the
value of reliability for air travellers is derived taking “anticipating departure time choice” into account, meaning that travellers will be assumed to determine their departure time from home optimally, given the prevailing known travel time distribution.

Chapter 3 shows how travellers choose their flight given that the arrival time at the destination of the flight is random. The analysis of Douglas and Miller (1974) and Anderson and Kraus (1981) already showed that travellers dislike arrival delays and arrival delay variability, but the user cost of arrival delay variability for air travellers has not been analysed in detail before and the dynamic choice of flights is usually ignored (Brey and Walker, 2011). The chapter derives the expected user cost of US air domestic air travel delays, taking into account scheduling behaviour of travellers. Travellers do not only consider mean arrival delays, but also face scheduling cost because they arrive too early or too late at their destination. They may respond to arrival delay variability by choosing an earlier connection. The model in chapter 3 is pretty general and can therefore be used for any scheduled service such as bus, tram or metro, as long as travellers plan their trip and know the arrival time schedule in advance.4

Chapters IV and V analyse the cost of travel time variability for car travellers. Chapter IV incorporates an advance in the theory of risk and uncertainty into transport behavioural modelling. There has been earlier studies investigating how travellers treat probabilities, but no earlier studies have analysed how costly probability weighting is. Most research in the transport area assumes that travellers make choices so as to maximise their expected utility (or minimise their expected travel cost). This can be viewed as a ‘rational modelling approach’, since deviations from this behaviour will lead by definition to a higher travel cost. However, there is a large experimental literature that shows that travellers may not behave as expected utility maximisers.5 Some recent empirical evidence in the transport literature shows that travellers indeed weight probabilities, meaning that the weights attached to different possible outcomes do not correspond to the probabilities assigned to those outcomes (Hensher and Li, 2010; Hjorth, 2011). However, it is unknown how persistent probability weighting is in

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4 For a treatment of unplanning travellers we refer to Fosgerau (2009).
5 For an introduction in non-expected utility theories and corresponding empirical support we refer to Wakker (2010). For overviews relating to transport we refer to Hjorth (2011) and Hensher and Li (2010).
revealed travel behaviour. In chapter IV rank-dependent utility theory is used to model departure time decisions of travellers. The chapter shows how scheduling decisions are affected by probability weighting, and derives the cost of non-optimally chosen departure times because of such probability weighting.

Next, Chapter V uses the scheduling model of Noland and Small (1995) and estimates the value of travel time savings and the value of schedule delay for morning commuters. The most common estimation method to address heterogeneity in preferences is the mixed logit model (McFadden and Train, 2000). One of the problems of applying the results of mixed logit models in policy applications is that it is unknown what the future distribution of preferences will look like. That is, given the long-term horizon of infrastructure investments it is important to recognise the fact that population characteristics change, and therefore the distribution of preferences may change as well. This provides an argument to use as much as possible socio-economic characteristics (income, gender, household composition etc.) in the estimation, since these are more available in future population statistics. For example, the study by Hague Consulting Group (1990) uses a lot of these individual characteristics to explain the Dutch value of travel time savings. The method of Chapter V builds on this idea using more sophisticated econometric estimation techniques and shows how to estimate the distribution of preferences, given the assumption that more similar people in terms of socio-economic characteristics have more similar preferences. The model is applied to a stated choice experiment intended to measure the willingness to pay for travel time savings and arriving at the preferred arrival time at work. Finally, Chapter VI concludes the thesis, and points out some directions for future research.

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6 Other problems related to estimation are: the choice of the mixing distribution (Fosgerau, 2006), the effect of non-traders (Fosgerau, 2007), the effect of ignoring correlation patterns between mixing distributions (Revelt and Train, 1998), small sample sizes and the specification of the heterogeneity, and the stability of preferences over the sequence of choices (Cherchi and Ortúzar, 2008; Hess and Train, 2011; Dekker et al., 2011).
2 Travel time variability and airport accessibility

2.1 Introduction

The accessibility of airports has been researched since several decades as it is an interesting topic for researchers, governments, airlines and airports. The work of Skinner (1976) and Harvey (1986) showed that the accessibility of airports in terms of travel time is of vital importance for the choice of an airport by air travellers. Increasing the accessibility of an airport can therefore be one of the possible strategic actions of airports to improve their market position.

As discussed by Kouwenhoven (2008), airport choice models can use generalised access cost as an accessibility indicator. In that case, all monetary cost for going to the airport such as parking cost and airport specific taxes are taken into account, while non-monetary cost such as travel time can be multiplied by the willingness to pay (WTP) values and then added to other monetary cost. Usually, such WTP values are estimated using stated choice experiments.

The WTP for a reduction in airport access travel time, or the value of access time (VOAT), has been frequently estimated in the literature. It has been found that the VOAT is considerably higher than the value of time for commuters. For example, Furuichi and Koppelman (1993) use RP data and find a value of 70 $/h for business travellers and 41 $/h for non-business travellers, although they add that there may be possible collinearity between travel time and travel cost so that the estimations may be biased.

7 This chapter is based on Koster, Kroes, and Verhoef (2011). Travel time variability and airport accessibility. Transportation Research Part B 45 (10), 1545-1559. The project “Reliable Accessibility of Airports” has been made possible with support of TRANSUMO (TRANsition SUstainable MObility). TRANSUMO is a Dutch platform for companies, governments and knowledge institutes that cooperate in the development of knowledge with regard to sustainable mobility. I like to thank two referees for very helpful comments and Chris Jacobs of the SPINLAB (VU University Amsterdam) for GIS assistance. Furthermore, I like to thank Peter Schout of DVS (Directorate General for Public Works and Water Management) for provision of the travel time data, and Sander Duijm and Matthijs de Gier of TNS NIPO for collection of the survey data.
Pels et al. (2003) find even higher values of 118 $/h for non-business and 174 $/h for business travellers. Hess et al. (2007) find similar values as Furuichi and Koppelman for business and non-business travellers using data from a stated preference study. Furthermore, Hess and Polak (2005) suggest that a possible reason for the high estimates of the VOAT could be that travellers see increasing travel times as an increase in risk to miss their flight. Hess and Polak (2005, 2006), Dresner (2006) and Ishii et al. (2009) also show that there is significant heterogeneity in the VOAT.

The main contribution of this chapter is that we include the cost of airport access travel time variability, using a scheduling model. Earlier models take into account schedule delay at the destination (Lijesen, 2006; Hess et al., 2007), but ignore access travel time variability. The only study that incorporates the effects of access travel time variability that we are aware of is a revealed preference study by Tam et al. (2008). They estimate the disutility of a safety margin that travellers apply when travelling to the airport. The safety margin in their study is defined as the difference between the preferred arrival time and the expected arrival time, and can be interpreted as the buffer that travellers take into account to cope with access travel time variability. They find that both business and non-business travellers are willing to pay money to decrease the safety margin by amounts between 1 and 1.3 times the WTP for reductions in travel time.

We extend the research of Tam et al. (2008) by explicitly explaining the determinants of the safety margin, using a scheduling model. In transport economics, the scheduling model has been frequently estimated for commuters (for overviews of empirical research see for example: Bates, 2001; De Jong et al., 2003; Brownstone and Small, 2005; Tseng, 2008; Li et al., 2010). It is an intuitive model, where travellers make a trade-off between monetary costs, travel time costs and the expected cost of being early and/or late when determining the optimal departure time from home. In this chapter, the WTP values for reductions in access travel time, schedule delay early, schedule delay late, and the probability to miss a flight, are estimated using stated choice data.

After that, a model is developed, to analyse the cost of access travel time variability for car travellers using empirical travel time distributions and taking into account “anticipating departure time choice”, meaning that in order to cope with access travel time variability, travellers may depart earlier from home. This final step is needed to
connect the estimated WTP values to real travel time data. The resulting generalised cost can be implemented in accessibility models that analyse airport choice behaviour of travellers (see, for example, Kouwenhoven 2008).

The main motivation to develop a separate model for air travellers is that the variability of travel time is important, because the cost of missing a flight is expected to be high. Therefore, air travellers can be expected to apply large buffers, to be sure that they are on time. Using our departure time choice model it is possible to test the hypothesis of Hess and Polak (2005,2006) that the high VOAT is the result of an increase in risk of missing a flight, because the risk to miss a flight is now included explicitly in the model and in the stated preference survey. Missing a flight results likely in additional cost of rebooking, rescheduling appointments, stress and waiting costs.

The setup of the chapter is as follows. In section 2.2, the scheduling model for air travellers is introduced. This model differs from the standard models used for commuters, in that air travellers likely have a large cost penalty if they arrive at the airport later than their final check-in time. Section 2.3 analyses the determinants of the preferred arrival time at the airport. In Section 2.4, binary mixed logit models are estimated to derive the WTP values for reductions in travel time and travel time variability, using data from a stated choice experiment. In section 2.5, a model is developed to derive the generalised access cost for car travellers taking into account access travel time and access travel time variability. Section 2.5 establishes the connection between the estimated WTPs and the observed travel time data and also models the behavioural response of travellers to access travel time variability. We use a real world travel time dataset to apply the model, and show how to calculate the cost of access travel time variability. Section 2.6 concludes and discusses the results.

2.2 The scheduling model for air travellers

The scheduling model of Noland and Small (1995) has been widely accepted as a standard tool of analysing the effects of travel time variability. Their model was based on earlier work of Vickrey (1969) and Small (1982). The central idea is that travellers make a trade-off between being earlier or later than their preferred arrival time (pat). In this

---

8 The Small (1982) scheduling model has a discrete penalty at the preferred arrival time.
chapter, the model is extended to account for the specific concerns of air travellers. Notably, the departure time from home ($t_0$) chosen by air travellers is expected to strongly depend on the probability of missing a flight, and the associated expected cost. Figure 2.1 illustrates the assumed structure of the air traveller's scheduling cost as a function of arrival time. The x-axis of Figure 2.1 indicates the time of day, and the y-axis indicates the scheduling cost. Suppose an air traveller has a certain flight departure time with a corresponding final check-in time ($FIT$). We assume that when a traveller is later than this final check-in time, he will certainly miss his flight, whereas he will catch it certainly otherwise. The cost of missing the flight ($\theta$) is likely to be high, and this is the reason why travellers may apply substantial buffers when going to the airport. Given the fact that travellers perform other activities at the airport such as shopping or drinking coffee, $pat < FIT$ is the optimised arrival time at the airport. Arrivals that are different from $pat$ result in higher travel costs. The way the function is drawn suggests that there is a distinctly positive probability of catching the flight for any arrival time at the airport before $FIT$; but of course $\theta$ could approximate 0 without loss of generality. The kinked function of Figure 2.1 may be taken as an approximation for a smooth function that has a steep segment near $FIT$ in reality. When leaving from home, an air traveller first estimates what the in-airport service time and variability will be, and how much time he wants to spend on airport activities. The airport service time is defined as the time for checking in, going through the passport control and security, walking to the gate and boarding the plane. Based on this subjective belief the traveller determines his preferred arrival time $pat$. Longer perceived in-airport service times will therefore result in an earlier $pat$ (for a given scheduled flight departure time). The $pat$ used in this chapter is defined as the time a traveller wants to arrive at the airport when access travel time is not variable, but airport service time may be variable. This definition is crucial when the estimation results are used in airport choice models, since it enables us to separate the behavioural response to airport service time variability and access travel time variability. In section 2.3 the determinants of the $pat$ are analysed.
Figure 2.1 - Scheduling cost function of an air traveler.
In Figure 2.1, $\beta$ is the shadow cost of being early and $\gamma$ is the shadow cost of being late, both per unit of time and both relative to some most desired arrival time. These shadow cost parameters indicate the cost of non-optimal arrivals at the airport. For $\beta$ this is mostly the disutility of long waits; for $\gamma$ it is the combined disutility of having less time than desired to spend at the airport, plus an increasing probability of missing the flight when airport service time is unexpectedly long. The parameter $\theta$ is to a large extent determined by the penalty cost of missing a flight, and so covers the cost for waiting, rebooking and other inconveniences.\(^9\) The expected cost of a traveller depends on these parameters and the travel time distribution, and the assumed structure is given by the cost function of equation (2.1):

\[
E(C) = \alpha \cdot E(T) + \beta \cdot E(SDE) + \gamma \cdot E(SDL) + \theta \cdot PMF + Z,
\]

where $E(C)$ is the expected access travel cost, $E(T)$ is the expected travel time, $E(SDE)$ is the expected schedule delay early, $E(SDL)$ is the expected schedule delay late, $PMF$ is the probability of missing the flight, and $Z$ are the other time-invariant expenses, such as parking cost. In equation (2.1), $\alpha$ is the value of airport access time ($VOAT$), $\beta$ is the value of schedule delay early ($VSDE$), $\gamma$ is the value of schedule delay late ($VSDL$) and $\theta$ the value of the probability to miss a flight ($VOPMF$). Denoting the departure time from home as $t_h$ and the travel time as $T[t_h]$, the schedule delay early ($SDE$) is given by $\max(0, pat - (t_h + T[t_h]))$ and the schedule delay late ($SDL$) by $\max(0, t_h + T[t_h] - pat)$. The expected values for the travel time and the schedule delay variables can be obtained by integrating over all possible probability weighted values of $T[t_h]$. Note the difference of the scheduling model of Small (1982) where there is a penalty for arriving later than the preferred arrival time.

The expected travel cost depend on the departure time from home since the travel time, the schedule delay components and the probability to miss a flight are affected by the choice of departure time. As implied by Figure 2.1, the probability to miss a flight depends indirectly on the preferred arrival time, because this in turn affects the departure time from home. A later preferred arrival time will result in a later departure.

\(^9\) For convenience, we assume that the value of $\gamma$ is the same before and after $FIT$, but we recognize that this is probably not the case in reality. The value of $\gamma$ after $FIT$ is not our core interest, however. So we have not optimised the design of the SP study to be discussed to allow for a separate estimation of two levels of $\gamma$. 
time from home and therefore in a larger probability to miss the flight. In the next section, we will analyse the determinants of the preferred arrival time.

2.3 Determinants of the preferred arrival time

2.3.1. Descriptive statistics of the survey.

An internet survey was held among Dutch air travellers, to collect the data that are necessary for the analysis of the access cost function. Only travellers who made an air trip in the last three months were invited. A total of 971 completed surveys were collected with 345 reporting about a business trip and 626 reporting about a non-business trip. In the survey, information was asked about the latest trip to the airport. This information was used to customise the stated choice experiment. It was found that 1.5% of the air travellers (0.52% of all flights) had actually missed a flight during the last year, due to delays during their access trip. The other summary statistics are given in Table 2.1. It is noteworthy that the modal share is quite similar for business and non-business travellers, except that business travellers take more often the train. This high share of train as an access mode is mainly caused by the fact that Schiphol Airport is very well connected by train, and most travellers in the survey use Schiphol Airport as their departure airport. The high share of taxi users of non-business travellers is also surprising, and may be due to the fact that Schiphol airport offers his own airport-taxi service, which has lower monetary travel cost than a standard taxi. The average access travel time, defined as the average travel time from the location of departure to the check in counter at the airport, is somewhat longer for non-business trips than for business travellers. The average number of flights per year for business travellers is more than twice that for non-business travellers. Finally, one can see that non-business travellers are travelling less often via Schiphol Airport and more often from German airports.
Table 2.1 — Summary statistics of the survey.

<table>
<thead>
<tr>
<th>access mode</th>
<th>non-business</th>
<th>business</th>
</tr>
</thead>
<tbody>
<tr>
<td>car driver</td>
<td>39.6%</td>
<td>38.6%</td>
</tr>
<tr>
<td>car passenger</td>
<td>25.4%</td>
<td>21.4%</td>
</tr>
<tr>
<td>taxi</td>
<td>8.9%</td>
<td>7.0%</td>
</tr>
<tr>
<td>train</td>
<td>20.1%</td>
<td>30.1%</td>
</tr>
<tr>
<td>other</td>
<td>5.9%</td>
<td>2.9%</td>
</tr>
<tr>
<td>total</td>
<td>100.0%</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

characteristics of the last trip

<table>
<thead>
<tr>
<th></th>
<th>non-business</th>
<th>business</th>
</tr>
</thead>
<tbody>
<tr>
<td>average access time</td>
<td>82</td>
<td>79</td>
</tr>
<tr>
<td>average # of flights</td>
<td>2.66</td>
<td>5.84</td>
</tr>
<tr>
<td>average duration</td>
<td>12 days</td>
<td>7 days</td>
</tr>
</tbody>
</table>

airport chosen

<table>
<thead>
<tr>
<th>airport</th>
<th>non-business</th>
<th>business</th>
</tr>
</thead>
<tbody>
<tr>
<td>Schiphol Airport</td>
<td>73.5%</td>
<td>79.7%</td>
</tr>
<tr>
<td>small Dutch airports</td>
<td>8.8%</td>
<td>5.5%</td>
</tr>
<tr>
<td>Belgian Airports</td>
<td>5.8%</td>
<td>7.0%</td>
</tr>
<tr>
<td>German Airports</td>
<td>11.3%</td>
<td>6.1%</td>
</tr>
<tr>
<td>other</td>
<td>0.8%</td>
<td>1.7%</td>
</tr>
<tr>
<td>total</td>
<td>100.0%</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

Table 2.2 — Sampling distribution of incomes.

<table>
<thead>
<tr>
<th>Yearly net household income (euros)</th>
<th>% sample</th>
<th>% total</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 23000</td>
<td>5.50%</td>
<td>8.13%</td>
</tr>
<tr>
<td>23000-34000</td>
<td>10.17%</td>
<td>12.63%</td>
</tr>
<tr>
<td>34000-45000</td>
<td>15.49%</td>
<td>14.59%</td>
</tr>
<tr>
<td>45000-56000</td>
<td>13.47%</td>
<td>12.69%</td>
</tr>
<tr>
<td>56000-68000</td>
<td>13.38%</td>
<td>11.36%</td>
</tr>
<tr>
<td>68000-91000</td>
<td>13.75%</td>
<td>12.01%</td>
</tr>
<tr>
<td>&gt;91000</td>
<td>10.91%</td>
<td>10.41%</td>
</tr>
<tr>
<td>unknown</td>
<td>17.32%</td>
<td>18.19%</td>
</tr>
<tr>
<td>Total</td>
<td>100.00%</td>
<td>100.00%</td>
</tr>
</tbody>
</table>

10 If travellers do not travel alone, on average there are 3 people in the car.
Table 2.2 shows the yearly household income distribution of our sample, compared to the income distribution of all travellers who made a flight in the last three months prior to the survey. The sample is well-balanced, but there is a slight under-sampling of low income travellers. Figure 2.2 shows the spatial distribution of the departure place of the respondents, based on 4-digit postcode levels. There are more departures in the western part of The Netherlands, not in the least because more people live and work there. For 86% of the business travellers the departure place is their home location. For non-business travellers this is true in 92% of the cases. This information is relevant for the analysis of airport choice, since residential locations are usually available in standard statistics while the work location of these travellers is often unknown.

2.3.2. Regression analysis
In this section we analyse the preferred arrival (pat) time at the airport using a basic regression analysis. We define $T_{airport}$ as the dependent variable in the regression. It is defined as the scheduled flight departure time minus the preferred arrival time at the airport, and gives the number of minutes before the flight departure that a traveller prefers to arrive at the airport if there would be a guarantee of no access travel time delays.$^{11}$ As implied by Figure 2.1, the $T_{airport}$ may be an important determinant of the cost of variable airport access time, as a larger value implies an earlier pat, and the resulting earlier departure time from home would reduce the probability to miss a flight. There are 926 observations included in the analysis. Travellers that arrive the previous day at the airport and sleep in a hotel are excluded from the analysis. Furthermore, travellers with a dependent variable lower or equal than 0, or with very extreme values, are excluded from the analysis because they most likely made a mistake when filling in the questionnaire.

---

$^{11}$ The exact phrasing of the question to obtain the pat is: “Suppose that you know for sure that there are no delays for your trip to the airport. What would be your preferred arrival time at the airport?”
Figure 2.2a — Spatial distribution of the departure place for business trips.
Figure 2.2b — Spatial distribution of the departure place for non-business (personal) trips.
### Table 2.3 — Regression results, dependent variable: ln(Tairport) in minutes.

<table>
<thead>
<tr>
<th></th>
<th>coefficient</th>
<th>t-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>3.363</td>
<td>24.97</td>
</tr>
<tr>
<td>ln[E(T)] (minutes)</td>
<td>0.053</td>
<td>2.32</td>
</tr>
<tr>
<td>ln[FTT] (minutes)</td>
<td>0.162</td>
<td>9.26</td>
</tr>
<tr>
<td>business (dummy)</td>
<td>-0.103</td>
<td>-2.94</td>
</tr>
<tr>
<td>retired (dummy)</td>
<td>0.090</td>
<td>1.70</td>
</tr>
<tr>
<td>5-10 flights per year (dummy)</td>
<td>-0.110</td>
<td>-2.12</td>
</tr>
<tr>
<td>More than 10 flights per year (dummy)</td>
<td>-0.168</td>
<td>-2.52</td>
</tr>
<tr>
<td>Check in luggage (dummy)</td>
<td>0.245</td>
<td>5.26</td>
</tr>
<tr>
<td>Check in online (dummy)</td>
<td>-0.108</td>
<td>-3.39</td>
</tr>
<tr>
<td>Flight departure between 0:00 and 7:00 (dummy)</td>
<td>-0.154</td>
<td>-3.16</td>
</tr>
</tbody>
</table>

**Model summary statistics**

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of observations</td>
<td>926</td>
</tr>
<tr>
<td>F(9, 916)</td>
<td>32.84</td>
</tr>
<tr>
<td>R²</td>
<td>0.244</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.237</td>
</tr>
<tr>
<td>Root mean squared error</td>
<td>0.461</td>
</tr>
</tbody>
</table>

In Table 2.3 the regression results are shown. The log of Tairport is the dependent variable, ln[E(T)] is the log of expected travel time and ln[FTT] is the log of the flight duration, both in minutes. Furthermore, variables for type of traveller (business), type of check-in and time of the day are included. Also type of access mode was included, but this variable appears to be non-significant and was dropped from the final model.

The results show that longer expected travel times and longer flight travel times result in a larger Tairport. Furthermore, business travellers prefer to arrive later than non-business travellers. Travellers who are retired prefer to arrive earlier (significant at the 90% level), likely because of less pressing scheduling constraints and possibly because they move less quickly in the airport.

Experience plays an important role. Travellers who fly between 5 and 10 times per year prefer to arrive on average 10 minutes later than travellers with less experience, and travellers who fly more than 10 times per year prefer to arrive on average 20 minutes later. Although the regressions controls for business travel, this result may be the result of a higher VOAT because experienced travellers may be busier and less interested in shopping at the airport. Another possibility is that it may indicate that uncertainty about in airport service times decreases, or risk avoiding reduces, when a traveller is more experienced. An experienced traveller has probably a better perception of the real in-airport service time than a non-experienced traveller, and possibly has
more knowledge about the possibilities to limit consequences of a late arrival at the airport. If a traveller needs to check in luggage he prefers to arrive approximately 15 minutes earlier. If a traveller checks in online he prefers to arrive 10 minutes later. A good guess for the average perceived expected check-in time is therefore 25 minutes. A longer access travel time is also associated with a higher $T_{airport}$. This might reflect that respondents do not really reply for the case where there is a guaranteed travel time from home to the airport, and building in a buffer. But it may also reflect that people who travel further are less experienced at that airport (they more often use different airports), or perhaps to a larger extent enjoy spending time at the airport.

The size of the airport probably influences the decision on the $pat$. Larger airports are more crowded and usually have longer check-in times. A possible way to control for this is by including airport dummies. However we did not do this because they are likely to be endogenous, since the airport that is chosen may in turn depend on the in-airport service time. Excluding this variable probably affects the estimates of $ln[E(T)]$ and $ln[FTT]$ since $E(T)$ and $FTT$ might be correlated with the type of airport. We tested the specification for omitted variable bias by running a regression with type of airport included and compare the results with the results of Table 2.3. The point estimates of Table 2.3 do not change significantly if airport variables are excluded, so they remain valid. Finally we tested if the check-in online dummy is endogenous by using education and type of airline as instrumental variables for checking in online. Using a Hausman test we found that the OLS regression does not suffer from endogeneity bias.\footnote{We used a probit estimation in the first stage and used the estimated probability as an instrument for the check-in online dummy. See Wooldridge (2002), p. 632 for more details about this procedure.}

### 2.4 Stated choice models

#### 2.4.1 The choice experiment

A stated choice experiment was developed and held among the same respondents as in the previous section. This to estimate the WTP values of the air travellers’ cost function of equation (2.1). An example of a choice question is given in Figure 2.3. The experiment is unlabeled, and respondents are asked to have their latest trip in mind when answering the questions. An ‘opt-out’ option was not included to avoid that respondents would
choose it simply because they do not want to put effort in making a choice. Above each choice question the circumstances of the trip are specified as a reminder, including trip destination, flight departure, mode of travel, final check-in time and preferred arrival at the check-in counter. These are based on earlier questions about the respondents’ latest trip. Using the latest trip as the reference is somewhat restrictive because the analysis is done conditional on the mode chosen by the traveller. If respondents travel by car, the parking cost is also provided. The preferred arrival is the time that a traveller would like to arrive at the airport if access travel time is guaranteed not to be variable. Before the experiment, it was explained that if travellers arrive before the final check-in time they will always catch their flight, so that the experiment controls for queuing at the check-in counters.\footnote{We tested for our final model if \textit{pat} is too early, since in the experiment there is no airport service time variability. This is not the case.}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fig23.png}
\caption{Example of a stated choice question (translated from Dutch).}
\end{figure}

In the SP experiment therefore $\gamma$ should only capture the disutility of spending a shorter than desired time at the airport, not an increased probability of missing a flight. Table 2.4 summarises the possible attribute levels in the experiment. As shown by Table 2.4, the first attribute of an alternative is the monetary travel cost which is calculated using the reference travel time of the respondent. The second and the third attribute are the

\begin{table}[h]
\centering
\begin{tabular}{|c|c|}
\hline
\textbf{Travel cost for your trip to the airport: 24 euros} & \textbf{Travel cost for your trip to the airport: 38 euros} \\
\hline
\textbf{Departure time: 14:10} & \textbf{Departure time: 12:25} \\
\hline
\textbf{Usual travel time: 1 hour and 35 minutes} & \textbf{Usual travel time: 1 hour and 35 minutes} \\
\hline
\textbf{Usual arrival time: 15:45} & \textbf{Usual arrival time: 14:00} \\
\hline
\textbf{Probability to miss your flight: 1\%} & \textbf{Probability to miss your flight: 0.5\%} \\
\hline
\end{tabular}
\end{table}
departure time from home and the usual travel time. The usual arrival time is implied by these two attributes. The travel time and arrival time when missing the flight are defined implicitly. That is, before the experiment, the respondents were instructed that if they miss their flight, they should assume it is because they arrive 15 minutes later than the final check-in time. This means that the associated implicit travel time is given by \((FIT+15-t_b)\). This information is needed, because otherwise the arrival time and travel time in case of missing a flight cannot be calculated.

Finally, the probability of missing a flight is given as a percentage. Within a choice-set, the later arrival will have a higher probability of missing a flight, because the pilot confirmed that respondents find it very unrealistic and confusing when a later arrival would result in a lower probability of missing a flight. Respondents could ask additional explanation about percentages if required. Only 6% of the respondents asked for additional explanation, and only 1 respondent did not understand what a percentage is after the explanation.\(^{14}\)

<table>
<thead>
<tr>
<th>Design Attribute</th>
<th>Levels(^{15})</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost</td>
<td>0.15,0.2,0.25,0.3,0.4,0.45</td>
<td>multiplied with reference travel time in minutes to obtain cost in euro's</td>
</tr>
<tr>
<td>Travel time</td>
<td>-15%,-5%,0%,10%,20%</td>
<td>deviation from reference travel time</td>
</tr>
<tr>
<td>Arrival</td>
<td>5,10,35,50,90,110,120,170</td>
<td>minutes before final check-in time</td>
</tr>
<tr>
<td>Probability to miss the flight</td>
<td>0, 0.5%, 1%, 1.5%, 2%, 3%</td>
<td></td>
</tr>
</tbody>
</table>

In the choice experiment, every respondent received 10 choices with 2 alternatives. The design has 13 blocks and is almost balanced for every respondent, meaning that every respondent received the attribute levels of Table 2.4 three or four times. A large number of efficiency tests have been performed in order to check if the design was able to reproduce a broad range of preference parameters. Furthermore, two internet tests were done in order to check the survey for possible programming mistakes. We refer to

\(^{14}\) However, this respondent is included in the analysis because it is unknown if the perception is also biased in a revealed preference situation.

\(^{15}\) If taxi is the access mode the level of the cost attribute as shown in the second column of table 2.4 is 0.3 higher.
Koster and Tseng (2010) for more details about stated choice experimental designs for scheduling models.

After the experiment, some additional questions were asked about how the choices were made. Some respondents (5%) were dropped from the analysis of the choice responses, either because they made mistakes in the questions about the reference trip or they indicated that they chose randomly between the alternatives. Almost 70% of the respondents indicated that they found the trade-offs realistic, which suggests that the attributes may indeed capture the most important aspects of the airport access utility function.

2.4.2 Econometric setup

Our goal is to estimate the airport access cost function of equation (2.1). To that end, a panel mixed logit model with covariates is estimated in WTP space (Train and Weeks 2005). It is assumed that the WTP distributions follow a lognormal distribution, in order to avoid negative values of the WTPs. The utility of individual $n$ for choice $t$ for alternative $j$ is given by equation (2.2):

\[(2.2)\quad U_{njt} = V_{njt} + \varepsilon_{njt}.\]

Total utility is an additive function of the deterministic utility and an error term, which is independently and identically extreme value distributed over choices, people and alternatives.\(^{16}\) The systematic part of the utility is given by equation (2.3):

\[(2.3)\quad V_{njt} = -\lambda \cdot \left( \text{cost}_{njt} + e^{Z_n} \cdot Y_{njt} \right).\]

In this equation $\text{cost}_{njt}$ are the monetary cost for the trip. $Z_n$ captures the individual specific covariates, including a dummy for the type of traveller (business or non-business) and the log of yearly income. The $e$-power is used because of the fact that we will use lognormal distributions for the WTPs. $Z_n$ is defined as:

\[(2.4)\quad Z_n = \tau_{bus} \cdot DBUS_n + \tau_{INC} \cdot \log(income)_n.\]

In this equation $DBUS_n$ is a dummy indicating if a traveller is a business traveller and $\log(income)_n$ is the log of the household’s yearly income. $\tau_{bus}$ and $\tau_{INC}$ are the

\(^{16}\) A multiplicative formulation as proposed by Fosgerau and Bierlaire (2009) was tested but resulted in a worse model fit.
parameters to be estimated. Next we define $Y_{njt}$, which is the product of the WTP values and the independent variables:

\[(2.5) \quad Y_{njt} = \alpha_n \cdot E(T)_{njt} + \beta_n \cdot E(SDE)_{njt} + \gamma_n \cdot E(SDL)_{njt} + \theta_n \cdot PMF_{njt}.\]

In order to capture unobserved heterogeneity in the time and scheduling coefficients of equation (2.5), we apply lognormal distributions with mean $\mu$ and standard deviation $\sigma$, which vary over WTPs. These distributions have mean $\exp(\mu+\sigma^2/2)$ and median $\exp(\mu)$.

For a given type of traveller and income level, the mean and median WTP are then given by equations (2.6a) and (2.6b):

\[(2.6a) \quad \text{WTP mean} = e^{Z_n} \cdot e^{\mu+\sigma^2/2} = e^{Z_n+\mu+\sigma^2/2},\]

\[(2.6b) \quad \text{WTP median} = e^{Z_n} \cdot e^\mu = e^{Z_n+\mu}.\]

The explanatory variable $PMF_{njt}$ is the probability to miss a flight, and is directly visible on the choice screen. For the other variables some additional calculation is needed. Define $UTT_{njt}$ as the usual travel time, $FIT_n$ as the final check-in time for individual $n$, and $t_{h_{njt}}$ as the departure time from home. In order to show the relationship with the choice screen of Figure 2.3, the independent variables of equation (2.5) are given by equations (2.7a)-(2.7c):

\[(2.7a) \quad E(T)_{njt} = (1 - PMF_{njt}) \cdot UTT_{njt} + PMF_{njt} \cdot \left( FIT_n + 15 - t_{h_{njt}} \right),\]

\[(2.7b) \quad E(SDE)_{njt} = (1 - PMF_{njt}) \cdot \max[0, pat_n - t_{h_{njt}} - UTT_{njt}],\]

\[(2.7c) \quad E(SDL)_{njt} = (1 - PMF_{njt}) \cdot \max[0, t_{h_{njt}} + UTT_{njt} - pat_n] + PMF_{njt} \cdot (FIT_n + 15 - pat_n).\]

All variables are in minutes. As explained before, the second arrival time is implicitly given in the choice question and is always set 15 minutes later than the $FIT$.

We estimate a panel mixed logit model, so we account for repeated observations of one individual. Conditional on the WTP values, the probability that an individual makes a sequence of choices $i = \{i_1, ..., i_T\}$ is given by the product of the logit probabilities (Train 2003):
(2.8a) \[ L_{ni}[WTP] = \prod_{t=1}^{T} \frac{e^{V_{ni,t}[WTP_n]}}{\sum_{j} e^{V_{nj,t}[WTP_n]}}. \]

The unconditional probability is then given by the integral over all values of the WTPs. We use a multivariate lognormal distribution \( g[WTP] \), where the marginal distributions may be correlated. The choice probability is then given by equation (2.8b) (Train, 2003):

(2.8b) \[ P_{ni} = \int L_{ni}[WTP]g[WTP]dWTP. \]

For the approximation of the integral 25000 Modified Latin Hypercube draws per individual are used (Hess et al., 2006). All models are estimated in Biogeme using maximum simulated likelihood (Bierlaire, 2003, 2008; Train, 2003).\(^{17}\)

2.4.3 Estimation results

The estimation results for the binary panel mixed logit models are given in Table 2.5a and the calculated mean and median values are given in Table 2.5b. Model 1 is the model with uncorrelated distributions. In model 2 we allow for correlated distributions. In model 1 all the estimated parameters are significant at the 5% level, except \( \tau_{inc} \). There is significant unobserved heterogeneity, and especially for the \( VOPMF \) the estimated standard deviation is large. This has a large effect on the mean values of the WTP distribution since the mean of a lognormal distribution depends on the estimated standard deviation. Although the mean is in a reasonable range, there is a possibility that the design was not able to produce reasonable trade-offs for schedule delay late and the probability to miss a flight for some of the respondents (see for example Fosgerau (2006) for a discussion). Consequently the median values are more stable and more reliable to use for policy analysis. The WTP values of business travellers are \( \exp(\tau_{bus}) = 1.3 \) times higher than for non-business travellers. Although \( \tau_{inc} \) is not significant, there is an income effect in both models. In model 2 correlated distributions are estimated.

\(^{17}\) We use FASTBIOGEME to estimate the models because it has the advantage of parallel computing possibilities. Therefore a high number of draws can be used while the running times stay reasonable. For more details about simulated likelihood and generating draws for correlated distributions using Cholesky decomposition, we refer to Train (2003), and Bierlaire (2003; 2008).
### Table 2.5a — Panel Mixed logit estimation results.

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th></th>
<th>Model 2</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>estimate</td>
<td>robust t-value</td>
<td>estimate</td>
<td>robust t-value</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>0.045</td>
<td>9.46</td>
<td>0.045</td>
<td>9.08</td>
</tr>
<tr>
<td>$\alpha_\mu$</td>
<td>2.99</td>
<td>14.78</td>
<td>3.17</td>
<td>13.91</td>
</tr>
<tr>
<td>$\alpha_\sigma$</td>
<td>0.63</td>
<td>2.62</td>
<td>0.39</td>
<td>0.87</td>
</tr>
<tr>
<td>$\beta_\mu$</td>
<td>3.01</td>
<td>18.87</td>
<td>2.96</td>
<td>16.75</td>
</tr>
<tr>
<td>$\beta_\sigma$</td>
<td>0.93</td>
<td>13.34</td>
<td>1.19</td>
<td>11.05</td>
</tr>
<tr>
<td>$\gamma_\nu$</td>
<td>3.58</td>
<td>21.96</td>
<td>3.17</td>
<td>17.47</td>
</tr>
<tr>
<td>$\gamma_\sigma$</td>
<td>1.54</td>
<td>18.42</td>
<td>1.66</td>
<td>10.53</td>
</tr>
<tr>
<td>$\theta_\mu$</td>
<td>1.69</td>
<td>7.96</td>
<td>1.63</td>
<td>6.59</td>
</tr>
<tr>
<td>$\theta_\sigma$</td>
<td>2.15</td>
<td>14.20</td>
<td>1.93</td>
<td>9.76</td>
</tr>
<tr>
<td><strong>Covariates</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\tau_{bus}$</td>
<td>0.28</td>
<td>2.94</td>
<td>0.31</td>
<td>3.02</td>
</tr>
<tr>
<td>$\tau_{INC}$</td>
<td>0.02</td>
<td>1.67</td>
<td>0.02</td>
<td>1.43</td>
</tr>
<tr>
<td><strong>Cholesky terms</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\rho_{VOAT_VSDE}$</td>
<td>--</td>
<td>--</td>
<td>0.40</td>
<td>2.00</td>
</tr>
<tr>
<td>$\rho_{VOAT_VSDL}$</td>
<td>--</td>
<td>--</td>
<td>-0.11</td>
<td>-0.67</td>
</tr>
<tr>
<td>$\rho_{VOAT_VOPMF}$</td>
<td>--</td>
<td>--</td>
<td>0.22</td>
<td>1.06</td>
</tr>
<tr>
<td>$\rho_{VSDE_VSDL}$</td>
<td>--</td>
<td>--</td>
<td>1.17</td>
<td>10.36</td>
</tr>
<tr>
<td>$\rho_{VSDE_VOPMF}$</td>
<td>--</td>
<td>--</td>
<td>-0.63</td>
<td>-2.30</td>
</tr>
<tr>
<td>$\rho_{VSDL_VOPMF}$</td>
<td>--</td>
<td>--</td>
<td>-0.68</td>
<td>-1.24</td>
</tr>
<tr>
<td><strong>Model summary statistics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Final log-likelihood</td>
<td>-4206.52</td>
<td></td>
<td>-4176.58</td>
<td></td>
</tr>
<tr>
<td>Number of observations</td>
<td>8830</td>
<td></td>
<td>8830</td>
<td></td>
</tr>
<tr>
<td>Number of individuals</td>
<td>883</td>
<td></td>
<td>883</td>
<td></td>
</tr>
<tr>
<td>Adjusted rho-square</td>
<td>0.313</td>
<td></td>
<td>0.315</td>
<td></td>
</tr>
<tr>
<td>Number of estimated parameters</td>
<td>11</td>
<td></td>
<td>17</td>
<td></td>
</tr>
<tr>
<td>Number of MLHS draws per individual per random parameter</td>
<td>25000</td>
<td></td>
<td>25000</td>
<td></td>
</tr>
</tbody>
</table>

A significant positive Cholesky term, indicating a positive correlation between the distributions, is found for the VSDE and VSDL distribution and the VSDE and VOAT distribution. Furthermore a negative value for the VSDE and the VOPMF distribution is found. The likelihood increases significantly when we allow for correlated distributions.

The median VOAT is slightly lower than earlier findings in the literature (Furuuchi and Koppelman, 1993; Hess and Polak, 2006). In the next section the median WTP values of model 2 will be used to illustrate the anticipating departure time choice model for a typical business and non-business traveller. A surprising result is that in model 2 no significant unobserved heterogeneity in the VOAT is found. The median values of both
models are higher than the commonly found values for commuters in The Netherlands (around 8 euros), presumably because travellers are less sensitive to monetary costs when travelling to the airport, because on average the income level is higher. A second explanation might be that there is a selection effect. Given the fact that air travel is fast, it might well be that this is the reason that travellers with a high disutility of time use this travel mode.

Table 2.5b — Calculated mean and median values.

<table>
<thead>
<tr>
<th>Distribution mean and median WTP values</th>
</tr>
</thead>
<tbody>
<tr>
<td>VOAT median</td>
</tr>
<tr>
<td>VSDE median</td>
</tr>
<tr>
<td>VSDL median</td>
</tr>
<tr>
<td>VOPMF median</td>
</tr>
<tr>
<td>VOAT mean</td>
</tr>
<tr>
<td>VSDE mean</td>
</tr>
<tr>
<td>VSDL mean</td>
</tr>
<tr>
<td>VOPMF mean</td>
</tr>
</tbody>
</table>

Calculated mean and median WTP at average income levels.

<table>
<thead>
<tr>
<th></th>
<th>business</th>
<th>non-business</th>
<th>business</th>
<th>non-business</th>
</tr>
</thead>
<tbody>
<tr>
<td>VOAT median</td>
<td>32.94</td>
<td>24.69</td>
<td>39.71</td>
<td>28.93</td>
</tr>
<tr>
<td>VSDE median</td>
<td>33.61</td>
<td>25.19</td>
<td>32.19</td>
<td>23.45</td>
</tr>
<tr>
<td>VSDL median</td>
<td>59.42</td>
<td>44.55</td>
<td>47.07</td>
<td>34.29</td>
</tr>
<tr>
<td>VOPMF median</td>
<td>8.98</td>
<td>6.73</td>
<td>8.51</td>
<td>6.20</td>
</tr>
<tr>
<td>VOAT mean</td>
<td>40.05</td>
<td>30.02</td>
<td>42.87</td>
<td>31.23</td>
</tr>
<tr>
<td>VSDE mean</td>
<td>51.84</td>
<td>38.86</td>
<td>65.34</td>
<td>47.61</td>
</tr>
<tr>
<td>VSDL mean</td>
<td>194.51</td>
<td>145.82</td>
<td>186.69</td>
<td>136.01</td>
</tr>
<tr>
<td>VOPMF mean</td>
<td>90.55</td>
<td>67.89</td>
<td>54.82</td>
<td>39.94</td>
</tr>
</tbody>
</table>

NOTE: Average value for log(income) is 11.03 for business travellers, and 10.83 for non-business travellers.

2.5 Empirical illustration

2.5.1 Introduction

In this section the model is developed to calculate the cost of airport access travel time variability for car travellers using real-world travel data. This is a crucial step in the analysis, because the connection is made between the estimated WTP values of the previous section, and the empirical travel time distribution. We take into account anticipating behaviour, meaning that travellers are assumed to optimise their departure time from home given their knowledge about the empirical travel time distribution (see for example: Noland and Small, 1995; Fosgerau and Karlström, 2010; Fosgerau and
Engelson, 2010). In order to keep the illustration as simple as possible, two representative travellers will be considered with values of the preferred arrival time close to the sample average and a common trip length. Both travel to Schiphol Airport, and have a free flow trip length of approximately 45-50 minutes. The basic assumptions for these representative travellers are given in Table 2.6.

Table 2.6 — Basic assumptions for the two representative travellers.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Business traveller</th>
<th>Non-business traveller</th>
</tr>
</thead>
<tbody>
<tr>
<td>DBUS</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>log(income)</td>
<td>11.03</td>
<td>10.83</td>
</tr>
<tr>
<td>Value of access time ((\alpha))</td>
<td>39.71</td>
<td>28.93</td>
</tr>
<tr>
<td>Value of schedule delay early ((\beta))</td>
<td>32.19</td>
<td>23.45</td>
</tr>
<tr>
<td>Value of schedule delay late ((\gamma))</td>
<td>47.07</td>
<td>34.29</td>
</tr>
<tr>
<td>Value of probability to miss a flight ((\theta))</td>
<td>8.51</td>
<td>6.20</td>
</tr>
<tr>
<td>pat</td>
<td>60 minutes before final check-in time</td>
<td>90 minutes before final check-in time</td>
</tr>
</tbody>
</table>

It is assumed that the behaviour of air travellers does not significantly change the behaviour of other travellers, because air travellers are only a very small fraction of the total traffic. Therefore, the empirical travel time distribution is assumed to be exogenous and we will not attempt to model the dependence of access travel time on departure time decisions of air travellers.

One might well argue that \(\text{pat}\) is also a choice variable in the model, because it depends on the \(WTP\) values as well. For example, travellers with a higher \(VOPMF\) are likely to have an earlier preferred arrival time. For the empirical illustration in this section this is not an issue because we use the assumed values of \(\text{pat}\) of Table 2.6. We thus assumed that the values in Table 2.6 are the true \(\text{pat’s}\), not reflecting any residual desire to reduce the impacts of variability of travel times when travelling to the airport.

2.5.2 The evaluation model

Recall that we denoted the difference between the final check-in time and the preferred arrival time as \(T_{airport}\). Unfortunately, the theoretical results for the optimal cost with optimised departure time, as given by Noland and Small (1995) and Fosgerau and
Karlström (2010), cannot be used in our case, since there is a discontinuity of schedule delay cost at the final check-in time, as shown in Figure 2.1.

We define a traveller’s headstart $H$ as $\text{pat}_h$. A traveller faces a time-of-day dependent cumulative probability distribution of travel times, $F(T;H)$, and a corresponding probability density function $f(T;H)$ with mean $\mu[H]$ and standard deviation $\sigma[H]$. The expected travel time for a given headstart is given by equation (2.9), and is simply the time-of-day dependent mean travel time:

\begin{equation}
E(T; H) = \int_{0}^{\infty} T \cdot f(T; H) \, dT = \mu[H].
\end{equation}

The expected schedule delay early is given by equation (2.10), where we integrate over all possible early arrivals. Because travel times are always positive, the integral starts at $T=0$ and ends at $T=H$, because then a traveller arrives exactly on time, and the schedule delay early will be 0:

\begin{equation}
E(SDE; H) = \int_{0}^{H} (H - T) \cdot f(T; H) \, dT.
\end{equation}

Similarly, the expected schedule delay late can be derived by integrating over all late arrivals:

\begin{equation}
E(SDL; H) = \int_{H}^{\infty} (T - H) \cdot f(T; H) \, dT.
\end{equation}

Finally, the probability of missing a flight ($\text{PMF}$) for a given departure time and a given scheduled flight time depends on the airport service time $T_{airport}$ defined earlier. $\text{PMF}$ can be written as:

\begin{equation}
\text{PMF}(H) = \int_{H+T_{airport}}^{\infty} f(T; H) \, dT.
\end{equation}

In this equation, the integral starts at the travel time when the flight will be missed ($T = H + T_{airport}$). For all travel times higher than this delay, travellers will miss their flight. The probability to miss a flight for a given $H$ is decreasing in $T_{airport}$. The objective function of the optimization problem for a traveller with given $T_{airport}$ is given by equation (2.13),
where equations (2.9)-(2.12) are multiplied with the corresponding WTP values of Table 2.6:

\[
E(C[H]) = \alpha \cdot E(T; H) + \beta \cdot E(SDE; H) + \gamma \cdot E(SDL; H) + \theta \cdot PMF(H).
\]

In this equation monetary costs such as fuel or parking costs are not included because these are assumed to be time-of-day independent. The decision of the traveller is to determine the optimal \( H \) that minimises the expected travel cost, based on the empirical travel time distribution and his WTP values:

\[
H^* = \operatorname{argmin} E(C[H]).
\]

There is no closed-form solution for this minimization problem, so we used numerical optimization to obtain the results reported later in this section.

### 2.5.3 The travel time data

Travel time data are obtained using loop-detector measurements on a highway road stretch for every 15 minutes of the day. The data are interpolated to obtain 1-minute interval data. We use a trip from Rotterdam to Schiphol Airport with a free flow travel time of around 45-50 minutes as an example. The mean and the standard deviation are plotted in Figure 2.4, where a time-of-day pattern with a morning and an evening peak is clearly visible. The figure shows that there is a clear positive relationship between the mean and the standard deviation of travel time. This phenomenon is analysed theoretically by Fosgerau (2010) and empirically by Peer et al. (2010), and is caused by the fact that there is bottleneck congestion on this road. Van Lint et al. (2008) found that the shape of the empirical travel time distribution is varying over time of day, and therefore no particular parametric form of the empirical travel time distribution is appropriate. Therefore we use nonparametric Kernel smooth density estimation to fit a time-of-day dependent travel time distribution.\(^{18}\)

\(^{18}\) The densities are estimated using the ksdensity function in Matlab with 500 equally spaced points. This function uses an optimal bandwidth for Normal densities. More detailed information about this bandwidth selection procedure can be found in Bowman and Azzalini (1997). Results are available upon request.
Figure 2.4 - Time of day dependent mean and standard deviation of travel time.
2.5.4 Empirical results

An example of an expected cost function for a given final check-in time 10:00 is given in Figure 2.5. Note that the costs are given as a function of $H$ in minutes before $pat$. Because $pat$ is not observed, we use the plausible values of Table 2.6. The expected cost for both travellers is optimal for a headstart of around 60 minutes. The expected cost for the business traveller is higher than for the non-business traveller, because of the smaller buffer at the airport and the higher WTP values and is very steep for small headways because of the higher risk of missing the flight. Cost estimates like these could subsequently be used in, for example, airport choice models (Kroes et al., 2011). If the impact of certain policies or investments on the travel time distribution is known, the same approach could be used for cost-benefit analysis. However, such exercises are beyond the scope of this chapter.

2.6 Conclusions and discussion

This chapter analysed the effect of airport access travel time variability on access travel cost. The mixed logit estimations show that, as expected, scheduling plays an important role in departure time decisions of travellers going to the airport. For both business and non-business travellers there is heterogeneity in the scheduling parameters. A connection was made between the estimated shadow cost of scheduling and equilibrium cost taking into account anticipating departure time choice of air travellers. Using a dataset of Dutch travel times we show that for business travellers the cost of variability are in between 0-30% of expected access travel cost (without spending on fuel and parking etc.), depending on the time of day. For non-business travellers this number is in between 0-25%. These numbers are somewhat higher than the values of Fosgerau and Karlström (2010) who analysed the cost of travel time variability for commuters. However, compared to the full expected cost of an air trip, including the ticket price and parking fees, the contribution of the cost of travel time variability is much lower (Kroes et al., 2011).
Figure 2.5 - Example of a cost function for FIT=10:00.
Figure 2.6a — Optimal expected access travel cost for a given preferred arrival time (non-business)
Figure 2.6b – Optimal expected access travel cost for a given preferred arrival time (business)
The model that is developed in section 2.5 has of course some limitations. One is that it is assumed that air travellers have a perfect perception of the empirical travel time distribution. For commuters, perfect perception may be a realistic assumption, because these travellers are usually experienced. But for air travellers it may well be that travellers do not know the empirical travel time distribution, and therefore make larger perception errors. This may result in non-optimal behaviour, and therefore the cost of variable travel times may be higher than estimated in section 2.5 (Koster and Verhoef, 2012).
The user cost of US air travel delays: a scheduling perspective

3.1 Introduction

This chapter studies the impact of US air arrival delay variability on the expected user cost for US domestic air travellers. As indicated by Bates et al. (2001) and De Palma and Lindsey (2001), travellers using a scheduled service face a different trade-off than car travellers, because of timetable constraints. Since airlines determine the scheduled departure and arrival times of the flights, travellers need to account for the timetable when they choose their flight. As argued by Tseng (2008), the intuitive behavioural response is similar to that of car travellers, since an increasing variability of arrival times will result in more travellers shifting to earlier connections. However, the difference with car travel is that the cost of travel time variability do depend on the timetable (Fosgerau and Karlström, 2010; Fosgerau and Engelson, 2010; Börjesson and Eliasson, 2011).

In the airport congestion literature the time-of-day decision making of air travellers is usually ignored but some studies look into the relationship between equilibrium provision of airline quality and scheduling preferences. Douglas and Miller (1974) take into account symmetric scheduling preferences and study the relationship between schedule delay cost and prices. Anderson and Kraus (1981) analyse the relationship between schedule delay and demand empirically, and show that schedule delay has a significant impact on demand. Daniel (1995) models delays in a more sophisticated way by simulating a stochastic bottleneck model and analyses the dynamic choice of atomistic airlines, accounting for the fact that the arrival rate of airlines at airports is endogenous. Brueckner (2002), Pels and Verhoef (2004) and Morisson and Winston (2007) study the internalization of delays by airlines and monetise travel delay costs by multiplying the

19 I like to thank Martijn Smit of the Department of Spatial Economics of VU University for help with the preparation of the dataset in STATA. Furthermore, I like to thank participants of the Kuhmo Nectar Conference 2011 for their valuable comments.
mean delay with the value of travel time savings, but ignore schedule delay cost. Brey and Walker (2011) study the dynamic choice of air travellers using a stated choice experiment and estimate the distribution of preferred arrival times at the destination airport.

This chapter does not focus on the causes of congestion and the potential internalization of congestion costs by airlines, but analyses air traffic delays from the travellers’ perspective. The main idea is that travellers are not only concerned with mean arrival delay cost, but also would like to arrive at their destination at some preferred arrival time. Air travel delays therefore potentially results in a costly disruption of travellers’ schedules and therefore travellers are willing to pay money to arrive at their preferred arrival time. Furthermore, travellers may also respond to arrival time variability by shifting to an earlier connection, than what they would choose without variability.

Mean delay cost, as currently used in most airport congestion models, might be a good proxy for expected scheduling cost. At least in departure time choice models for car travellers it has been found that mean delay cost are strongly related to the cost of expected schedule delay. This is because the standard deviation of travel times is strongly related to the mean travel time, and the cost of expected schedule delay is again strongly related to the standard deviation of travel time. Congestion therefore results in a higher cost of travel time variability. In this chapter we show empirically that for US air travel delays, mean delay is a good proxy for expected user cost, meaning that the expected user cost because of delays can be approximated using an empirical reduced-form linear function of the mean delay. Using data on US domestic air traffic delays, we show that the costs of arrival time variability are substantial, and that for reasonable parameter values, the expected user cost of air traffic delays are approximately 27% higher than previously found.

---

20 See for example Rupp (2009) for a recent study on causes and internalization of arrival delays for US air travel and Santos and Robin (2010) for a European perspective.

21 This is because with bottleneck congestion mean delay and the standard deviation of delay are closely related (Peer et al. 2010; Fosgerau 2010). For recent empirical analysis supporting this we refer to Fosgerau and Karlström (2010) and chapter 2 and 4 of this thesis.
3.2 Behavioural model

The behavioural trip timing model in this section builds on earlier work of Bates et al. (2001), Tseng (2008) and Fosgerau and Karlström (2010). Using the expected scheduling cost model of Noland and Small (1995) they show how travellers choose their optimal connection given their scheduling preferences and the distribution of arrival delays. Scheduled services impose more constraints on the potential anticipating behaviour because travellers cannot freely choose their departure times, and therefore it is likely that the cost of arrival time variability will be higher than in the case of car travel. Tseng (2008) was the first who studied this anticipating behaviour in more detail, and finds that arrival time variability significantly affects expected user cost. We extend earlier models by taking into account that arrival times of flights are not equally spaced over time-of-day. This is important when arrival times are variable, since anticipating behaviour to earlier connections depends on how connections are spaced in time. If a connection is nearby in arrival time, the probability that a traveller will choose this connection will be higher meaning that there is an interaction between frequency and the expected cost of arrival time variability.

Consider the following set-up. For a given OD-pair, on a given day \( v = 1 \ldots V \), travellers can choose between \( N_v \) connections labelled by \( n_v = 1 \ldots N_v \). It is assumed that \( N_v \geq 2 \), in order to have a possible trade-off between connections on day \( v \). The headway \( H_{vz} \) is the difference in the scheduled arrival times of connections \( n_v \) and \( n_v+1 \). On day \( v \) there are \( N_v \) connections and therefore there are \( N_v-1 \) values for the headway, implying that \( z = 1 \ldots N_v-1 \). This setup therefore accounts for unequally spaced flights over the time of the day, since \( H_{v1} \ldots H_{v(N_v-1)} \) are not necessarily equal.

The scheduled arrival time is defined by \( sat_{n_v} \), and the scheduled arrival time of the first connection (\( sat_1 \)) is normalised to 0. It is assumed that all travellers have a preferred arrival time (\( pat \)) at their destination airport, which is somewhere in between the scheduled arrival times of connections 1 and \( N_v \), meaning that \( 0 \leq pat \leq sat_{N_v} \). One might argue that from a system equilibrium perspective locating the arrival time at the beginning or endpoint of the market is not optimal from a profit perspective (see for example: Brenner, 2005; Rath and Zhao, 2001). For simplicity this is ignored in this
chapter for two reasons. First, analysing a full equilibrium model is highly complicated in
the current setting. Second, the cost of arrival time variability is likely to be higher for
morning travellers at the beginning of the market, because they cannot anticipate to
earlier connections. The \( pat \) is distributed over the time of day with a probability density
function \( \Phi'_{\text{pat}} \). We make simplifying assumptions about the distribution of \( pat \) in
order to keep the model tractable, and assume that \( pat \) is uniformly distributed over the
day, meaning that \( \Phi'_{\text{pat}} = 1/sat_{N,\text{pat}} \).

Furthermore we assume that travellers have what we may call \( \alpha-\beta-\gamma \) preferences
(Vickrey, 1969; Small, 1982).\(^{22}\) The shadow cost of mean arrival delay is given by \( \alpha \), the
shadow cost of arriving earlier than the preferred arrival time is given by \( \beta \), and the
shadow cost of arriving later than the preferred arrival time is given by \( \gamma \). Empirical
research usually finds that arriving late is more costly than arriving early, meaning that
\( \gamma > \beta \), although we may add that the evidence for air travellers is mixed (Brownstone and
Small, 1995; Warburg et al., 2006; Tseng, 2008; Koster et al., 2011; Hess and Adler,
2011).

The arrival delay \( D \) is distributed with a cumulative distribution function \( F[D] \), and
corresponding probability density function \( F'[D] \). \( D \) can be negative, meaning that
passengers may arrive earlier at their destination than the scheduled arrival time. We
standardise the delay to make the mean delay (\( \mu \)) and the standard deviation of delay (\( \sigma \))
explicit. To that end, define \( x = (D - \mu) / \sigma \), as the standardised delay, where \( x \) is distributed
with a standardised distribution \( G[x] \) and corresponding probability density function
\( G'[x] \). Throughout our analysis it is assumed that the distribution of arrival delay does not
vary over the day, meaning that \( \mu \) and \( \sigma \) are independent of the time of the day.

\(^{22}\) Other scheduling preferences can be used (Vickrey, 1973; Tseng and Verhoef, 2008; Fosgerau and
Engelson, 2010), but no empirical evidence for such preferences is available in the context of aviation. The
model developed in this chapter can easily be extended to another cost function in equation (3.1).
A traveller choosing connection \( n_v \) having a delay \( D \), and a scheduled arrival time \( sat_{n_v} \), has a generalised travel cost \( C[pat; D; n_v] \):

\[
C[pat; D; n_v] = p_{n_v} + \alpha \cdot D + \beta \cdot \max(0, pat - (sat_{n_v} + D)) + \\
\gamma \cdot \max(0, sat_{n_v} + D - pat)^\lambda.
\]

The first part of this equation \( p_{nv} \) is the cost for using the connection other than delay and scheduling cost. This includes the ticket price, the (monetised) cost of scheduled travel time, the service quality and frequent flyer miles. For the remainder of our analysis \( p_{nv} \) is assumed to be constant over the day and therefore we can normalise \( p_{nv} \) to 0. Therefore, on a given day \( v \), travellers base their choice of connection only on the delay and scheduling cost.

The second part of equation (3.1) is the additional arrival time delay cost, which is the value of mean arrival delay savings multiplied by the delay. The third and the fourth part of equation (3.1) are the cost of not arriving at the preferred arrival time multiplied with the corresponding shadow cost. The parameter \( \lambda \) captures possible non-linear effects in the schedule delay cost. For the main part of our analysis we assume \( \lambda = 1 \), but in our sensitivity analysis we will consider cases where \( \lambda > 1 \), meaning that large delays are relatively more costly and small delays relatively less costly, compared to linear schedule delay cost. It may well be that a delay decreases the scheduling cost for some travellers that arrive early if \( D \) equals 0, because they arrive closer to their \( pat \). However, because \( \alpha \) is in general found to be higher than \( \beta \), individual trip cost will always increase if \( D \) increases. If \( \alpha < \beta \), travellers prefer a longer flight over landing too early.

Following Noland and Small (1995), the expected user cost is then given by equation (3.2). We substitute the standardised delay \( D = \mu + \sigma \cdot x \) into equation (3.1). The expected cost is then given by the integral over the cost of a delay, multiplied with the corresponding probability:

\[
EC[pat; \mu; \sigma; n_v] = \int C[pat; \mu + \sigma \cdot x; n_v] \cdot G'[x]dx.
\]

\(^23\) For simplicity, our analysis focuses on direct connections and does not take into account transfers.

\(^24\) For \( \lambda > 1 \), this may be the case for very early arrivals. With non-linear scheduling cost the units are important. For the mean delay and the schedule delay these are in hours.
We assume that travellers know the travel time distribution $F[D]$. This is a strong assumption for air travellers since the knowledge of $F[D]$ is mainly driven by experience and flight trips are made less regularly than car commuting trips. However, as shown in Chapter 4, travellers that use weighted probabilities or misperceive the probability distribution, will always have higher (or equal) expected user cost compared to the user equilibrium cost that will be derived from equation (3.2), since the trip timing is not optimal anymore.\(^{25}\) This assumption secures that we make a conservative estimate of the cost of variability. Travellers then choose the connection with the lowest expected cost from the set of $N_v$ available connections on that day. This optimal connection is given by equation (3.3):

\[
(3.3) \quad n_v[pat, \mu, \sigma]^* = \text{argmin}_{n_v \in \{1..., N_v\}} EC[pat; \mu; \sigma; n_v].
\]

This optimal connection is a function of the $pat$, because travellers with a later $pat$ are likely to prefer travelling with a later connection. More precisely, equation (3.3) is the solution to an integer optimization problem, and is a non-decreasing stepwise function in $pat$. Since we are not able to find an analytical solution without specifying $F[D]$, we use numerical optimization to find $n_v[pat, \mu, \sigma]^*$, and use shorthand notation $n_v[.]^*$ to denote the optimal connection.\(^{26}\) The corresponding equilibrium expected cost for a given $pat$ is then given by $EC[pat; \mu; \sigma; n_v[.]^*]$, where $n_v$ in equation (3.2) is replaced by $n_v[.]^*$. The average total expected user equilibrium cost on a day are then given by the integral over the user equilibrium cost, multiplied by the probability density function of the preferred arrival times $\Phi_v[pat]$, and a scale factor $M_v$ that represents total demand over the day:

\[
(3.4) \quad ATEC_v[\mu, \sigma] = M_v \cdot \int_0^{SAT_{N_v}} EC[pat; \mu; \sigma; n_v[.]^*] \cdot \Phi_v[pat] dpat.
\]

\(^{25}\) Koster and Verhoef (2012) use a model for car travellers. However the argument remains similar for travel with a scheduled service. Models based on the expected utility theory, will always give the lower bound of the user equilibrium expected cost. Any deviations because of structural misperceptions or probability weighting result in non-optimal departure times and therefore will result in higher (or equal) expected user equilibrium cost. Other behavioural profiles might be considered, for example that travellers ignore delays completely in their trade-offs. The specification of the user expected cost function then will not change, but the solution for the optimal connection will change and expected user equilibrium cost will be higher than in our analysis.

\(^{26}\) For some specific distributions (uniform/exponential) closed-form solutions are available (see for example Fosgerau and Karlström 2010). But given the fact that delay distributions in our dataset do not have a particular shape, we estimate nonparametric distributions and use a numerical grid search to determine the optimal connection for each $pat$. 
For simplicity we assume $M_v$ is equal to 1. This means that equation (3.4) is the average expected user equilibrium cost over all preferred arrival times for day $v$.

To determine the cost of travel time variability, and to be able to compose it into various meaningful concepts, we define a number of benchmarks. The first benchmark we analyse concerns the cost level $ATEC_v[0,0]$, where it is assumed that $\mu=\sigma=0$ and there are no delays at all. This means that there is only deterministic scheduling cost. A closed-form for the deterministic scheduling cost is derived in Appendix 3A for the non-linear scheduling cost function of equation (3.1), assuming $\mu=\sigma=0$. For the linear case ($\lambda=1$), the resulting average deterministic scheduling cost for day $v$ is given by the following equation:

$$ATEC_v[0,0] = \sum_{z=1}^{N_v-1} \frac{1}{2} \cdot \frac{H_{vz}^2}{sat_{N_v}} \cdot \beta \cdot \gamma + \beta \cdot \gamma,$$

(3.5)

The deterministic scheduling cost increase quadratically in the headway $H_{vz}$ and increase if the schedule becomes more binding (increasing $\beta$ and $\gamma$). Assuming $sat_{N_v}$ is fixed, adding flights will decrease scheduling cost, as long as the scheduled arrival time of the new flights is not identical to that of existing flights with available seats. Therefore, the value of increased frequency also depends on the scheduled arrival times of the other flights.

As a second benchmark we analyse the cost under the assumption that there is no arrival time variability, meaning that we compare $ATEC_v[\mu, \sigma]$, with $ATEC_v[\mu, 0]$. In this case, travellers only consider the cost of an expected arrival time $sat_{nv} + \mu$, where $\mu$ is a deterministic constant. As shown in Appendix 3B, some travellers then choose a different optimal connection, meaning that $n_v[pat, \mu, 0]^*$ is different from $n_v[pat, 0, 0]^*$. Average total cost without arrival time variability can be found by integrating over all possible preferred arrival times in a way similar to equation (3.4). Previous studies assumed a uniform distribution of $pat$, $\Phi_v[pat]=1/sat_{N_v}$. In Appendix 3B we show that for a uniform distribution of preferred arrival times, $ATEC_v[\mu, 0]$ is given by the following equation:

27 This corresponds to the results of De Palma and Lindsey (2001), Tseng (2008) and Fosgerau (2009). In their analysis, they assume $N_v=2$, $V=1$ and $sat_{N_v} = H_{vz}$.
Equation (3.6) shows that with a uniform distribution of preferred arrival times the mean delay does not affect the average scheduling cost and therefore the average total expected cost increase linearly in the mean delay. However, the mean delay does affect the individual scheduling cost of a traveller and with a non-uniform distribution of pat, the total user cost of mean delay do depend on the values of schedule delay. This is shown in more detail in Appendix 3B. The implication of this result is that improvements in mean arrival delay affect the schedule if the preferred arrival times are not distributed uniformly. Some empirical evidence that preferred arrival times may not be uniformly distributed over time of day is given by Warburg et al. (2006) and Brey and Walker (2011). Warburg et al. (2006) show that business travellers usually prefer to arrive in the morning.

For every OD-pair we will derive an aggregate measure of expected user cost including scheduling cost. To that end, we average equations (3.4)-(3.6) over all days of the year, where days with more flights are weighted heavier because it is likely that more travellers travelled on these days (we do not have passenger numbers per day). This average is given by \( \overline{ATEC_{OD}}[\mu, \sigma] = \frac{1}{\sum_{v=1}^{V} N_v} \cdot \sum_{v=1}^{V} N_v \cdot ATEC[\mu, \sigma]_v \). We then define the total cost of arrival time variability as \( \overline{ATEC_{OD}}[\mu, \sigma] - \overline{ATEC_{OD}}[\mu, 0] \), and the total cost of mean arrival delays as \( \overline{ATEC_{OD}}[\mu, \sigma] - \overline{ATEC_{OD}}[0,0] \).

### 3.3 Data

We use the “On-Time Performance” database of the year 2010, which includes scheduled and realised arrival times of domestic flights in the United States operated by airlines that carry at least 1% of US domestic flights.\(^{28}\) Because there are systematic differences in the distributions of arrival delays between origins with the same destination, the analysis is performed for every OD-pair. The reason for these systematic differences in mean and standard deviation of arrival delays is that both at the origin and the destination delays occur. For example, adverse weather conditions or lack of airport

\(^{28}\) The dataset and the corresponding documentation can be downloaded at http://www.transtats.bts.gov/.
capacity may occur both at the origin and the destination. Another important aspect of using OD-pairs is that this seems closer to appropriate perspective for an air traveller. Travellers are not so much concerned with the aggregate arrival delay distribution at the destination airport, but rather face the delay distribution when travelling from their origin to their destination. We take the choice of origin and destination as given, meaning that we ignore the fact that in a multi-airport region travellers may choose between flights departing from multiple airports, or may change destination due to differences in arrival time delay costs.

We include 560 OD-pairs with the highest number of flights in 2010. These OD-pairs account for 40% of the total number of domestic flights in our dataset. The mean arrival delay ($\mu$) and the standard deviation of arrival delay ($\sigma$) for the OD-pairs are given in Figure 3.1. The standard deviation of delays is increasing in the mean delay. Some OD-pairs have negative mean delays while the mean arrival delay reaches a maximum at
0.32 hours. Standard deviations for all OD-pairs are higher than the mean delay and reach values from 0.22 to 0.93 hours.

3.4 Results

3.4.1 Analysis for one OD-pair

The analysis is performed on a daily basis and in this section we show for one OD-pair the intermediate steps to obtain the results of equations (3.2)-(3.6). We choose the OD-pair Atlanta-Houston for this purpose since it is typical in terms of yearly number of flights (4134), mean arrival delay (0.15 hours), and standard deviation of arrival delay (0.48 hours). From the data the daily headways and scheduled arrival times are obtained. For each OD-pair a nonparametric density function of the delays is estimated using kernel smoothing. It is assumed that the arrival delay distribution does not change over daytime and over the days.\(^{29}\) Figure 3.2 shows the estimated nonparametric probabilities.

The next step is to calculate the total expected cost for one day. In order to do so, we assume values of \(\alpha = \$45\) per hour, \(\beta=\$15\) per hour and \(\gamma=\$30\) per hour (roughly based on: Morrison and Winston, 2007; Wardman, 2004). Lijesen (2007) shows that the evidence on the value of frequency is mixed, not in the last place because of differences in measurement methods (stated or revealed preference) and definitions of schedule delays. As argued before, an additional flight on a day may not reduce scheduling cost if the scheduled arrival time of this new flight is similar to another flight on that day. Although, probably not fully comparable, Wardman (2004) finds in a meta-study that for long distance train trips the value of headway is approximately 0.2 times the value of travel time savings, implying for our case a value of headway of \$10. For the deterministic case, where flights are equally spaced, our assumed values result in a lower value of \$5. A general finding for air travellers is that the values of schedule delay are lower than the value of time.

\(^{29}\) Estimation is done in Matlab using the ksdensity function using 500 equally spaced points. Bandwidths are optimal for a normal density (see Bowman and Azzilini, 1997).
Figure 3.2 – Probabilities as a function of arrival delays (in hours) for OD pair Atlanta-Houston.
Figure 3.3a — $n_{[n_{\text{pat}, i}, 0]}$ for a representative day for OD-pair Atlanta-Houston. Predicted arrival time in hours from the arrival of the first connection.
Morrison et al. (1989) finds very low values of schedule delay, but uses a different definition of schedule delay and Warburg et al. (2006) find values of schedule delay approximately 50% of the value of travel time but also include the probability of being late in the cost function. Finally, Hess and Adler (2011), find values of schedule delay of approximately 20% of the value of time. However, from these studies it is unclear how the preferred arrival time is obtained and how the value of frequency is related to the values of schedule delay. As indicated by Koster et al. (2011) this is crucial, since otherwise anticipating behaviour is included in the preferred arrival time resulting in biased estimates for the values of schedule delay. In the sensitivity analysis of section 3.4.3, we show how the results do depend on the assumed values of $\beta$ and $\gamma$. For this example we use the day with the schedule that is most observed in the data as a representative day. For this day there are 11 flights, implying that $N_v=11$.

Figure 3.3a shows the solution for the optimal connection as a function of the $pat$. It starts at the first connection and increases with 11 steps. The irregular pattern is caused by the fact that flights are not equally spaced over time-of-day. Therefore the headways are not equal over the time of the day.

Figure 3.3b shows the expected user cost as a function of the preferred arrival time. The scheduled arrival times of the connections are indicated with vertical lines, where 0 indicates the scheduled arrival time of the first connection. The expected user cost function for each connection as a function of the preferred arrival time is convex shaped, and is given by the dashed lines. The traveller, with $pat=0$ has the lowest expected cost for travelling with the first connection, and highest expected user cost for travelling with the last connection. The black line is the lower envelope of all the expected cost curves and gives the equilibrium expected cost $EC[pat;\mu;\sigma;N_v[.]^\star]$.

Figure 3.3c zooms in on this equilibrium cost in more detail. For this day, $ATEC_v[\mu,\sigma]$ equals $18.39$, $ATEC_v[\mu,0]$ equals $15.94$ and $ATEC_v[0,0]$ equals $8.87$. This means that the cost of arrival time variability are equal to $2.44$ ($18.39-15.94$ ), and the total cost of variable delays are equal to $9.51$ ($18.39-8.87$), which is 35% higher than what is found using the deterministic measure $\alpha \cdot \mu$. Figure 3.3c also shows that the minimal user equilibrium cost is independent of $H_v$. This cost is equal to what would be found if travellers could freely choose a departure time, and connections arrive continuously (see
Fosgerau and Karlström, 2010). The optimal decision for this traveller then corresponds to the scheduled arrival time of the connection offered by the timetable. The analysis per day enables us to show how the costs of arrival time variability change over the year. There may be fluctuations in scheduling cost, for example because airlines may schedule more flights during some periods in the year and due to day of the week variations in the schedule. Figure 3.4 shows that there is mainly variation in $ATEC_v[\mu, \sigma]$ due to differences in the deterministic scheduling cost. That is, the difference between actual expected cost and cost that would be incurred if $\sigma=0$ is nearly constant, so that fluctuations over time must be due to fluctuations in deterministic cost components. The cost of arrival time variability $ATEC_{OD}[\mu, \sigma] - ATEC_{OD}[\mu, 0]$ has a mean of $2.37$, with a low standard deviation of $0.14$.

### 3.4.2 Analysis of the full dataset

For each OD-pair the analysis of section 3.4.1 is repeated, and we calculate the cost of arrival time variability for each OD-pair. Figure 3.5 shows the $ATEC_{OD}[\mu, \sigma] - ATEC_{OD}[\mu, 0]$ as a function of $\sigma$. These are the averaged values over all days for a given OD-pair. The expected user cost of arrival time variability increases more than proportionally in the standard deviation of arrival delays and is in the range of 1-6 euro's per traveller.
Figure 3.3b — Expected user cost functions (dashed lines) and equilibrium cost (black line) as a function of pat.
Figure 3.3c — User equilibrium cost (black line) and minimal equilibrium cost (dashed line) as a function of $p_{\text{at}}$. 

Preferred arrival time in hours from the arrival of the first connection vs. expected user cost in euros.
Figure 3.4 — $\text{ATEC}_v[\mu, \sigma]$, $\text{ATEC}_v[\mu, 0]$, and $\text{ATEC}_v[0, \sigma]$ per day of the year.
Figure 3.5 — Cost of arrival delay variability as a function of $\sigma$. Note: no constant is included in the regression equation because if $\sigma=0$, the cost of arrival time variability should be is 0.

Next, figure 3.6 shows the total expected user cost because of arrival delays as a function of the mean arrival delay $\mu$. The first observation is that the expected user cost can be approximated well by a linear function of $\mu$ for a broad range of OD-pairs and markets. This is good news for policy makers and airport congestion modellers, since the mean delay is then a good proxy for the total expected user cost because of delays and the complex dynamic choice problem of the travellers can be written in reduced form. Of course this can only be done for policy measures that do not disrupt the relationship. The lower linear line represents the equation $\alpha \cdot \mu$ and we thus see that the additional expected scheduling cost due to arrival time variability is substantial. The slope of the lower line is by assumption $\$45$. If we include expected scheduling cost, we find a slope of $\$57$, meaning that the expected user cost of arrival delays are underestimated by 27% if variable arrival times are ignored.
The linearity result is persistent for a broad range of OD-pairs and parameter values. This means that for small changes of the mean delay the slope of the trend line can be interpreted as the ‘implied’ value of mean delay savings, meaning that it also includes the expected schedule delay cost. The lower line indicates the cost when only the mean delay is included in the user cost function. This means that the effect of air travel delays increase expected user cost more than previously thought and therefore the potential welfare gains obtained from congestion pricing schemes as proposed by Brueckner (2002), Mayer and Sinai (2003) and calculated by Morrison and Winston (2007) will be significantly larger if arrival time variability is included in the user cost function. However, if the estimate of the value of travel delay savings ($\alpha$) is based on revealed preference data, it will likely pick up the expected scheduling costs as well, meaning that the current estimates of congestion cost may already incorporate expected scheduling cost.

Figure 3.6— Expected user cost of arrival delays as a function of mean arrival delay.
3.4.3 Discussion of the assumptions

3.4.3.1 Assumption on equality of prices over time of the day
Throughout our analysis we assumed that the cost $p_{n_v}$ for other components than delays is constant over time-of-day for a given day $v$. This is probably not a realistic assumption since airlines may differentiate their prices over time-of-day in order to maximise their profits, or travellers may have a preference for a certain airline because of frequent flyer miles or other quality differences. If $p_{n_v}$ is not constant over time of day, the choice of the optimal connection, as given in equation 3.3, will also depend on the cost components $p_1\ldots p_{N_v}$. Given the assumption that $p_{n_v}$ is constant over the time of the day, the decision to choose the optimal connection $n_v[.]^*$ solely based on delay cost. Any other connection that is chosen will therefore raise the expected user cost because of delays by definition, otherwise $n_v[.]^*$ is not optimal. If $p_{n_v}$ is not equal over time of the day, travellers choose $n_v[.]^*$ or a different connection. If they choose $n_v[.]^*$, the expected cost of delays is equal to what we found. If they choose another connection the expected cost of delays are higher. This means our estimate of the cost of delays is conservative since including $p_{n_v}$ in the cost function, would certainly increase equilibrium (expected) cost because of delays, since the decision of the travellers is no longer optimal in terms of average and schedule delay cost.

3.4.3.2 Non-linear scheduling cost function
For non-linear schedule delay functions it is a-priori unknown if the equilibrium cost will increase or decrease. If $\lambda > 1$, for arrivals closer to $pat$ the scheduling cost will be lower than in the linear case. More precisely: if the arrival is less than an hour from $pat$, the scheduling cost will be lower. For arrivals further away (more than an hour from $pat$), the scheduling cost will be higher. Therefore, the effect of non-linear scheduling preferences depends on the timetable and the distribution of delays.

To show the numerical effect of non-linear scheduling preferences on the results, we re-estimated the user cost assuming a convex scheduling cost function, with values of $\lambda=1.3$ and $\lambda=1.6$ in equation (3.1). The resulting figures are given in Appendix C. Compared to the model with linear scheduling cost, the costs of arrival time variability
are approximately 8% higher for λ=1.3 and 19% higher for λ=1.6. The expected user cost because of arrival delays can still well be approximated by a linear function of mean arrival delay. This is in line with the formal proof, and it again shows that a linear scheduling cost function results in a lower bound estimate of the cost of arrival time variability if the real cost function is more convex. Using similar reasoning as above, our cost are of course an overestimation if λ<1.

3.4.3.3 Distribution of preferred arrival times
Third, we test how the results depend on the assumed probability density function of the preferred arrival times. A priori there is no clear cut theoretical answer how a different distribution of pat affects our results. Some recent empirical evidence of Brey and Walker (2011) for domestic air travellers suggests that the distribution of preferred arrival times is not uniform and may follow a bimodal pattern over the time of the day. Therefore we perform some numerical sensitivity checks to see how the results are affected.

To keep the analysis tractable, we consider three other non-uniform distributions of pat. First, we assume that the probability is linearly decreasing over time-of-day, meaning that a larger share of travellers prefers to arrive in the morning. This may be typical for business travellers who usually prefer to arrive in the morning (Warburg et al., 2006). Second, it is assumed that the probability is increasing in time-of-day, meaning that a larger proportion of travellers prefer to arrive in the evening. Third, it is assumed that the probability is symmetrically U-shaped, meaning that more travellers prefer to arrive in the morning and evening than during daytime. As shown in Appendix 3C, the replications of Figure 3.6 hardly change, and therefore the calculated average expected user cost due to delays are rather independent of the assumptions on the distribution of preferred arrival times.

3.4.3.4 Values of schedule delays and proportional heterogeneity in preferences
The cost of arrival time variability does of course depend on the assumed values of schedule delay. If α, β and γ change in the same proportion, the results derived in this chapter only change in an absolute sense, while the relative contribution of arrival time
variability to total costs remains the same. This type of heterogeneity is elsewhere referred to as “proportional heterogeneity”, and may be caused by the fact that there is heterogeneity in the marginal utility of income, causing $\alpha$, $\beta$ and $\gamma$ to vary in fixed proportions (Van den Berg and Verhoef, 2011). This can be seen from the cost function of equation 3.1. If we multiply the assumed willingness to pay values $\alpha$, $\beta$ and $\gamma$ with a constant $k_i > 0$, the corresponding expected user cost are given by equation 3.9:

$$EC[pat; \mu; \sigma;n_v] = k_i \cdot \int C[pat; \mu + \sigma \cdot x; n_v] \cdot G[x]dx.$$  

This shows that the expected user cost is homogeneous of degree 1, and therefore the user equilibrium cost will shift with a fixed constant and the relative contribution of the cost of arrival time variability remains constant for all $k_i > 0$.

Suppose that we keep $\alpha$ constant and that we multiply $\beta$ and $\gamma$ by $k_i$. Because it is assumed that $\mu$ is equal over the time of the day, the choice of a connection only depends on the ratio of $\gamma/\beta$. The results can then easily be derived for other values of schedule delay, as long as the ratio $\gamma/\beta$ remains the same. If the base values we chose for $\beta$ and $\gamma$ are multiplied by $k_i$, the cost of arrival time variability will be $k_i$ times higher because the cost of mean delay and scheduling are additive. Following the result of Figure 3.6, this means that the expected user cost for group $i$ with corresponding $k_i$ can be written in reduced form as: $(\alpha + k_i \cdot 12.12) \cdot \mu$, where $k_i = 1$ corresponds to the result of figure 3.6. Assuming values for $k_i$ in the range of 0.3-2, this results in expected user cost of arrival delays that is in the range 8%-54% higher than the deterministic case $\alpha \cdot \mu$.

### 3.5 Final comments and discussion

This chapter showed that air travel delay variability for US domestic air travel, may raise the expected user cost of delays of air travellers with 27%, given our assumptions the value of delay savings and scheduling preferences. Given the discussion of the assumptions in the previous section, we view this as a conservative estimate. We showed for a broad range of origin-destination pairs that expected user cost because of air travel delays can be well approximated by a linear function of the mean delay. Therefore, the expected scheduling cost will be substantial. Our result strengthens the argument for introducing airport congestion pricing, since the welfare losses due to delays are
significantly higher than when only mean delay is taken into account in the user cost function.

On the other hand, it is not clear if current revealed preference studies already implicitly include the expected cost of schedule delay in their estimation, because expected scheduling cost are so closely related to the mean delay cost. Our model might then explain the high values of times that are sometimes found in RP studies. If this is the case, current estimates of delay cost are more likely to be correct. Therefore there is a need for good estimates of the values of schedule delay and mean delay savings for air travellers, using revealed and stated preference data, in order to better disentangle the different cost components, which in turn may help to better prioritise policies that affect mean delays and variability in different ways.

Second, future studies may investigate how the mean delay and standard deviation of delays are related to congestion on the origin and the destination airport and the rest of the network, to gain more insights in the empirical relation between airport congestion and arrival time variability. Peer et al. (2010) investigate such relationships for car travellers.

Third, it is interesting to study how ticket prices are related to headways and arrival time variability. In our analysis we assumed that the price of the connections is constant over time of day. As argued before, this is not a problem for the purpose of this chapter, since it results in a lower estimate of the expected user cost because of arrival delays. However, the current model sheds no light on the anticipating behaviour of airlines to arrival time variability.

Finally, it is interesting to study the effects of delays for scheduled services such as trains or metros to see if the linearity of expected user cost in the mean delay holds as well for these services. Because these topics are beyond the scope of this chapter, we leave them for future research.
Appendix 3A Derivation of deterministic scheduling cost

3A.1 Uniform pat distribution

We assume that the pat distribution is uniform and assume that \( p_{nv} = 0 \) and \( \mu = 0 \). In the deterministic case, travellers then always choose between two connections. Connection \( z \) has a normalised scheduled arrival time 0, and connection \( z+1 \) has a scheduled arrival time \( H_{vz} \). The pats are distributed between 0 and \( H_{vz} \) with probability \( 1/sat_{Nv} \).

The cost functions are:

\[
C_z = \beta \cdot pat^\lambda,
\]

\[
C_{z+1} = \gamma \cdot (H_{vz} - pat)^\lambda.
\]

The next step is to determine for which values of pat travellers choose connection \( n_v \).

Solving for the switching pat gives:

\[
pat^* = H_{vz} \cdot \frac{1}{\beta^\lambda + \gamma^\lambda}.
\]

This means that all travellers on the interval \([0; pat^*]\) choose to travel with connection \( n_v \).

All travellers on the interval \([pat^*; H_{vz}]\) travel with connection \( z+1 \). As long as \( \gamma > \beta \), a decrease in \( \lambda \) will lead to a decrease in \( pat^* \) meaning that more travellers use connection \( n_v \).\(^{30}\)

The average (over preferred arrival times) deterministic scheduling cost is then given by the integral over all preferred arrival time in between 0 and \( H_{vz} \):

\[
DSC_{vz} = \int_0^{pat^*} C_z \cdot \frac{1}{sat_{Nv}} dpat + \int_{pat^*}^{H_{vz}} C_{z+1} \cdot \frac{1}{sat_{Nv}} dpat.
\]

\[
DSC_{vz} = \frac{\gamma \cdot \left( \frac{H_{vz} \cdot \beta^\lambda}{\beta^\lambda + \gamma^\lambda} \right)^{1+\lambda}}{sat_{Nv} \cdot (1 + \lambda)} + \frac{\beta \cdot \left( \frac{H_{vz} \cdot \gamma^\lambda}{\beta^\lambda + \gamma^\lambda} \right)^{1+\lambda}}{sat_{Nv} \cdot (1 + \lambda)}.
\]

The result of De Palma and Lindsey (2001), Fosgerau (2009) and Tseng (2008) is the result assuming \( \lambda = 1 \) and \( sat_{Nv} = H_{vz} \) in equation (3.A.6).

\[
DSC_{vz} = \frac{\gamma \cdot \left( \frac{H_{vz} \cdot \beta}{\beta + \gamma} \right)^2}{2 \cdot sat_{Nv}} \quad + \quad \frac{\beta \cdot \left( \frac{H_{vz} \cdot \gamma}{\beta + \gamma} \right)^2}{2 \cdot sat_{Nv}} = \frac{H_{vz}^2 \cdot \beta \cdot \gamma}{2 \cdot sat_{Nv} \cdot (\beta + \gamma)}.
\]

\(^{30}\) Note that \( \frac{\partial pat^*}{\partial \lambda} = \frac{H_{nv}(\beta \gamma)^{1+\lambda} \log[\frac{\beta^\lambda}{(\beta^\lambda + \gamma^\lambda)^{1+\lambda}}]}{(\beta^\lambda + \gamma^\lambda)^{2+\lambda} \cdot \lambda} < 0 \), if \( \gamma > \beta \).
Appendix 3B shows that for a uniform distribution of preferred arrival times the mean delay does not affect the scheduling cost and the average cost of mean delay are then given by equation (3.A.7):

\[ ATEC_v[\mu,0] = \alpha \cdot \mu + \sum_{z=1}^{N_v-1} DSC_{vz}. \]  

### 3A.2 Other pat distributions

It is assumed that schedule delay cost is linear, so \( \lambda=1 \) and for ease of exposition we illustrate the calculation of scheduling cost for the case that \( \mu=0 \). The switching \( pat \) does not change, but the average cost of mean delay will change. If we assume a linearly decreasing probability for the preferred arrival times, \( \Phi_v(pat) = \frac{2\cdot(sat_{N_v}-pat)}{sat_{N_v}^2} \). The deterministic scheduling cost is then given by equation (A.3.8):

\[ DSC_{vz} = \frac{H_{vz}^3 \cdot \beta \cdot \gamma \cdot (2 \cdot \beta + \gamma)}{3 \cdot sat_{N_v}^2 \cdot (\beta + \gamma)^2}. \]  

If we assume a linearly increasing probability for the preferred arrival times, \( \Phi_v(pat) = \frac{2\cdot pat}{sat_{N_v}^2} \). The deterministic scheduling cost is then given by the following equation:

\[ DSC_{vz} = \frac{H_{vz}^3 \cdot \beta \cdot \gamma \cdot (\beta + 2 \cdot \gamma)}{3 \cdot sat_{N_v}^2 \cdot (\beta + \gamma)^2}. \]  

If we assume a U-shaped probability for the preferred arrival times, with a minimum probability at \( \frac{sat_{N_v}}{2} \), the distribution of preferred arrival times is given by: \( \Phi_v(pat) = \frac{12}{sat_{N_v}^2} \cdot \left[ pat - \frac{sat_{N_v}}{2} \right]^2 \). The deterministic scheduling cost is then more cumbersome and is given by the following equation:

\[ DSC_{vz} = \frac{3 \cdot H_{vz}^2 \cdot \beta \cdot \gamma}{2 \cdot sat_{N_v} \cdot (\beta + \gamma)} - \frac{2 \cdot H_{vz}^3 \cdot \beta \cdot \gamma \cdot (\beta + 2 \cdot \gamma)}{sat_{N_v}^2 \cdot (\beta + \gamma)^2} + \frac{H_{vz}^4 \cdot \beta \cdot \gamma \cdot (\beta^2 + 3 \cdot \beta \cdot \gamma + 3 \cdot \gamma^2)}{sat_{N_v}^3 (\beta + \gamma)^3}. \]
Appendix 3B The value of improvements in mean arrival delay

This appendix shows how the distribution of pat affects the value of improvements in mean delay. For simplicity we consider a day with 2 connections. The headway $H$ is the difference between the scheduled arrival times of the connections. We normalise the scheduled arrival time of the first connection to 0, so the scheduled arrival time of the second connection is $H$. The arrival delay is not stochastic and airlines arrive always late with mean delay $\mu$. The cost of travelling with connection 1 is then given by:

$C_1 = \begin{cases} \alpha \cdot \mu + \gamma \cdot (\mu - pat), & \text{if } pat \leq \mu \\ \alpha \cdot \mu + \beta \cdot (pat - \mu), & \text{if } pat > \mu \end{cases}$

(3.B.1)

Travellers taking connection 1 are late if their $pat$ is close to the scheduled arrival time of connection 1 and early otherwise. Travellers using connection 2 are always late. The cost of using connection 2 is then given by:

$C_2 = \alpha \cdot \mu + \gamma \cdot (H + \mu - pat)$.

(3.B.2)

The next step is to determine for which value of $pat$ travellers are indifferent between the two connections. This is done by solving $C_1 = C_2$. The switching $pat$ is then given by:

$pat^* = \left(\frac{\gamma}{\beta + \gamma}\right) \cdot H + \mu$.

(3.B.3)

This means that mean arrival delay also affects the scheduling decision of the traveller. Total cost, averaged over all preferred arrival times, is then given by the following equation:

$ATC = \alpha \cdot \mu + \int_0^\mu \gamma \cdot (\mu - pat) \cdot \Phi'_\nu(pat) dpat + \int_\mu^{\mu*} \beta \cdot (pat - \mu) \cdot \Phi'_\nu(pat) dpat$

$+ \int_{\mu*}^H \gamma \cdot (H + \mu - pat) \cdot \Phi'_\nu(pat) dpat$.

(3.B.4)

The first derivative with respect to $\mu$ shows how the total cost changes with the mean delay. Note that $\frac{\partial pat^*}{\partial \mu} = 1$.

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31 As long as the mean delay is bounded, so: $-\frac{\gamma H}{(\beta + \gamma)} < \mu < \frac{\beta H}{(\beta + \gamma)}$ travellers do not shift to earlier connections. Our numerical program handles all cases of $\mu$, but to limit the mathematical derivations, we illustrate in this appendix the case where: $-\frac{\gamma H}{(\beta + \gamma)} < \mu < \frac{\beta H}{(\beta + \gamma)}$. This is the case that is most common in our empirical application.
(3.B.5) \[
\frac{\partial ATC}{\partial \mu} = \alpha + \gamma \cdot \Phi_v(\mu) - \beta \cdot [\Phi_v(pat^*) - \Phi_v(\mu)] + \gamma \cdot (1 - \Phi_v(pat^*)).
\]

Collecting terms and further rewriting gives:

(3.B.6) \[
\frac{\partial ATC}{\partial \mu} = \alpha + (\gamma + \beta) \cdot (\Phi_v(\mu) - \Phi_v(pat^*)) + \gamma.
\]

Equation (3.B.6) therefore shows that the distribution of preferred arrival times affects the marginal change in average travel cost for changes in the mean delay. For a uniform cumulative distribution of preferred arrival times \( \Phi_v(\mu) = \frac{pat}{H} \), and equation (3.B.6) reduces to \( \alpha \), meaning that even when \( \mu \) affects the schedule of the traveller, scheduling cost average out over travellers. However, for other shapes of the \( pat \)-distribution this is not the case. For example, if we assume a linearly decreasing probability for the preferred arrival times, \( \Phi_v'(pat) = \frac{2(H-pat)}{H^2} \), and the derivative is given by:

(3.B.7) \[
\frac{\partial ATC}{\partial \mu} = \alpha - \left[ \frac{\beta \cdot \gamma}{\beta + \gamma} - \frac{2 \cdot \gamma \cdot \mu}{H} \right].
\]

If we assume a linearly increasing probability for the preferred arrival times, \( \Phi_v'(pat) = \frac{2 \cdot pat}{H^2} \), equation (3.B.6) reduces to:

(3.B.8) \[
\frac{\partial ATC}{\partial \mu} = \alpha + \left[ \frac{\beta \cdot \gamma}{\beta + \gamma} - \frac{2 \cdot \gamma \cdot \mu}{H} \right].
\]

If we assume a U-shaped probability for the preferred arrival times, with a minimum probability at \( \frac{H}{2} \), the distribution of preferred arrival times is given by: \( \Phi_v'(pat) = \frac{12}{H^3} \cdot \left[ pat - \frac{H}{2} \right]^2 \), and equation (3.B.6) reduces to:

(3.B.9) \[
\frac{\partial ATC}{\partial \mu} = \alpha + \frac{2 \cdot \beta \cdot \gamma \cdot (\gamma - \beta)}{\beta + \gamma} + \frac{12 \cdot \beta \cdot \gamma \cdot \mu}{(\beta + \gamma) \cdot H} - \frac{2 \cdot \gamma \cdot \mu^2}{H^2}.
\]

This means that changes in the mean delay also affect the scheduling decision of the traveller, and that with a non-uniform distribution of preferred arrival times total cost of mean delay are not simply \( \alpha \cdot \mu \).
Appendix 3C Results of the sensitivity analysis

In this appendix we replicate Figure 3.6 in order to see how the results are affected for changes in the assumptions. Figure 3.7 shows the relationship between mean arrival delay and $\overline{TCMD_{OD}}$ assuming $\lambda=1.3$. The value of savings in mean delay (including expected scheduling cost) is around $62 and is higher than in the case of a linear specification of schedule delay ($\lambda=1$). Figure 3.8 shows the relationship between mean arrival delay and $\overline{TCMD_{OD}}$ assuming $\lambda=1.6$. The $\overline{TCMD_{OD}}$ is again higher than in the linear case and the slope is around $68$. For this dataset, a more convex shaped scheduling function (increasing value of $\lambda$) will result in higher cost of arrival time variability. If the scheduling cost function is more convex, the expected user cost can less well be approximated by a linear function of the mean arrival delay.

![Graph](image)

$y = 57.123\mu + 0.7632$

$R^2 = 0.9635$

Figure 3.7—Expected user cost of arrival delays as a function of mean arrival delay, assuming $\lambda=1.3$. 
If we assume a linearly increasing probability for the preferred arrival times, $\Phi_\nu'(pat) = \frac{2 \cdot pat}{sat_N^2}$. A larger share of travellers then prefers to arrive in the evening. Figure 3.9 shows the result. If we assume a linearly decreasing probability for the preferred arrival times, $\Phi_\nu'(pat) = \frac{2 \cdot (sat_N - pat)}{sat_N^2}$. Figure 3.10 shows the result. If we assume a U-shaped probability for the preferred arrival times, $\Phi_\nu'(pat) = \frac{12}{sat_N^3} \cdot [pat - \frac{sat_N}{2}]^2$. Figure 3.11 shows the result.
Figure 3.9 — Expected user cost of arrival delays as a function of mean arrival delay, assuming $\Phi_v'(pat) = \frac{2 \cdot pat}{sat_Nv^2}$.

Figure 3.10 — Expected user cost of arrival delays as a function of mean arrival delay, assuming $\Phi_v'(pat) = \frac{2 \cdot (sat_Nv - pat)}{SAT_Nv^2}$.
Figure 3.11—Expected user cost of arrival delays as a function of mean arrival delay, assuming \( \Phi_v'(pat) = \frac{12}{sat_{Nv}} \cdot \left[ pat - \frac{sat_{Nv}}{2} \right]^2 \).
4 A rank dependent scheduling model

4.1 Introduction

The last decade researchers and policy makers have paid considerable attention to user benefits from an increased reliability of transport systems. Stated preference and revealed preference estimations show that travellers are willing to pay money to avoid travel time variability caused by unreliable transport systems (for overviews: RAND Europe, 2004; Brownstone and Small, 2005; Tseng, 2008; Li et al., 2010). Early research of Gaver (1968) and Knight (1974) already revealed the intuitive mechanism that an increase in the standard deviation of travel time leads to earlier departure times and corresponding higher travel costs. Our model uses this intuition and builds on the work of Small (1982) and Noland and Small (1995), that uses the concept of schedule delay to analyse the costs of travel time variability. In this view, travellers are not so much concerned by statistical measures as the standard deviation or the variance, but dislike travel time variability primarily because they can arrive early or late. They, of course, to some extent can anticipate on variable travel times by choosing their departure time optimally.

In the model of Noland and Small (1995), the natural assumption was made that travellers treat probabilities in an essentially linear way; travellers treat a probability that is twice as high as twice as likely. From the behavioural economic literature there is however quite some evidence that this is not the case in practice, and that probabilities

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32 This chapter is based on Koster and Verhoef (2012), forthcoming in Journal of Transport Economics and Policy. We like to thank Peter Wakker and participants of the ETC 2009 for valuable comments on earlier versions of this chapter. Furthermore, we like to thank Jasper Knockaert for provision of the data. The usual disclaimer applies. The data were gathered in the context of the Dutch peak avoidance project ‘Spitsmijden’. This research was partly funded by TRANSUMO. The project “Reliable accessibility of airports” was made possible with support of TRANSUMO (TRANsition SUsstainable MObility). TRANSUMO is a Dutch platform for companies, governments and knowledge institutes that cooperate in the development of knowledge with regard to sustainable mobility.
are weighted in a non-linear way (Wakker, 2010). Some recent empirical evidence shows that this may also be true for travel decisions (Hensher and Li, 2010).

In this chapter, we show how such probability weighting affects the choice of departure time, and how the travel costs are affected by probability weighting. The chapter is organised as follows: in the next section we show the relationship of our model with earlier literature. In section 4.3, we introduce probability weighting. In section 4.4, we present the behavioural model. In section 4.5, this model is applied using camera data from a highway in The Netherlands. Section 4.6 concludes and gives directions for future research.

4.2 Literature

The scheduling model of Small (1982) has become the workhorse model for evaluating the costs of travel time variability. The model is based on earlier work of Vickrey (1969) and shows how departure time decisions affect travel costs and how travellers choose their departure time ($t_h$) given their preferred arrival time ($pat$). The central idea is that travellers make a trade-off between travel time costs, and costs of being early or late. In the simplest setting, the cost function of a traveller with departure time from home $t_h$ is linear in its arguments and is given by equation (4.1), where the headstart $H$ is defined as $pat - t_h$ and $T$ as the total travel time. A discrete penalty for lateness, originally present in Small’s model, is not included to keep the model simple and because it is usually found to be insignificant, at least in Dutch applied research (see for example: Tseng, 2008). Other costs, such as fuel costs, are ignored also for simplicity. We then have:

$$C[H] = \alpha \cdot T + \beta \cdot SDE + \gamma \cdot SDL,$$

where:

$$SDE = \max(0, H - T),$$
$$SDL = \max(0, T - H).$$

In equation (4.1) the amount of time being early, or schedule delay early, is given by $SDE$ and schedule delay late is given by $SDL$. The value of travel time ($VOT$) is given by $\alpha$, the value of schedule delay early ($VSDE$) by $\beta$, and the value of scheduling delay late ($VSDL$)
by $\gamma$. These values have been frequently estimated in the literature.\textsuperscript{33} Empirical work shows that usually the relation $\beta < \alpha < \gamma$ holds.

This chapter is not concerned with the estimation of the WTP coefficients of equation (4.1). The main focus in this chapter will be how the departure time choice of a traveller is affected by these parameters and by the travel time when it is stochastic.

The original model of Small (1982) was extended to the case of stochastic travel times by Noland and Small (1995). They assume that the cost function is linear in its arguments and define the expected costs as in equation (4.2), where travel times are distributed with a probability density function $f(T)$.

\begin{equation}
E(C[H]) = \alpha \cdot E(T) + \beta \cdot E(SDE) + \gamma \cdot E(SDL),
\end{equation}

where:

\begin{align*}
E(T) &= \int_0^\infty T \cdot f(T) dT, \\
E(SDE) &= \int_0^H (H - T) \cdot f(T) dT, \\
E(SDL) &= \int_H^\infty (T - H) \cdot f(T) dT.
\end{align*}

Trip time decisions in this model are thus analysed in an expected costs framework where it is assumed that the travel costs are linear in its arguments. Travellers determine their optimal headstart given $f(T)$, $pat$ and $\alpha$, $\beta$ and $\gamma$. For the exponential and the uniform distribution Noland and Small (1995) showed the relationship between the optimal total expected costs and the distribution parameters. Later research analysed the model for a time dependent lognormal, Weibull and gamma travel time distribution (Koster et al., 2009) and for a general travel time distribution (Fosgerau and Karlström, 2010). The main motivation for these extensions was given by the fact that the parameters of the travel time distribution are not constant over time-of-day, and that the distribution of travel time is skewed (Van Lint et al., 2008). A particularly nice result of Fosgerau and Karlström (2010) is that the expected costs of a traveller who chooses his

\textsuperscript{33} For overviews of empirical studies we refer to Brownstone and Small (2005), Tseng (2008) and Li et al. (2010b).
optimal departure time are linear in the standard deviation of travel times if it is assumed that the standardised distribution is independent of the departure time.

A critical assumption of the Noland and Small model is that travellers know the distribution of travel time, and treat probabilities in a linear way, meaning that the ratio of weights attached to different outcomes is equal to the ratio of the probabilities. Because the model is usually applied for calculating the costs of commuting, the main argument for the first assumption is that travellers learn from earlier experiences. Ettema and Timmermans (2006) noted that the assumption of perfect knowledge can be unrealistic, and they therefore introduce the concept of a subjective probability distribution to analyse the potential benefits of travel information. In their model they assumed that travel information will result in a better perception of the probability distribution, and therefore in lower travel costs. However they do not study the relationship between the subjective and the objective probabilities explicitly. Therefore changes in the parameters of the objective distribution cannot be analysed as long as the relationship with the subjective distribution is not known, and cost-benefit analysis is not possible. Furthermore they assume that the subjective probabilities are treated in a linear way.

The second assumption of the Noland and Small (1995) model is that travellers treat probabilities in a linear way, so perceived probabilities are not affected by the risk attitude of the traveller. Batley (2007) analyses scheduling decisions using prospect theory with a discrete representation of departure times. He uses a transformation of the utility value of a prospect to analyse the effect of variable travel times when travellers are risk averse or risk seeking. The risk attitude in his model is then captured by the curvature of the utility function. Our approach differs from the approach of Batley (2007) in that we transform the probabilities, instead of the utility values of the arrivals. The idea of transforming the probabilities goes back to the work of Preston and Baratta (1948) and Mosteller and Nogee (1951). This approach is intuitive, since the risk perception of travellers is likely to primarily affect the perceived probabilities rather than the utility function. Recent empirical work by Hensher and Li (2010) in the context of travellers’ decisions, suggests that the risk perception would affect both perceived
probabilities and the utility function. This extension could be made to our model, but for now we choose to focus on probability weighting.

The risk perception of travellers is affected by at least two factors. The first factor is how travellers understand the concept of probability. It could be that travellers cannot make a distinction between different outcomes, and for example simply treat all outcomes as equally likely. The second factor is how pessimistic or optimistic travellers are. Pessimistic travellers will pay more attention to bad outcomes and therefore they assign a higher weight to these outcomes (Wakker, 2010). In this chapter, rank dependent utility theory is used to analyse departure time decisions when probabilities are weighted. The intuition behind rank dependence is that the attention that is given to a certain outcome does not only depend on the probability of that outcome, but also on the ranking of the outcomes. We use a probability weighting function for a general cumulative travel time distribution. This weighting function transforms the probabilities into decision weights (Diecidue and Wakker, 2001).

This chapter makes two contributions to the literature. First, we show analytically how probability weighting affects departure time decisions of travellers for a time-of-day independent travel time distribution. Although assuming such a travel time distribution is not realistic, we do this to show the basic intuition of the effect of probability weighting on departure time choice. Second, the rank dependent scheduling model is formulated for a time-of-day dependent travel time distribution and is compared to the standard scheduling model, to analyse how large the effect of probability weighting is on expected travel costs. If the effect is not large, policy makers can ignore probability weighting and use the simpler expected costs model to analyse the effect of travel time variability on the behaviour of travellers. This will be less costly to analyse, since there is no need to measure the probability weighting functions of individual travellers.

4.3 Rank dependent utility
This section introduces the concept of rank dependent utility which can explain the violations of behaviour consistent with expected utility as revealed by Allais (1953). Allais (1953) showed that decision makers transform probabilities when they face a risky choice, and that they do not treat probabilities linearly. This gave rise to the
development of new behavioural theories that could explain why expected utility maximization is violated.

A central element in rank dependent utility models is the probability weighting function, which defines a relationship between the cumulative density function (CDF) and the weighted CDF. In our context, this weighted CDF is used by the traveller to determine the optimal departure time from home. When a continuous representation of probability is used, a probability weighting function is needed that can describe a transformation of the cumulative density function of the travel times \( F(T) \). The weighting of the CDF, rather than weighting the probabilities themselves, is central in rank dependent utility theory and is based on the work of Quiggin (1982) and Schmeidler (1986). They extend the earlier theory of Kahneman and Tversky (1979) where the probabilities of the probability density function (PDF) were weighted. This model leads to problems since stochastic dominance may be violated. Quiggin (1982) analysed the case where the cumulative probabilities of events were known and transformed by a probability weighting function. These weighted cumulative probabilities are called decision weights. Schmeidler (1986) analysed the case where the probabilities were unknown. In his model he proposed event-decision weights because the weights are based on the ordering of the events.

Tversky and Kahneman (1992) based their model – which is well known as cumulative prospect theory (CPT), as opposed to “original prospect theory” of Kahneman and Tversky (1979) – on the work of Quiggin (1982) and Schmeidler (1986). The difference between CPT and rank dependent utility is that CPT is able to account for loss aversion and reference dependence. This means that travellers evaluate outcomes as gains or losses compared to a reference point. Loss aversion is measured through a utility function which is kinked at the reference point and is ignored in this chapter since it is difficult to determine in this context whether there exists a clearly defined reference point of the traveller, and if so, what it is. CPT also uses separate probability weighting functions for the loss and the gain domain. For example, De Borger and Fosgerau (2008) estimate loss aversion in a study on the VOT. An intuitive concept could be to weight the

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34 If the weighting function of the PDF is nonlinear, there is the possibility of an increasing utility but a lower evaluation value of an outcome (Wakker, 2010).
probabilities for early and late arrivals separately, or to use the reference arrival of $t_n + \mathbb{E}(T[t_n])$. However, it is not clear if the travellers use the mean or the mode (or another measure) as their reference point.

The shape of the weighting function can be explained by two behavioural factors. First, travellers can be 'likelihood insensitive'. Likelihood insensitivity means that travellers do not understand the concept of probability well. There are two types of likelihood insensitivity, which we can picture by imagining a graph with the CDF on the horizontal axis and the weighted CDF on the vertical axis. A frequently found weighting function is the inversely S‐shaped which is relatively horizontal in the middle and steep at both ends, meaning that travellers overweight extreme outcomes (Tversky and Wakker, 1995). Another possibility is the S‐shaped weighting function, where in the extreme case travellers entirely ignore the variability of travel times and treat the travel distribution as if it has 1 possible outcome.

Second, travellers can be pessimistic (risk averse) or optimistic (risk seeking). In the rank dependent scheduling model this risk attitude is modelled with the weighting function instead of the utility function. The three typical cases of pessimism (risk aversion), optimism (risk seeking) and likelihood insensitivity are given in Figure 4.1 (Wakker, 2010). Here we assume that the outcomes are ranked from good to bad. The probabilities are weighted according to equation (4.3), where $F(T)$ is the measured CDF and $W[F(T)]$ the weighted CDF.

\[
(4.3) \quad w[F(T)] = \frac{\partial W[F(T)]}{\partial T} = \frac{\partial W[F(T)]}{\partial F(T)} \cdot f(T).
\]

The probabilities of the measured PDF are given by $f(T)$, and are weighted by the first derivative of the weighted CDF with respect to the cumulative density function $F(T)$ to obtain the weights. In the next section it is analysed how probability weighting affects the choice of departure times.
Figure 4.1— Examples of pessimism or risk aversion (upper), optimism or risk seeking (middle) and S-shaped likelihood insensitivity (lower), when outcomes are ranked from best (left) to worst (right).
4.4 Optimal choice of departure time

4.4.1 Ranking of the outcomes

In this section we discuss the ranking of the outcomes in terms of travel costs. We assume that the preferences are bundled, meaning that we do not use different probability weighting functions for $T$, $SDE$ and $SDL$. Therefore, the decision weights are applied to the full outcome, i.e. the full set of attributes jointly, and not to individual attributes separately. For late arrivals, it is clear that a longer travel time implies, for a given departure time, a higher travel cost: both travel delay and schedule delay costs would increase. But when we make the conventional assumption that $\beta < \alpha$, a longer travel time also implies higher travel costs for early arrivals (again given the moment of departure). This assumption, $\beta < \alpha$, is rather intuitive, as it boils down to assuming that an early arriving traveller prefers terminating the trip above making a detour and benefiting at a rate $(\beta - \alpha)$ from such a voluntary trip duration extension.

Bundling is therefore justified in our context, implying that travellers can be assumed to rank the possible outcomes for a given departure time according to travel times. Our approach thus differs from the one proposed by Hensher and Li (2010), where travel times are ranked in terms of late arrival (least attractive), on-time arrival (most attractive) and early arrivals (in between). Their approach is not applicable in our setup, in which also the size of the schedule delay is important in determining the rank of the outcome, and not only the fact whether a traveller arrives early or late.

We rank the travel times from good to bad, which results in a travel cost ranking from low to high. The rank dependent travel costs are given by equation (4.4), where the travel time distribution is dependent on $H$. For simplicity we assume that the unit WTP values ($\alpha$, $\beta$ and $\gamma$) are independent of the time of day (see Tseng and Verhoef, 2008, for further discussion):

\begin{equation}
RD(C[H]) = \int_{0}^{\infty} C[H] \cdot \frac{\partial W[F[T;H]]}{\partial F[T;H]} \cdot f[T;H]dT.
\end{equation}
Inserting the cost function of equation (4.1) in equation (4.4), this can be rewritten as:

\[ RD(C[H]) = \alpha \cdot \mu_w[H] + \beta \cdot \int_0^H (H - T) \cdot \frac{\partial W[F[T; H]]}{\partial F[T; H]} f[T; H] dT + \]

\[ \gamma \cdot \int_H^\infty (T - H) \cdot \frac{\partial W[F[T; H]]}{\partial F[T; H]} f[T; H] dT. \]

(4.5)

In this equation, \( \mu_w[H] \) is the weighted mean travel time which depends on the departure time from home and therefore on the headstart \( H \), because the travel time distribution depends on \( H \). This rank dependent cost function will be used in the next sections to determine the optimal headstart and the numerical analysis.

4.4.2 Optimal choice of headstart

In this section the optimal headstart for a traveller is determined for a time-of-day independent travel time distribution, so we assume \( F[T; H] = F[T] \). Our analysis in this section follows Fosgerau and Karlström (2010). This section is mainly to show the intuitive effects of changes in the probability weighting function on the choice of departure time. We standardise the travel time distribution such that \( T = \mu + \sigma x \), where \( \mu \) is the mean, \( \sigma \) the standard deviation of travel times and \( x \) is a stochastic variable distributed with a cumulative distribution function \( G[x] \). Fosgerau and Karlström (2010) showed that in this case the first derivative of the expected cost function of equation (4.2) is given by:

\[ \frac{\partial E(C[H])}{\partial H} = -\gamma + (\beta + \gamma) \cdot G \left[ \frac{H - \mu}{\sigma} \right]. \]

(4.6)

The solution for the optimal headstart can be found by setting this first order condition to 0, and solve for \( H \). The optimal headstart is given in equation (4.7) and is linear in the standard deviation of travel times:

\[ HF^* = \mu + \sigma \cdot G^{-1} \left[ \frac{\gamma}{\beta + \gamma} \right]. \]

(4.7)

This solution holds for a general distribution and is unique because the cost function is convex for all values of \( H \).\textsuperscript{35} Now assume that a traveller chooses the optimal \( H \) according

\textsuperscript{35} As long as \( G'[x]>0 \) the solution is unique. Note that the second derivative of the expected cost function is given by:\( G'[(H-\mu)/\sigma] \cdot (\beta+\gamma)/\sigma >0. \)
to the weighted cumulative distribution function $W[G[x]]$. The first-order condition of equation (4.6) changes into:

$$\frac{\partial R_D(H)}{\partial H} = -\gamma + (\beta + \gamma) \cdot W\left[H - \mu \over \sigma\right].$$

The solution for the optimal headstart when probabilities are weighted is given by equation (4.9) where the inverse of $W$ is taken with respect to $G(x)$:

$$HW^* = \mu + \sigma \cdot G^{-1}\left[\frac{\gamma}{\beta + \gamma}\right].$$

Again, the optimal headstart is linear in the standard deviation of travel times and the solution is unique because the rank dependent cost function is convex in $H$. Figure 4.2 shows the implication of this result.

Figure 4.2— Optimised choice of headstart for optimistic (W₁) and pessimistic (W₂) travellers. The vertical axis shows the value of the (weighted) cumulative probability.

---

36 Suppose we want to solve $W[G[x]] = z$ for $x$. First substitute $y = G[x]$, so $W[y] = z$. Solving for $y$ using the inverse rule gives the solution $y = W^{-1}[z]$ which implies $G[x] = W^{-1}[z]$ if we substitute back $y = G[x]$. Applying the inverse rule again for $x$ gives $x = G^{-1}[W^{-1}[z]]$. The solution is unique because $W[G[x]]$ is a strictly increasing function in $G[x]$, and $G[x]$ is a strictly increasing function in $x$. 
In Figure 4.2 the optimal headstart for the standard scheduling model is given by $HF$. First, assume that a traveller is optimistic. This means that probabilities of low travel costs are overweighted and probabilities of high travel costs are underweighted. The weighting function is given by $W1$ in Figure 4.2. This weighting function is always above the $G[x]$ function (except for the corners). This means that the solution for the optimal headstart – which is given by $H1$ in the figure – is always smaller than $HF$. If travellers are pessimistic, the weighting function is given by $W2$ and is always below $G[x]$. In that case the optimal headstart is always larger than $HF$.

The effects of optimism and pessimism on the travel costs were analysed by Koster (2009). As expected, optimistic travellers will arrive late more frequently, and pessimistic travellers arrive early more frequently. In the empirical application, he finds that it is more costly to be an optimistic than a pessimistic traveller.

![Figure 4.3](image)

**Figure 4.3— Optimised choice of headstart with likelihood insensitivity. The vertical axis shows the value of the (weighted) cumulative probability.**

The case of likelihood insensitivity is given in Figure 4.3, where the weighting function is inversely S-shaped. The effect on the optimal headstart ($H3$) depends on the value
If we define $c^*$ as the intersection point of $W_3[,]$ and $G[,]$, the optimal headstart is lower than $HF$ for $\gamma/(\beta+\gamma) < c^*$, and higher than $HF$ for $\gamma/(\beta+\gamma) > c^*$. If $\gamma/(\beta+\gamma) = c^*$, travellers choose the optimal headstart and the costs of probability weighting are 0.

### 4.4.3 Extension to a model with a time-of-day dependent travel time distribution

In this section we formulate the model for a time-of-day dependent travel time distribution. It is assumed that the traveller optimises $H$ given his rank dependent cost function of equation (4.5). Denote the optimal headstart with probability weighting by $HW$, and without probability weighting (so when $W[F[T;H]] = F[T;H]$) by $HF$. The costs of probability weighting ($COPW$) are given by equation (4.10) and are equal to the extra costs because of probability weighting, compared to the expected costs model.

\begin{equation}
\text{(4.10)} \hspace{1cm} COPW = E(C[HF]) - E(C[HW]).
\end{equation}

The $COPW$ are always $\geq 0$ because the expected costs are calculated on the basis of objectively expected costs. Travellers never can do better than the expected costs model. As already shown by Fosgerau and Karlström (2010), there is no closed-form solution available if the travel time distribution depends on $H$. Therefore we will use numerical examples in the next section to calculate the costs of probability weighting.

### 4.5 Empirical application

In this section we will analyse, for a numerical example, the effects of likelihood insensitivity, and of optimism and pessimism. From a policy perspective it is useful to consider both phenomena, since the type of information that will improve the departure time decision will differ. If travellers are likelihood insensitive they need more information about how to deal with probabilities, how to understand differences between probabilities, and possibly feedback on their decisions can help to improve these on future occasions (see for example Van de Kuilen 2009 for a recent empirical test). If travellers are optimistic or pessimistic, more experience in travelling or more information on expected values can help to obtain a more appropriate view of the travel time distribution. In our numerical analysis we will use the weighting function of Prelec (1998) given in equation (4.11):
The weighted CDF of equation (4.11) is not defined at the point $F[T] = 0$, but in the limit $W_{Prelec}$ will go to 0 if $F(T)$ goes to 0 and it equals 1 if $F(T)$ equals 1. The first derivative with respect to $T$ is always larger than 0 as long as $\theta > 0$. When $\eta=\theta=1$, equation (4.11) reduces to $F(T)$. When the parameter $\eta$ increases, the weighting function shifts down and travellers are more pessimistic: they will overweight the probabilities of bad outcomes, so high travel costs will result. The parameter $\theta$ controls the shape of the weighting function. When $\theta$ goes to 0, the weighting function will be extremely inverse S-shaped. This means that travellers treat the distribution as if it has two mass points at the extremes. If $\theta$ goes to infinity, the distribution collapses into one intermediate mass point and the weighting function will be extremely S-shaped.

The travel time data we use has been obtained using license plate detection for a highway road stretch between Gouda and Zoetermeer, located near The Hague in the dense south-western part of the Netherlands, between March 2008 and July 2009. Only workdays are included, and school holidays are omitted. The free-flow travel time is around 5 minutes. The individual car data is aggregated to 5 minute time-of-day intervals. For every day the median travel time of an interval is used as a travel time observation. The median is used instead of the mean, because the mean is more influenced by outliers caused by the fact that there are ramps along the link, allowing some travellers to temporarily leave the road between the two points of measurement. The final dataset is interpolated to obtain 1 minute interval data. A travel time distribution has been fitted for every time period using a kernel smooth density estimator.\textsuperscript{37} Therefore, no distributional assumptions are needed.\textsuperscript{38} The time-of-day dependent mean and variance are plotted in Figure 4.4.

\textsuperscript{37} For each time period, we fit the travel time distribution using an optimal data-driven bandwidth, and use 100 equally spaced points (Bowman and Azzalini, 1997). All programming has been done in Matlab 7.6.0.
\textsuperscript{38} For example, Noland and Small (1995) assumed that the delays are exponential or uniformly distributed. Koster et al. (2009) assumed that the delays are Weibull, gamma or lognormal distributed and Fosgerau and Karlström (2010) assumed that the standardised distribution of travel times does not change over day-time.
Figure 4.4—Time-of-day dependent mean and standard deviation of the observed travel time distribution.
We choose typical values for the model parameters which are based on earlier estimations for Dutch commuters: $VOT = 8\text{€/h}$, $VSDE=0.6*VOT$ and $VSDL = 1.4*VOT$ (Tseng, 2008). For the parameters of equation (4.11) we choose the base values obtained from studies about gambling: $\theta=0.65$ and $\eta=1.1$ (Wakker, 2010), and will perform a sensitivity analysis afterwards.

First, we show in Figure 4.5 how the optimal headstart is affected by probability weighting. We do so by plotting the expected costs with and without probability weighting for an optimistic ($\eta=0.5$) and a pessimistic ($\eta=1.5$) traveller with $pat =8:30$.

![Figure 4.5 — The effect of optimism and pessimism on the optimal $H$ for a time-of-day dependent travel time distribution ($pat =8:15$).](image)

As expected, the rank dependent costs of the optimistic traveller is lower than without probability weighting, and the rank dependent costs for the pessimistic travellers is higher. The intuitive result of section 4.4.2 remains the same for a time-of-day dependent distribution. Optimistic travellers choose a smaller headstart than that without probability weighting, and pessimistic travellers choose a longer headstart. Note that the optimal head starts are given by the global minima of the curves in Figure 4.5.
Figure 4.6: The COPw for a numerical example.
The resulting optimal expected costs for all preferred arrival times are plotted in Figure 4.6. The travel time distribution is treated as given in our exercise, so no changes in equilibrium have been considered: the system is assumed to be in equilibrium already. The lowest line in Figure 4.6 gives the expected travel time costs without probability weighting. Those costs are proportional to the mean travel time. The middle line includes the expected scheduling costs. These scheduling costs are in the range of 10-31 per cent of the expected costs without probability weighting, and are somewhat higher than the empirical results of Fosgerau and Karlström (2010). The upper line indicates the expected travel costs when travellers apply probability weighting. The cost of probability weighting, $COPW$, are between 0 and 8 per cent of the total travel costs, and the average $COPW$ over the whole peak period are around 3 per cent of the total travel costs. The irregularities in travel costs with probability weighting can be explained by the fact that the distribution of travel times at different times of the day is estimated independently.39

Figure 4.7 shows the average share of the $COPW$ in the total expected costs over the whole peak period for different parameter combinations of the weighting function. The $COPW$ ranges from 0-24 per cent, and can be considered substantial when travellers are likelihood insensitive and pessimistic. The interpretation of the results is not straightforward because it is not possible to disentangle the effect of likelihood insensitivity and optimism/pessimism completely. For travellers that are not likelihood insensitive ($\theta=1$), optimism ($\eta<1$) is more costly than pessimism ($\eta>1$). However the effect is rather small and the $COPW$ are less than 3 per cent of total travel costs.

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39 We tested if for a given $t_{pat}$ a traveller can have an earlier (or equal) expected arrival time with a later $t_p$. This is never the case, and therefore the expected arrival time is strictly monotonically increasing if $H$ decreases. Therefore the irregularities are not explained by the fact that there are few departure times with low expected costs.
The effect of changes in the likelihood sensitivity parameter is higher. For values of $\theta<1$, higher pessimism is slightly more costly than optimism. For values of $\theta>1$, higher pessimism is approximately as costly as higher optimism. The combination of extreme pessimism and likelihood insensitivity results in the highest $COPW$ (24.2 per cent). Empirical investigation and estimation of the probability weighting function must show what the appropriate values of $\theta$ and $\eta$ are that can be used in cost-benefit analysis.

Finally, we analyse the effect of different WTP values on the average share of the $COPW$ in the total expected costs. Since only the relative values of $VSDE$ and $VSDL$ do matter for this Table 4.1, gives the results in terms of several values of $VSDE$ and $VSDL$ relative to $VOTT$, keeping $\eta$ and $\theta$ at the base values. Table 4.1 shows that the average share of the $COPW$ in the total travel costs is not so much changing for different WTP values and is in the range of 1.5-3.9 per cent.
Table 4.1 — Average percentage of the COPW in total travel costs for different WTPs.

<table>
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<th>β</th>
<th>γ=α</th>
<th>γ=1.2α</th>
<th>γ=1.4α</th>
<th>γ=1.6α</th>
<th>γ=1.8α</th>
<th>γ=2α</th>
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<td>0.2α</td>
<td>1.6</td>
<td>1.7</td>
<td>1.8</td>
<td>1.9</td>
<td>2.0</td>
<td>2.1</td>
</tr>
<tr>
<td>0.4α</td>
<td>2.3</td>
<td>1.9</td>
<td>2.3</td>
<td>2.4</td>
<td>2.4</td>
<td>2.6</td>
</tr>
<tr>
<td>0.6α</td>
<td>2.9</td>
<td>3.1</td>
<td>3.1</td>
<td>3.0</td>
<td>2.7</td>
<td>2.9</td>
</tr>
<tr>
<td>0.8α</td>
<td>2.8</td>
<td>3.4</td>
<td>3.7</td>
<td>3.7</td>
<td>3.9</td>
<td>3.8</td>
</tr>
</tbody>
</table>

4.6 Conclusions

In this chapter, we developed a rank dependent scheduling model. Using the concept of probability weighting we are able to derive the costs of likelihood insensitivity, optimism and pessimism. If the parameterised probability weighting function for car travellers is similar to what has been found in the literature on gambling, then we find costs of probability weighting (COPW) for car travellers in the morning peak that are on average around 3 per cent. We show that this result is rather robust for different assumptions on the WTP values. This figure, however, naturally changes when the probability weighting function changes; for the ranges of parameters we tested, we found the COPW in the range of 0 – 24 per cent.

The results must be interpreted with caution since there are very few studies in the area of travel behaviour that investigate the shape of the probability weighting function in the context of the scheduling model. The empirical estimation of probability weighting functions and the extension of the theoretical model using time-of-day dependent WTP values, non-linear utility functions and loss aversion can be interesting directions for future research.

Another extension could address our assumption that the travel time distribution is exogenous. Therefore an interesting direction for future work can be to use an equilibrium model where the travel time distribution is determined by the number of travellers and the variation in road capacity.
5

Analysing Observed Preference
Heterogeneity in Choice Experiments: A
Local Likelihood Estimation Approach

5.1 Introduction

Discrete choice models are widely used in economics in subjects as diverse as the demand for new products (e.g. Brownstone and Train, 1998), residential location choice (e.g. Bayer et al., 2005), brand choice (e.g. Swait and Erdem, 2007) and the value of travel time and reliability in transport economics (e.g. Small et al., 2005). The goal of discrete choice models is to estimate the conditional probability that an alternative is chosen as a function of explanatory variables $X$. However, assumptions on the functional form of the regression equation or the error distribution are arbitrary, as these are usually unknown. Inference based on the estimated coefficients may therefore be incorrect (Horowitz and Savin, 2001). During the last two decades, semiparametric or nonparametric models have been developed that relax assumptions regarding functional forms. Consider the following model:

$$
E(y|X) = G[v(X; \beta)],
$$

where $y$ is a dichotomous dependent variable, $X$ is a matrix of explanatory variables and $\beta$ is a vector of parameters that is unknown. Many widely used parametric models have this form, including linear regression, Probit, Logit and Tobit models (Horowitz and Härdle, 1996). Often, it is then assumed that $G[\cdot]$ is known and that $v(\cdot)$ is $X\beta$.

This chapter is concerned with estimating $v(\cdot)$ using flexible estimation techniques. A large literature focuses on the semiparametric estimation of $v(\cdot)$, given the assumptions

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40 This chapter is joint work with my brother, friend and colleague Hans Koster who is working also at the Department of Spatial Economics, VU University Amsterdam. Part of the work was done while I was visiting the Danish Technical University, Department of Transport. I like to thank Mogens Fosgerau, Katrine Hjorth, Thijs Dekker, Jan Rouwendal, Piet Rietveld and Vincent van den Berg for their valuable comments. The usual disclaimer applies.
on $G[\cdot]$.$^{41}$ The most popular application is the mixed Logit model that allows for unobserved heterogeneity in consumer demand, often given an assumption on the multivariate distribution of preferences $\beta$ (see, among others, Revelt and Train, 1998; Brownstone and Train, 1998; McFadden and Train, 2000; Small et al., 2005; Harding and Hausman, 2007). Other methods have been used to estimate $\nu(\cdot)$ nonparametrically, such as local polynomial methods (Fosgerau, 2007), a Box-Cox type Logit model (De Lapparent et al., 2002) or smoothing cubic splines (Fukuda and Yai, 2010), to name just a few.

Although these methods clearly offer a great potential to analyse unobserved heterogeneity and non-linearity in $\nu(\cdot)$, they do not link heterogeneity in preference parameters to observed characteristics of individuals. Therefore, these methods may not allow for extrapolation and predictions, as the source of heterogeneity remains unknown to the researcher (Horowitz and Savin, 2001). Especially for transport policy analysis it is interesting to know the sources of heterogeneity, as investment decisions have a long time-horizon and therefore changes in the population need to be taken into account.$^{42}$ When the distribution of individuals in the population changes (for example, the share of high-income earners in a specific area increases), predictions from a mixed Logit excluding this high-income variable will generally be incorrect. A method that explicitly links heterogeneity to observable individual characteristics may provide better predictions when the distribution of individuals changes. This provides an argument to explain as much as possible preference heterogeneity by observable individual characteristics (e.g. income, age, gender), as we expect that heterogeneity in preference parameters is to large extent caused by observable differences between individuals.

This chapter contributes to the choice modelling literature by proposing an econometric framework to analyse preference heterogeneity conditional on individual characteristics, using data from a stated choice experiment.$^{43}$ More specifically, we

$^{41}$ Many scholars also have developed methods that aim to relax assumptions concerning $G[\cdot]$ or estimate fully nonparametric binary choice models (see among others Han, 1987; Matzkin, 1992; Ichimura, 1993; Sherman, 1993; Klein and Spady, 1993; Horowitz and Härdle, 1996).
$^{42}$ For a discussion of the effect of preference heterogeneity on the distributional effects of transport policies we refer to Van den Berg and Verhoef (2011).
$^{43}$ Choice experiments are often used to estimate preference parameters which serve as inputs for analysing the potential demand for new products (Brownstone and Train, 1998). These experiments
estimate a semiparametric binary choice model, where the preference parameters $\beta$ are individual-specific and are dependent on individual characteristics.\textsuperscript{44} We estimate semiparametric distributions of preferences, by employing local-likelihood methods proposed by Fan et al. (1995), Fan and Gijbels (1996) and Fan et al. (1998) and by assuming that individuals who are more similar in terms of socio-economic characteristics will have more similar preference parameters.\textsuperscript{45} To learn about how preferences vary over the population, we will summarise the results by regressing the estimated preference parameters on individual characteristics. A similar approach is used in the literature on hedonic pricing (Bajari and Kahn, 2005; Bajari and Benkard, 2005).

Our estimation procedure has several advantages compared to other techniques. First, our method focuses on observed heterogeneity and adequately defines the sources of heterogeneity. Compared to other estimation techniques, our approach has the advantage that it relates heterogeneity to observable individual characteristics, and enables us to make better predictions when the composition of the population changes. For example, the income may increase, travellers will get older and more women may enter the job market. Our results can be used to predict the new distributions of WTP-values. It is common to allow for observed heterogeneity in transport models and therefore researchers have included individual characteristics in the estimation. For example, Hague Consulting Group (1990) analysed the value of travel time savings (VOT) and find that there are a lot of observables (income, gender, household composition etc.)

\textsuperscript{44} This type of model related to local linear techniques that are often applied in the hedonic price literature, where parameters are estimated \textit{conditional} on the geographic location (also known as geographically weighted regression) (McMillen and Redfearn, 2010). However, these methods are neither extended to binary choice models, nor conditioned on individual characteristics.

\textsuperscript{45} We use a different setup than that of Fosgerau (2007), because we condition on observable individual characteristics, whereas Fosgerau conditioned on $X$. Our method shares some similarities with the residential sorting models of Bayer et al. (2005), Bayer and Timmins (2007) and Bayer et al. (2007), where preference parameters are interacted with individual characteristics in a to obtain individual-specific preference parameters. Our estimation procedure is more flexible and uses fewer degrees of freedom.
that affect that the VOT. Our method provides a more flexible econometric technique to analyse preference heterogeneity.

Second, our method does not make any distributional assumptions on the preferences (in contrast to most applications of the mixed Logit model). It also allows for all interactions between individual characteristics and preferences, but it is shown that it uses far fewer degrees of freedom than fully nonparametric estimation of \( v(\cdot) \) (so, our method does not suffer from the well-known curse of multidimensionality) (Horowitz and Savin, 2001; Bontemps et al., 2008; McMillen and Redfearn, 2010, Park et al., 2010). Third, although our procedure is very flexible, it is computationally light and can be estimated using routines available in standard statistical software packages.

We apply our method to estimate commuters’ value of travel time and value of arriving at the preferred arrival time at work. The data is obtained using a stated choice experiment held among participants of a real-world rewarding experiment to combat congestion. Previous studies show that commuters are willing to pay for travel time savings and reductions in schedule delay, where schedule delay refers to arriving at a different time at work than the preferred arrival time (Small, 1982; Lam and Small, 2001; Brownstone and Small, 2005; Small et al., 2005). We estimate the willingness to pay values (WTP) for reductions in travel time (VOT), schedule delay early (VSDE) and late (VSDL). We show that the sample average WTP-values are close to the values estimated by an ordinary Logit model, which increases confidence in the estimation procedure. It is shown that there is substantial observed heterogeneity in the VOT, VSDE and VSDL. We link heterogeneity to observable individual characteristics, by regressing the estimated parameters on individual characteristics in a second stage. For example, we find that individuals with high incomes have a higher value of time and scheduling costs. Women have 25% higher values of schedule delay and presence of young kids in the household increases the VSDE with 33%, as young kids usually impose strong scheduling constraints.

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46 Some exceptions are Ichimura and Thompson (1998), Fosgerau (2006), Fosgerau and Nielsen (2010) and Train (2010) who employ distribution-free estimation techniques. Others estimate individual level parameters directly (see for example, Louviere et al., 2008).

47 We use Matlab to estimate this model, but the model can also be estimated in Stata.
The chapter continues as follows. Section 5.2 introduces the econometric setup. In Section 5.3, we discuss the choice experiment followed by the empirical results in Section 5.4. Section 5.5 concludes.

5.2 Econometric setup

5.2.1 Introduction

This subsection discusses the motivation behind the estimation approach, based on a simple example. Suppose we aim to estimate the value of travel time savings (VOT) and aim to investigate heterogeneity in the VOT. We do so by setting up a stated preference experiment where individuals trade-off a hypothetical monetary reward ($R$) and travel time ($T$). We have collected data for the dummy variables high income ($INC$) and female ($FEM$), and we aim to test if these variables affect the VOT. Utility ($U$) is given by the sum of a deterministic part ($V$) and a stochastic part ($\varepsilon$). The standard specification of the deterministic part of the utility without any interaction terms is then given by:

\[
V = \beta_R \cdot R + \beta_T \cdot T.
\]

The VOT is then given by $-\beta_R / \beta_T$ and shows how much of the reward the traveller is willing to give up for a decrease in travel time. Gender and income can affect the sensitivity to rewards and the sensitivity to travel times. Furthermore, it may be that for some reason the income effect for men is different than for females. In order to test for all these possibilities we can specify the model as:

\[
V = (\beta_R + \beta_{R,INC} \cdot INC + \beta_{R,FEM} \cdot FEM + \beta_{R,INC,FEM} \cdot INC \cdot FEM) \cdot R + \\
(\beta_T + \beta_{T,INC} \cdot INC + \beta_{T,FEM} \cdot FEM + \beta_{T,INC,FEM} \cdot INC \cdot FEM) \cdot T.
\]

The specification of equation (5.3) is a nonparametric specification in the sense that no assumptions on $V$ are imposed for the dummy variables $FEM$ and $INC$. In the remainder of the chapter, we will refer to this model as the saturated model (so, the model where all possible interactions between individual characteristics and explanatory variables are taken into account). In equation (5.3), $\beta_R$ and $\beta_T$ are the sensitivities to changes in rewards and travel times for men with low income. The corresponding VOT is then:
One key observation from equation (5.4) is that more similar people in terms of the variables $INC$ and $FEM$ have more similar estimated VOT values. This is plausible from an economic perspective, and it is this intuition that motivates the econometric approach developed in the next section. The main drawback of the saturated specification (see (5.3)) is that it is very demanding in terms of data. For two characteristics it can be estimated, but the number of parameters to be estimated increases rapidly if more individual characteristics are included. To overcome this problem we use kernel smoothing, a technique that will be explained in more detail in the next sections.

5.2.2 Local Logit estimation

Fan et al. (1995), Fan and Gijbels (1996) and Fan et al. (1998) introduce local likelihood estimation. This estimation procedure can be used to estimate choice probabilities in a stated choice experiment, under the assumption that more similar choices in terms of weighting variables, result in more similar estimated choice probabilities. The term ‘local’ means that each local point (e.g. individual, observation) is treated as a reference point. Conditional on the local point, a weight is assigned, which defines the (multidimensional) distance between the local point and the other points in the dataset. It is up to the researcher which variables to include as weighting variables. For example, Fosgerau (2007) includes the explanatory variables ($X$) in the weight matrix, meaning that choices of respondents with more similar $X$ will have more similar estimated choice probabilities. Local Logit can also be used to analyse nonlinearities in the preference parameters caused by individual characteristics.48 This approach is also used by Frölich (2006), who analyses the effect of having children on the employment rate. He shows that with local Logit estimation, more can be learned from the data compared to ordinary Logit regression.

48 Park et al. (2010) study the theoretical properties of our estimator and show that the rate of convergence does not depend on the presence of discrete explanatory variables. They also use simulation to show that local likelihood estimation performs well, even for small sample sizes.
The dependent variable $y$ is the choice that is made. In our case it is binary; it is 1 if alternative 1 is chosen and 0 otherwise. Suppose that $I$ individuals make $T$ choices each, out of $J$ alternatives with $K$ explanatory variables. The probability that alternative $j$ is chosen is a function of the $IT \times J \times K$ matrix of explanatory variables $X$, and the $IT \times K$ matrix of preference parameters $\beta$. We use the notation $\beta_i$ to indicate the $K \times 1$ vector of preference parameters of individual $i$. Because later on we condition on individual characteristics, $\beta_i$ does not change over the sequence of choices of an individual, so $\beta_{i1} = \beta_{i2} = \cdots = \beta_{iT}$. Furthermore, we use $x_{it}$ to denote the $J \times K$ matrix of explanatory variables for choice $t$ of individual $i$, and $x_{itj}$ as the $1 \times K$ vector of explanatory variables for alternative $j$ of choice $t$ of individual $i$.

Since we are interested in observed heterogeneity, we estimate how individual characteristics $Z$ affect the preference parameters $\beta$. We condition on individual characteristics $q = 1 \ldots Q$ and $Z$ is a $IT \times Q$ matrix with characteristics. The preference parameters depend in a nonlinear way on $Z$. This means that all interactions of the different variables in $Z$ are modelled implicitly. The probability that individual $i$ chooses alternative $j^*$ for choice $t$ is given by the standard Logit formula and is given by:

$$P_{it}^*(\beta_i; x_{it}) = \frac{e^{x_{itj}^T \beta_i}}{\sum_{j=1}^J e^{x_{itj}^T \beta_i}}.$$

The goal is to estimate the probabilities of the chosen alternatives as close as possible to 1. The vector of preference parameters of individual $i = 1, \ldots, I$ can then be estimated by maximising the local likelihood:

$$\hat{\beta}_i = \arg\max_{\beta_i} \sum_{l=1}^I \sum_{t=1}^T w^{it}[Z; \lambda] \cdot \log[P_{it}^*(\beta_i; x_{it})].$$

Equation (5.6) shows that the local log-likelihood is calculated by taking the log of the probability of the chosen alternative, multiplied by a $IT \times 1$ vector of weights $w^{it}[Z; \lambda]$. The log of the probability of the chosen alternative depends on the independent variables and the preference parameters, and the local likelihood needs to be maximised in order to arrive at the local estimate $\hat{\beta}_i$. The weights depend on the socio-economic ‘distance’ of an individual compared to the other individuals, and on the $Q \times 1$ vector of
bandwidths $\lambda$. More specifically, in the example of the previous section, the socio-economic distance is determined by the variables $INC$ and $FEM$. Estimation of a local Logit model for these variables yields the estimation of a Logit model for each unique combination of $INC$ and $FEM$. Because $INC$ and $FEM$ are dummy variables this yields the estimation of four binary Logit models. People with exactly the same $INC$ and $FEM$ have the same weights in the likelihood function and therefore the estimated preference parameters $\hat{\beta}_i$ are the same.

The bandwidths $\lambda$ determine the degree of smoothing. For strong smoothing (a high bandwidth), the weights are uniform and the model reduces to the ordinary Logit model. For weak smoothing (a low bandwidth), the model becomes a saturated model, as in equation (5.3). This is an appealing feature of the estimation setup, as the saturated model and the ordinary Logit model are special cases of our model.

5.2.3 Kernel functions

The individual-specific weights are based on the socio-economic distance between individuals and are calculated using a kernel function. When the difference in socio-economic space between individual $i$ and an other individual becomes smaller, the other individual is weighted heavier in the local regression of $i$ (and vice versa). This implies that if people are more alike, they have more similar preferences.

We include $Q$ variables in the kernel function. Each of these variables has a corresponding kernel function $K^q(\cdot)$ and bandwidth $\lambda_q$. When $\lambda_q$ increases, more observations in the ‘neighbourhood’ are taken into account in the Logit estimation of $i$. Larger bandwidths may create a larger bias when the underlying function is nonlinear (Fan and Gijbels, 1996). A lower bandwidth leads to a better model fit and therefore to a higher value of the likelihood function, but increases the variance of the estimator. In the present analysis, we assume $\lambda_1 = \lambda_2 = \cdots = \lambda_Q = \lambda$, so the bandwidth is equal for all variables in the weight matrix. A univariate bandwidth simplifies the analysis and results in substantial saving in computation time.49

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49 This is because the computation time increases exponentially in $Q$. We refer to Yang and Tschernig (2002) for a discussion on multivariate bandwidths. The analysis of multivariate bandwidth optimisation...
We employ a mixed kernel function, implying that the kernel function does not need to be the same for each variable. A general specification of the weights is then:

\[(5.7) \quad w^i[Z; \lambda] = \prod_{q=1}^{Q} K^q(\lambda; z_{iq} - z_q).\]

In this equation \(z_{iq} - z_q\) is the distance of individual \(i\) to all other individuals for vector \(z_q\). The kernel function \(K^q\) is a multidimensional distance metric that decreases in the distance between individual \(i\) and the other individuals. For a fixed number of individuals \(I\) and number of choices \(T\), adding characteristics to the kernel leads to a sparser socio-economic space.

In our analysis we only use categorical individual characteristics. Racine and Li (2004) show that for these variables one needs a kernel function that has the possibility to be an indicator function and that has the possibility to smooth out a categorical variable. The last property does not hold if a continuous kernel function is used for dummy variables, because the kernel function never can have weights that are equal for all observations. For a model with ordered categorical variables, the kernel function is (Hall et al., 2007; Racine and Li, 2004):

\[(5.8a) \quad K^q(\lambda; z_{iq} - z_q) = \begin{cases} 1, & \text{if } z_{iq} = z_q \\ \lambda|z_{iq} - z_q|, & \text{if } z_{iq} \neq z_q. \end{cases}\]

For unordered categorical variables the kernel function is given by:

\[(5.8b) \quad K^q(\lambda; z_{iq} - z_q) = \begin{cases} 1, & \text{if } z_{iq} = z_q \\ \lambda, & \text{if } z_{iq} \neq z_q. \end{cases}\]

In equations (5.8a) and (5.8b), the bandwidth \(\lambda\) has to be between 0 and 1. One can verify that if \(\lambda\) equals 1, the weights are equal to 1 and therefore the variable \(q\) is smoothed out, implying that the variable has no effect on the estimated preference parameters. If \(\lambda = 0\), Equations (5.8a) and (5.8b) are indicator functions, which implies that the sample is divided in two parts, when the variable of interest is a dummy

---

*and possible shortcuts to reduce computation times are beyond the scope of this chapter. However, in our sensitivity analysis we do an additional check on multivariate bandwidths.*
variable. For example, if we include the variable $FEM$ in the weight matrix, and assume $\lambda = 0$, a separate Logit model will be estimated for males and females.

We use a mixed Kernel function, so we use both ordered and unordered categorical variables.\footnote{It is also possible to include continuous individual characteristics by using a Gaussian or exponential weighting function. As in equation (7), the weights are then a product of the different characteristics with different kernel functions (Racine and Li, 2004).} If $\lambda = 0$, we have a saturated specification, meaning that for every combination of characteristics a separate model is estimated. When $\lambda = 1$, the model is identical to the ordinary binary Logit model without covariates. For intermediate values of $\lambda$, the model will use fewer parameters than in a fully saturated specification, but more than in the binary Logit case. This is because information of neighbouring individuals is used for the estimation of the preferences of the local reference individual. However, we cannot arbitrarily choose $\lambda$, and therefore in the next section we show how to determine $\lambda$.

5.2.4 Model and bandwidth selection

The next step is to determine which socio-economic characteristics to include in the kernel and which bandwidth to select. A socio-economic characteristic that is included in the kernel function only potentially affects the estimated preference parameters. In order to investigate if adding a socio-economic characteristic significantly improves the model, we use the corrected Akaike Information Criterion ($AICC$) statistic as proposed by Hurvich et al. (1998) to be defined below. The $AICC$ is similar to the well known $AIC$-criterion, but includes a correction for small sample sizes. It trades off bias (as measured by the likelihood) and variance, or equivalently, the model fit versus the number of parameters used in the model (Akaike, 1973; Davidson and McKinnon, 2004).

The number of parameters in our semiparametric model is approximated using the sum of the diagonal elements (trace) of the hat matrix $\text{tr}(\hat{H})$. This hat matrix is derived in Appendix A, and the elements on the diagonal provide an indication how an observation influences the model fit (Hoaglin and Welsch, 1978). The $AICC$ of Hurvich et al. (1998) is minimised to determine the optimal bandwidth and is given by:
\[ AICC(\lambda) = \frac{-2 \cdot LL[\hat{\beta}]}{IT} + \frac{IT + \text{tr}(\hat{H})}{IT - \text{tr}(\hat{H}) - 2} \]

In this equation \( IT \) is the number of observations in our dataset. \( LL[\hat{\beta}] \) is the global likelihood of the model evaluated at the \( IT \times K \) matrix of all the locally estimated parameters \( \hat{\beta} \). The first part of equation (5.9) is the average global likelihood and is the measure of model fit. A higher average global likelihood will result in a lower value of the \( AICC(\lambda) \). A decrease in the bandwidth will result in a better model fit, and therefore in a higher average global likelihood. The proxy for the number of parameters is given by \( \text{tr}(\hat{H}) \), which is the trace of the hat matrix. The last part of equation (5.9) therefore accounts for the number of parameters in the model. An increase in \( \text{tr}(\hat{H}) \) results in a higher value of the \( AICC \). A decrease in the bandwidth will result in a higher number of parameters, so in an increase in \( \text{tr}(\hat{H}) \).

The \( AICC \) is used to determine the optimal bandwidth given a set of covariates and to test the model specification against other specifications (e.g. the ordinary Logit model). Using this criterion, we also determine which characteristics add significant explanatory power by testing a model including all individual characteristics in the kernel against an alternative where one characteristic of interest is omitted. As a widely accepted rule of thumb, an alternative model is considered as significantly better if the \( AICC \) decreases with more than \( 3/(IT) \) (Charlton, 2009).

5.3 Experimental setup and data

5.3.1 Setup of the choice experiment

A stated choice experiment is developed to collect data about the preferences of morning-commuters participating in a peak-avoidance project. The questionnaire was send to them via an Internet link. In order to reduce congestion commuters participating in this project are rewarded if they do not travel between cameras A and B during the morning peak (6:30-9:30). Travelling outside the peak usually results in savings of travel time cost, but comes with a higher scheduling cost. The reward that travellers receive is
to compensate for this additional scheduling cost. An example of a choice question is given by Figure 1.51

![Your preferred arrival time if there is no delay is: 8:40.](image)

<table>
<thead>
<tr>
<th>Departure time from home</th>
<th>Alternative 1</th>
<th>Alternative 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probability</td>
<td>6:05</td>
<td>6:50</td>
</tr>
<tr>
<td>Total travel time</td>
<td>80%</td>
<td>90%</td>
</tr>
<tr>
<td></td>
<td>20%</td>
<td>10%</td>
</tr>
<tr>
<td>Travel time from home to camera A</td>
<td>30 min</td>
<td>20 min</td>
</tr>
<tr>
<td></td>
<td>40 min</td>
<td>35 min</td>
</tr>
<tr>
<td>Travel time from camera A to camera B</td>
<td>15 min</td>
<td>10 min</td>
</tr>
<tr>
<td></td>
<td>15 min</td>
<td>10 min</td>
</tr>
<tr>
<td>Travel time from camera B to work</td>
<td>5 min</td>
<td>5 min</td>
</tr>
<tr>
<td></td>
<td>10 min</td>
<td>10 min</td>
</tr>
<tr>
<td>Arrival time at work</td>
<td>6:35</td>
<td>7:10</td>
</tr>
<tr>
<td></td>
<td>6:45</td>
<td>7:25</td>
</tr>
<tr>
<td>Reward</td>
<td>4 euro</td>
<td>0 euro</td>
</tr>
</tbody>
</table>

Figure 5.1 — Example of a choice question.

The departure time experiment is done conditional on the choice of car as a transport mode. Respondents were asked to choose between two departure times. To reflect that travel time is variable, each departure time has two possible travel times with a corresponding probability, arrival time at work and reward. Above the choice question, the preferred arrival time ($PAT_t$) of the traveller is given as a reminder. It is based on previous questions in the questionnaire and is defined as the time that a traveller would like to arrive at work if there is no possibility to receive a reward, and there is no travel time delay. The lay-out has been pre-tested in a focus-group and internet pre-tests were carried out to ensure that respondents understand the questions well. The attribute values for travel times are pivoted around the average travel time of the respondent to enhance realism (see Hensher, 2010). The efficiency of the experimental design has been pre-tested using extensive simulation. More details about stated choice experimental designs for scheduling models are given in Koster and Tseng (2010) and Knockaert et al. (2011).

We excluded respondents who stated that they answered randomly and for whom no observed characteristics were available. In total we are left with 486 individuals in our dataset, making 10 choices each. For each individual we have information on gross 51 It is possible that a travel delay between home and camera A results in missing the reward. Therefore we also offered choices where the reward is stochastic.
monthly income, level of education, gender, age and household composition (single, kids, etc.). The summary statistics of the individual characteristics are presented in Table B1 in Appendix B.

Compared to the Dutch average, we have a large share of high incomes and highly educated travellers. In our sample, about 84% has a bachelor degree or higher. We also have a relatively high share of males in our sample (76%). Almost 50% of the individuals in our sample do not have kids and more than 75% is between 25 and 50 years old.

5.3.2 Utility specification at the local level

We assume that the deterministic part of the utility \( V_{itj} \) of individual \( i \) facing choice \( t \) and choosing alternative \( j \) is explained by three types of variables: expected reward \( E(R)_{itj} \), expected travel time \( E(T)_{itj} \) and expected schedule delay \( E(SD)_{itj} \). Schedule delay is defined as the deviation of an arrival time from the preferred arrival time \( PAT_i \). Vickrey (1969) and Small (1982) introduced this scheduling model, where arrivals different from \( PAT_i \) result in a disutility. Their model was extended to a model with stochastic travel times by Noland and Small (1995), where each departure time from home can have multiple outcomes for the arrival time at work. The expected utility of individual \( i \) that makes choice \( t \) by choosing alternative \( j \) is defined as follows:

\[
U_{itj} = \frac{1}{\theta_i} \cdot V[\beta_i; E(R)_{itj}, E(T)_{itj}, E(SD)_{itj}] + \varepsilon_{itj}.
\] (5.10)

Equation (5.10) shows that utility is an additive function of the deterministic part and the random component \( \varepsilon_{itj} \). The \( \beta_i \)'s are individual-specific and are only exactly the same for respondents with the same characteristics. The scale of utility \( \theta_i \) is made explicit and cannot be estimated together with the preference parameters (see Train and Weeks, 2005). In order to capture travel time variability, each departure time from home \( DT \) has \( A \) possible outcomes of the travel time resulting in \( A \) corresponding arrival times. The schedule delay of mass point \( a = 1 \ldots A \) is given by the following equations:

\[
SDE_{itja} = \max(0; PAT_i - DT_{itj} - T_{itja}), \tag{5.11a}
\]
These equations define the scheduling model introduced by Vickrey (1969) and Small (1982). Schedule delay disutility is a piecewise linear function of arrival time. So, besides the disutility of travel time, there is additional disutility of not arriving at the preferred arrival time, where the marginal disutilities of being early and late are valued differently by travellers. As Figure 5.1 shows, every departure time has 2 possible outcomes for the travel time, implying that $A = 2$. Both arrival times have a corresponding probability $p_{itj}$ and $1 - p_{itj}$ respectively. The model variables are the averaged values over these two mass points and are calculated as:

\begin{align}
E(R)_{itj} &= p_{itj} \cdot R_{itj1} + (1 - p_{itj}) \cdot R_{itj2}, \\
E(T)_{itj} &= p_{itj} \cdot T_{itj1} + (1 - p_{itj}) \cdot T_{itj2}, \\
E(SDE)_{itj} &= p_{itj} \cdot SDE_{itj1} + (1 - p_{itj}) \cdot SDE_{itj2}, \\
E(SDL)_{itj} &= p_{itj} \cdot SDL_{itj1} + (1 - p_{itj}) \cdot SDL_{itj2}.
\end{align}

The deterministic part of the utility is then given by the sum of the expected reward, expected travel time and expected schedule delay variables multiplied by the preference parameters:

\begin{equation}
V_{itj} = \frac{1}{\theta_i} \cdot (\beta_{R,i} \cdot E(R)_{itj} + \beta_{T,i} \cdot E(T)_{itj} + \beta_{SDE,i} \cdot E(SDE)_{itj} + \beta_{SDL,i} \cdot E(SDL)_{itj}).
\end{equation}

It is assumed that other transport cost are equal for both alternatives. In order to compare the local estimates, the WTP-values are used. These are defined as follows:

\begin{align}
VOT_i &= -\frac{\beta_{T,i}}{\beta_{R,i}}, \\
VSDE_i &= -\frac{\beta_{SDE,i}}{\beta_{R,i}}.
\end{align}
(5.14c) \[ VSDL_i = -\frac{\beta_{SDL,i}}{\beta_{R,i}}. \]

These values are used to compare the estimates of each individual. As the scale parameter \( \theta_i \) may vary over the different local estimates, the absolute values of the locally estimated preference parameters for different individuals cannot be compared directly. In equations (5.14a), (5.14b) and (5.14c), the scale parameter drops out and the estimates of the different individuals can be compared. In order to have a plausible model from an economic perspective, we assume that the WTP-values should be larger or equal than 0. This additional constraint is added to the model and bandwidth selection procedure. So, we choose the model with the lowest AICC out of the set of economically plausible models.

### 5.4 Estimation results

#### 5.4.1 Baseline results

In this section we present the estimation results. We start with a simple model where we only include one individual characteristic in the kernel function (see equation (5.7)). In Section 5.4.2, we discuss the models with one individual characteristic included in the kernel. So, we provisionally assume that heterogeneity in preferences is caused by only one individual characteristic, for example, income, gender or age. Subsequently, we present a model including all characteristics in Section 5.4.3. We then regress the estimated preference parameters on individual characteristics. Table 5.1 summarises the main estimation results. It provides the average values of time and schedule delay of the sample for the models that are estimated.
### Table 5.1 — The average value of time, schedule delay early and late for different estimation procedures

<table>
<thead>
<tr>
<th></th>
<th>Binary Logit</th>
<th>Semiparametric Logit with univariate kernel</th>
<th>Semip. Logit w/multivariate kernel</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Income</td>
<td>High Education</td>
<td>Age &lt;25</td>
</tr>
<tr>
<td>VOT</td>
<td>32.62</td>
<td>38.22 (8.55)</td>
<td>38.85 (6.08)</td>
</tr>
<tr>
<td>VSDE</td>
<td>22.97</td>
<td>24.93 (4.06)</td>
<td>24.89 (2.62)</td>
</tr>
<tr>
<td>VSDL</td>
<td>16.20</td>
<td>18.27 (2.75)</td>
<td>18.34 (1.95)</td>
</tr>
<tr>
<td>CV VOT</td>
<td>--</td>
<td>0.223</td>
<td>0.156</td>
</tr>
<tr>
<td>CV VSDE</td>
<td>--</td>
<td>0.163</td>
<td>0.105</td>
</tr>
<tr>
<td>CV VSDL</td>
<td>--</td>
<td>0.151</td>
<td>0.106</td>
</tr>
<tr>
<td>$\lambda'$</td>
<td>--</td>
<td>0.350</td>
<td>0.250</td>
</tr>
<tr>
<td>AICC($\lambda'$)</td>
<td>2.121</td>
<td>2.119</td>
<td>2.120</td>
</tr>
<tr>
<td>$\text{tr}(\tilde{H})_{d=\lambda'}$</td>
<td>--</td>
<td>11.800</td>
<td>9.261</td>
</tr>
<tr>
<td>AICC (0)</td>
<td>2.121</td>
<td>2.124</td>
<td>2.122</td>
</tr>
<tr>
<td>$\text{tr}(\tilde{H})_{d=0}$</td>
<td>7.991</td>
<td>31.450</td>
<td>15.750</td>
</tr>
</tbody>
</table>

| Number of Choices (N) | 4,860 | 4,860 | 4,860 | 4,860 | 4,860 | 4,860 |
| Number of Individuals (I) | 486 | 486 | 486 | 486 | 486 | 486 |

**NOTE:** WTP-values are in euros per hour. CV denotes the coefficient of variation and is the standard deviation divided by the mean. The standard deviations of the WTP-values are between parentheses. For all models AICC is improving with more than 3/N points compared to the ordinary Logit, but high education and Age <25 are only marginally significant (Charlton 2009). N/A stands for ‘not available’: the number of parameters is too high to estimate the model. All variables in the multivariate estimation are significant, implying that if we leave them out, the AICC increases with more than 3/N points.

The average WTP-values are rather similar to the ordinary Logit model, except for the model with a multivariate kernel function, where the sample average WTP-values are slightly higher. The pattern VOT>VSDE>VSDL is the same for all models and is remarkable, since usually VSDL>VSDE is found in the literature (Lam and Small, 2001; Brownstone and Small, 2005; Li et al., 2010). However, we have a relative high share of individuals with an early preferred arrival time in our dataset, as we only analyse the preferences of individuals participating in the rewarding experiment, so this result is not too surprising. However, only VOT>VSDE is required for an economic plausible model (otherwise, travellers prefer longer trips over arriving too early). In general, the WTP-values are higher than found by earlier estimations in the literature (see for example: Brownstone and Small, 2005; Tseng, 2008; Li et al., 2010). There may be two reasons for this. First, on average we have a high share of high-income travellers in our sample and since these have a lower marginal utility of income they are less sensitive to rewards than average commuters. Second, it is very likely that travellers are less sensitive to
rewarding incentives than to the payment of a congestion toll or higher costs of fuel. This difference in valuation of gains and losses is a common finding in prospect theory studies (see for an overview: Wakker, 2010). All semiparametric models are statistically significantly better than the ordinary Logit model. As a benchmark we provide the saturated model ($\lambda = 0$) in Table 5.1, which implies that we estimate separate Logit models for each value of the variable included in the weight matrix. This benchmark case is not available for the multivariate model because the number of unique individuals is too large to estimate separate models. The proxy for the number of parameters is given by $\text{tr}(\mathbf{H})$, and as Table 5.2 indicates, the semiparametric models only use slightly more degrees of freedom than the ordinary Logit model.

### 5.4.2 Univariate kernel weights

The estimated WTP-values for several income classes are shown in Figure 5.2. Not surprisingly the WTP-values increase in income in a similar way. This effect is due to the effect of income on the sensitivity to rewards, as all WTP-values have the reward coefficient in the denominator (see equations (5.14a), (5.14b) and (5.14c)).

It is shown in Figure 5.3 that travellers with a higher education have higher WTP-values. However, education is a proxy for income, so it is still unclear if there is a separate education effect. The VOT is affected more strongly than the values of schedule delay, which may reflect more flexible job starting of highly educated people. Figures 5.4 and 5.5 present the effect of age. People younger than 25 have lower WTP-values, while older people have a higher VSDL. However, because variables such as age and income may be correlated, we need a multivariate analysis to disentangle the effects of income and age.
5.4.3 Multivariate kernel weights

In our dataset, income is correlated with the variables age and high education, and therefore a multivariate analysis is preferred. We include all variables listed in Table 5.B.1 in Appendix 5B (i.e. income, education, gender, household characteristics and age). Figure 5.6 presents the estimated distributions of the estimated WTP-values. The normalised spread, as measured by the coefficient of variation (CV), is largest in the VOT, implying that we observe the most heterogeneity in the VOT (CV = 0.53). The heterogeneity of the VSDE and VSDL distributions is comparable (CV = 0.40 and 0.41 respectively).

Starting from the multivariate weight matrix, for each individual characteristic q we tested if leaving the variable out of the weight matrix will significantly increase the AICC with 3/(JT). For the univariate analysis, some variables do not have a significant effect, whereas in the multivariate analysis they do have a significant impact. This implies that
these variables mainly affect the preference parameters via interactions with other variables. Figure 5.6 does not reveal where individuals are in the distribution. Therefore we perform a second stage regression, enabling us to investigate how individual characteristics relate to the WTP-values. This second stage regression can be used as a simple linear representation of our estimation results. As dependent variables, we take the log of the estimated WTP-values.52

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52 We also estimated similar models where we do not transform the dependent variables logarithmically, but the results are qualitatively similar. The dependent variables are generated regressors, so these need to be modelled as measured with error (Gawande, 1997, Davidson and McKinnon, 2004). We therefore use bootstrapped standard errors.
Table 5.2 — Regressions of individual characteristics and VOT, VSDE and VSDL.

<table>
<thead>
<tr>
<th></th>
<th>log(VOT)</th>
<th>log(VSDE)</th>
<th>log(VSDL)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Income €2500-€3500</td>
<td>0.196</td>
<td>0.214</td>
<td>0.202</td>
</tr>
<tr>
<td>Income €3500-€5000</td>
<td>0.468</td>
<td>0.361</td>
<td>0.333</td>
</tr>
<tr>
<td>Income &gt;€5000</td>
<td>0.670</td>
<td>0.560</td>
<td>0.541</td>
</tr>
<tr>
<td>Education – Bachelor Degree</td>
<td>0.225</td>
<td>0.100</td>
<td>0.130</td>
</tr>
<tr>
<td>Female</td>
<td>0.280</td>
<td>0.236</td>
<td>0.221</td>
</tr>
<tr>
<td>Single</td>
<td>-0.072</td>
<td>-0.115</td>
<td>-0.152</td>
</tr>
<tr>
<td>No Kids</td>
<td>0.029</td>
<td>-0.010</td>
<td>0.012</td>
</tr>
<tr>
<td>Young Kids</td>
<td>0.400</td>
<td>0.282</td>
<td>0.191</td>
</tr>
<tr>
<td>Kids at Primary School</td>
<td>-0.331</td>
<td>-0.290</td>
<td>-0.317</td>
</tr>
<tr>
<td>Age&lt;25</td>
<td>-0.563</td>
<td>-0.470</td>
<td>-0.381</td>
</tr>
<tr>
<td>Age&gt;50</td>
<td>-0.150</td>
<td>0.038</td>
<td>0.158</td>
</tr>
<tr>
<td>Constant</td>
<td>3.061</td>
<td>2.804</td>
<td>2.496</td>
</tr>
<tr>
<td>Number of observations</td>
<td>486</td>
<td>486</td>
<td>486</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.693</td>
<td>0.650</td>
<td>0.622</td>
</tr>
</tbody>
</table>

NOTE: Bootstrapped standard errors are between parentheses (1000 replications). The reference category is a married (or living together) male person of 25-50 years old that have kids that are all older than 12 years and a monthly income higher than €2500 and an educational degree lower than bachelor.

The income effect is strong and most pronounced for the higher income classes. Switching from an income lower than €2,500, to the highest income class increases the VOT with 95%.\(^{53}\) Also the increase of VSDE and VSDL is substantial and around 73%. Education has a positive effect on WTP-values even if we control for income effects. Higher educated people have 25% higher VOT and approximately 12% higher VSDE and VSDL. The effect on the VOT is higher than for the VSDE and VSDL, confirming that highly educated people are less sensitive to rewards, as they tend to have more flexible job starting times. Females have higher WTP-values than males. This is a common finding in the literature, which could reflect that females are more often responsible for the kids in the household, and therefore have more scheduling constraints (Kwan, 1999; Lam and Small, 2001; Brownstone and Small, 2005; Schwanen, 2008).

Travellers that are single have lower WTP-values, especially for the scheduling variables. A plausible explanation is that there are no other people in the household that impose scheduling constraints on them. Previous research already showed that time budgets decrease because the presence of children in the household (Becker, 1985; Browning, 1992). Indeed, having young kids increases the VOT, VSDE and VSDL with respectively 50, 33 and 21%. The effect is higher on the VSDE than on the VSDL,

\(^{53}\) The effect is calculated as follows: \(\exp(0.67) - 1\) = 0.954 (see Halvorsen en Palmquist, 1980).
reflecting that commuters with young kids face more scheduling cost in the early morning. The results for people with kids at primary school is surprising, as we would expect a positive coefficient, given the fact that scheduling constraints are more stringent because of the fixed starting times of schools (Schwanen and Ettema, 2009). Finally, younger and older commuters have a lower VOT, but the effect of age>50 is positive for VSDE and VSDL.

5.4.4 Sensitivity analysis for multivariate kernel weights
The bandwidth is an important parameter in semiparametric regressions. We therefore test if the model improved significantly if we choose a different bandwidth for each variable in the weight matrix. Because it was not possible to analyse the full grid of possible bandwidths, we use \( \lambda = 0.4 \) (see Table 5.1) and then test for each variable whether a change in the bandwidth results in a significant improvement in model fit as measured by the \( AICC \). We find, somewhat surprisingly, that only a decrease in the bandwidth of age>50 to 0.15 leads to a significant improvement in the \( AICC \). Nevertheless, if we compare the results of Table 5.3 to the first three columns of Table 5.B.2, the results for the first and second stage regression are very similar. We are also interested how the results are affected by the choice of bandwidth by re-estimating the model for a 10% higher (\( \lambda = 0.44 \)) and a 10% lower (\( \lambda = 0.36 \)) bandwidth. The results are given in the columns 4-9 of Table 5.B2 and are comparable to the results in Tables 5.1 and 5.2.

5.5 Conclusions
We analysed observed taste heterogeneity using a local maximum likelihood estimation approach. We show that local Logit estimation is a powerful tool to analyse heterogeneity in the WTP-values related to observable individual characteristics. The main benefit compared to an ordinary Logit model is that more can be learned from the data. On the other hand, fewer degrees of freedom are used than in a saturated model.

We use the corrected \( AIC \) criterion to test the ordinary Logit model against semiparametric specifications, and to test if variables add significant explanatory power to the model. Using data from a stated choice experiment, we showed that there is
substantial observed heterogeneity in WTP for reductions in travel time and schedule delay. The results of our second stage regression show a significant impact on WTP-values for many individual characteristics. For example, we find that individuals with high incomes have a higher value of time and scheduling costs and women have 25% higher values of schedule delay.

Compared to other estimation techniques, our approach has the advantage that it relates heterogeneity to observable individual characteristics, and enables us to make better predictions when the composition of the population changes. For example, the income may increase, travellers will get older and more women may enter the job market. Our results can be used to predict the new distributions of WTP-values.

Future research may extend the analysis to a multinomial Logit model. For example, Dekker et al. (2011) use a local multinomial Logit model to test if preferences are stable over the sequence of choices in a choice experiment. The current setup does not allow for unobserved heterogeneity within socio-economic groups and this may result in an estimation bias. Currently we are working on a local latent class model which also has the possibility to correct for unobserved heterogeneity.

Appendix 5A Derivation of the hat matrix for the binary Logit model

In order to derive the hat matrix for the binary Logit model we need some intermediate steps that are described in detail by Brunsdon et al. (1998), Ruppert et al. (2003) and Charlton (2009). We have $I$ individuals making $T$ choices each. In total we have $N = IT$ rows in our dataset. We number each row by $n = 1, \ldots, N$, and define $\Delta X$ as the $N \times K$ matrix with differences in the independent variables between alternatives 1 and 2 (this can be done because we use a local linear-in-parameters specification of the utility). We denote $\Delta x_n$ as the $1 \times K$ vector of differences in the explanatory variables for observation $n$. The estimated hat matrix $\hat{H}$ has size $N \times N$, and we denote the $n^{th}$ row of the $\hat{H}$ by $\hat{h}_n$. Following Brunsdon et al. (1998) and Ruppert et al. (2003), $\hat{h}_n$ is then given by:

$$\hat{h}_n = \Delta x_n \hat{\Omega}^n \Delta X' \hat{S}^n,$$

(5.A.1)
where $\hat{\Omega}^n$ is the $K \times K$ locally estimated covariance matrix that is obtained when estimating the local model using the weight variables of observation $n$ as the reference point. If local standard errors are high, this will result in high values of $\hat{h}_n$. Furthermore, high values of the matrix $\hat{S}^n$ (to be defined later) result in higher values on the trace of the hat matrix. When the bandwidth decreases, the model uses more degrees of freedom, so the trace of the hat matrix will increase (Hoaglin and Welsch, 1978). If the bandwidth approaches 1, the trace of $\hat{H}$ converges to the number of parameters estimated in an ordinary Logit model.

To account for possible correlation of the error term over the sequence of choices of an individual and minor misspecification at the local level, we use a robust covariance matrix, clustered at the individual level (Wooldridge, 2003). In that case $\text{tr}(\hat{H})$ will be higher than the number of parameters if $\lambda$ equals 1, because the standard errors are underestimated in the cross-sectional estimation (see Table 5.1, second column).

The next step is to determine $\hat{S}^n$ in equation (5.A.1). Therefore, we use the variance function, which is the second derivative of the log-likelihood function evaluated at the $K \times 1$ local estimate $\hat{\beta}_n$ (Ruppert et al., 2003):

$$M^n[\Delta X \hat{\beta}_n] = \frac{e^{\Delta X \hat{\beta}_n}}{(1 + e^{\Delta X \hat{\beta}_n})^2} \cdot w^n[Z; \lambda].$$

This vector has size $N \times 1$. The variance function is \textit{locally} defined and evaluated at the \textit{local} estimate $\hat{\beta}_n$. $\hat{S}^n$ in equation (5.A.1) is defined as follows (see Ruppert et al., 2003):

$$\hat{S}^n = \text{diag}(M^n[\Delta X \hat{\beta}_n]).$$

Let $\hat{\beta}$ the $N \times K$ matrix with all the locally estimated parameters of the individuals. Furthermore, let $LL[\hat{\beta}]$ the \textit{global} likelihood of the estimated model. To evaluate the performance of a chosen bandwidth, we minimise the corrected Akaike Information Criterion proposed by Hurvich et al. (1998) which is given by:

\footnote{For small datasets, equation (A.1) can be calculated easily. However, for larger $N$ the matrix $\hat{S}^n$ becomes too large and therefore a less computational intensive routine is needed (Greene, 2003). As we only use the trace of the hat matrix, it is sufficient to calculate only the diagonal elements $\hat{h}_{nn}$. We do so by calculating the $n^{th}$ column of $\hat{S}^n$, which we define as $\hat{S}^n_n$. This is a $N \times 1$ vector with on the $n^{th}$ row the variance element. This results in $\hat{h}_{nn} = \Delta x_n \hat{\beta}_n^{\prime} \Delta X \hat{S}_n^n$. The trace of the hat matrix is then the sum of these diagonal elements: $\text{tr}(\hat{H}) = \sum_{n=1}^{N} \hat{h}_{nn}$. The hat matrix for the multinomial Logit model is discussed in Dekker et al. (2011).}
\begin{equation}
AICC(\lambda) = \frac{-2 \cdot LL[\hat{\beta}]}{N} + 1 + \frac{2 \cdot (\text{tr}(\hat{H}) + 1)}{N - \text{tr}(\hat{H}) - 2'}
\end{equation}

Taking the last two terms together and substituting $N = IT$, this is equal to equation (5.9).

Appendix 5B Descriptive statistics and sensitivity analysis

Table 5.B.1 — Descriptives of the individual characteristics

\begin{center}
\begin{tabular}{l|c}
\hline
Characteristics & Mean \\
\hline
Income <€2500 & 0.066 \\
Income €2500–€3500 & 0.340 \\
Income €3500–€5000 & 0.401 \\
Income >€5000 & 0.193 \\
Education – Bachelor Degree or higher & 0.842 \\
Female & 0.237 \\
Single & 0.165 \\
No Kids & 0.430 \\
Young Kids (<5 years) & 0.212 \\
Kids at Primary School & 0.263 \\
Old Kids (>12 years) & 0.095 \\
Age<25 & 0.014 \\
Age 25–50 & 0.761 \\
Age>50 & 0.224 \\
Number of Individuals & 486 \\
\hline
\end{tabular}
\end{center}
### Table 5.B.2: Sensitivity Analysis.

#### First Stage

<table>
<thead>
<tr>
<th></th>
<th>'Multi-variate' bandwidth</th>
<th>Bandwidth (( \lambda )) = 0.36</th>
<th>Bandwidth (( \lambda )) = 0.44</th>
</tr>
</thead>
<tbody>
<tr>
<td>VOT</td>
<td>45.540 (35.972)</td>
<td>44.697 (29.872)</td>
<td>41.041 (16.165)</td>
</tr>
<tr>
<td>VSDE</td>
<td>28.772 (20.414)</td>
<td>27.811 (14.155)</td>
<td>25.942 (7.576)</td>
</tr>
<tr>
<td>VSDL</td>
<td>22.43 (24.124)</td>
<td>20.697 (11.597)</td>
<td>19.226 (5.756)</td>
</tr>
<tr>
<td>Number of Choices</td>
<td>4,850</td>
<td>4,850</td>
<td>4,850</td>
</tr>
<tr>
<td>Number of Individuals</td>
<td>485</td>
<td>485</td>
<td>485</td>
</tr>
</tbody>
</table>

| Income €2500–€3500   | 0.297 (0.089)             | 0.304 (0.071)                     | 0.293 (0.102)                     |
|                      | (0.034)                   | (0.029)                           | (0.027)                           |
| Income €3500–€5000   | 0.534 (0.088)             | 0.419 (0.073)                     | 0.392 (0.101)                     |
|                      | (0.029)                   | (0.027)                           | (0.027)                           |
| Income >€5000        | 0.836 (0.110)             | 0.709 (0.089)                     | 0.693 (0.113)                     |
|                      | (0.034)                   | (0.030)                           | (0.030)                           |
| Education – Bachelor | 0.207 (0.039)             | 0.139 (0.030)                     | 0.180 (0.041)                     |
|                      | (0.034)                   | (0.034)                           | (0.034)                           |
| Degree               | 0.234 (0.043)             | 0.205 (0.036)                     | 0.197 (0.040)                     |
|                      | (0.027)                   | (0.027)                           | (0.027)                           |
| Female               | 0.207 (0.043)             | 0.139 (0.036)                     | 0.180 (0.040)                     |
|                      | (0.030)                   | (0.034)                           | (0.034)                           |
| Single               | -0.127 (0.043)            | -0.165 (0.036)                    | -0.198 (0.040)                    |
|                      | (0.034)                   | (0.034)                           | (0.034)                           |
| No Kids              | 0.114 (0.053)             | 0.061 (0.044)                     | 0.087 (0.049)                     |
|                      | (0.031)                   | (0.031)                           | (0.031)                           |
| Young Kids           | 0.442 (0.041)             | 0.329 (0.030)                     | 0.245 (0.031)                     |
|                      | (0.024)                   | (0.030)                           | (0.031)                           |
| Kids at Primary School | -0.345 (0.038)          | -0.293 (0.029)                    | -0.302 (0.032)                    |
|                      | (0.033)                   | (0.033)                           | (0.033)                           |
| Age<25               | -0.531 (0.114)            | -0.448 (0.096)                    | -0.332 (0.068)                    |
|                      | (0.034)                   | (0.034)                           | (0.034)                           |
| Age>50               | -0.233 (0.059)            | 0.173 (0.047)                     | 0.415 (0.053)                     |
|                      | (0.029)                   | (0.037)                           | (0.037)                           |
| Constant             | 2.921 (0.096)             | 2.650 (0.077)                     | 2.292 (0.082)                     |
|                      | (0.573)                   | (0.569)                           | (0.569)                           |
| Number of Observations| 485                      | 485                               | 485                               |
| \( R^2 \)            | 0.613                     | 0.573                             | 0.569                             |

**Note:** See Tables 5.1 and 5.2. One observation is excluded due to a non-positive WTP-value when \( \lambda = 0.36 \).
Conclusion

This study developed methods to assess the cost of travel time variability for air and car travellers. As Table 1.1 in Chapter 1 shows, the cost of travel time variability can be determined in three steps. First, researchers need to develop a behavioural microeconomic model that is able to capture travellers’ responses to travel time variability. Second, this model needs to be validated and calibrated using empirical data. Third, the model needs to be applied using observed or simulated travel time data in order to see how large the costs of travel time variability are.

Each of the chapters in this thesis contributes to at least one of these steps. The behavioural models are extensions of the scheduling model of Noland and Small (1995). In these models, travellers dislike arriving at a different time than their preferred arrival time. They anticipate travel time variability by leaving earlier from home or choosing an earlier flight, and therefore the dynamic choice of the traveller is incorporated in an intuitive way. Chapters 2 and 5 make use of discrete choice econometric methods to estimate the cost of arriving early and late for air travellers going to the airport, and for car commuters participating in a real world reward experiment. Chapters 2, 3 and 4 apply the models using observed travel time data.

In Chapter 2 we analysed the cost of travel time variability for air travellers going to the airport. We analysed the effect of airport access travel time variability on access travel cost. The mixed logit estimations show that scheduling plays an important role in departure time decisions of travellers going to the airport. For both business and non-business travellers there is heterogeneity in the scheduling parameters. A connection was made between the estimated shadow cost of scheduling and equilibrium user cost, taking into account anticipating departure time choice of air travellers. Using a dataset of Dutch travel times we showed that for business travellers the cost of variability are in the range of 0-30% of expected access travel cost, depending on the time of day. For non-
business travellers this share is in the range of 0-25%. The high percentages correspond to the peak hours and there is a strong relation between the cost of travel time variability and average travel time cost. These numbers are somewhat higher than the values found by Fosgerau and Karlström (2010), who analysed the cost of travel time variability for commuters, but are comparable to the values found by Peer et al. (2010) for Dutch car travellers.

Chapter 3 analyses the cost of arrival delay variability for air travellers. We showed that air travel delay variability for US domestic air travel may increase the expected user cost of delays of air travellers, with our central estimate being 27%. Given our assumptions on scheduling preferences, on the generalised price for other cost components than delays, and on the values of schedule delay, we view this as a conservative estimate. We showed that for the 40% busiest origin-destination pairs in the US, expected user cost from air travel delays can be well approximated as a linear function of the mean delay, which considerably simplifies applications of the models in policy analysis, at least for the cases that would leave the relation itself intact.

Chapter 4 shows how probability weighting affects departure time decisions of car travellers and develops a rank dependent scheduling model. Using the concept of probability weighting we are able to derive the costs of likelihood insensitivity, optimism and pessimism. If the parameterised probability weighting function for car travellers is similar to what has been found in the literature on choice under risk, then we find costs of probability weighting ($\text{COPW}$) for car travellers in the morning peak that are on average around 3 per cent. This low number is due to the fact that travellers overweigh the probabilities of both good and bad outcomes. Therefore, on average they do a good job in choosing their optimal departure time from home. We show that this result is rather robust for different assumptions on the WTP values. This result questions whether there is a strong need for models that estimate probability weighting functions, given the complicated nature of these models, and the low relevance for policy evaluation that the 3% figure suggests. This figure, however, naturally changes when the probability weighting function changes; for the ranges of parameters we tested, we found the cost of probability weighting in the range of 0 – 24 per cent. Therefore, for extreme probability weighting, the cost of probability weighting may still be substantial.
Chapter 5 estimates a scheduling model for car travellers using a semiparametric estimation technique called local maximum likelihood estimation. We analyse heterogeneity related to observable individual characteristics and show how to estimate a semiparametric distribution of preferences, given the assumption that more similar people in terms of socio-economic characteristics have more similar preferences. The model is applied to a stated choice experiment designed to measure the willingness to pay for travel time savings and arriving at the preferred arrival time at work. We find that there is substantial observed heterogeneity and that the estimation procedure explains the data significantly better than fully parametric regression techniques. The proposed method has the advantage that the heterogeneity of preferences is related to observed characteristics and therefore it is easier to apply in long-term forecasting in transport models, since in the long-run populations may change. Furthermore, the estimation approach works well for small datasets.

In order to provide policy makers a good perspective on the value of reliability, several lessons can be learned from this study. First, excluding the benefits of improved reliability in CBAs may lead to a significant underestimation of user benefits from infrastructure investments. Current transport project appraisal should therefore include indicators for the benefits of increasing reliability.

Second, our study suggests that the cost of travel time variability is strongly related to the mean travel time delay. Although policy makers should be aware of the fact that the cost of travel time variability do depend on the time of the day, it seems that the cost of travel time variability is strongly related to increases in travel delay. For policy measures that do not break the relationship between the mean and the standard deviation of travel times, the mean delay multiplied by a fixed factor can be used as a proxy for the cost of travel time variability. Policies that improve the mean delay, such as road capacity expansions, will also reduce the cost of travel time variability.

Third, current estimates of the value of time obtained from simple time/money trade-offs might be biased if researchers do not account for scheduling cost. Longer travel times will lead to an earlier departure or a later arrival, and therefore these simple trade-
offs also capture a part of scheduling cost of the traveller.\textsuperscript{55} In these SP studies researchers should clearly indicate if a longer travel time comes with an earlier departure time or a later arrival time. Because scheduling cost are ignored in these experiments, it may be that SP values obtained from simple time/money trade-offs are upward biased.

Fourth, estimates of the value of time for air travellers based on revealed preference data may be upward biased if scheduling is not accounted for. Chapter 4 shows that expected scheduling cost is strongly related to the mean arrival delay, and therefore revealed preference estimates of the value of time will likely pick up the expected scheduling cost. As argued before, this might not be a problem for evaluation studies as long as the user cost can be approximated by the mean delay.

Fifth, travel time variability cannot simply be measured by the standard deviation of travel times, but is defined by the information set of the traveller and the full distribution of travel times that does depend on the time of the day. The latter is captured appropriately in our study, but study of the information set is an important issue that should not be neglected. If drivers are well informed about the current travel situation and have knowledge about for example weather and incidents, the cost of travel time variability is lower than what is estimated in this study and other studies in the literature.

Small and Verhoef (2007) stated that:

\textit{“The theory of time allocation is well developed and permits us to rigorously address conceptual issues concerning value of time and reliability. Despite uncertainty, a consensus has developed over many of the most important empirical magnitudes for values of time, permitting them to be used confidently in benefit assessment. Another decade should bring similar consensus to value reliability”} (Small and Verhoef 2007, p.55)

The literature seems to be reaching a consensus that scheduling models are able to capture travel decisions of travellers facing variable travel times in an appropriate and realistic way. However, it is as yet undecided which scheduling model to use, and more

\textsuperscript{55} In the Small (1982) model of scheduling cost \textit{departing} earlier has no cost, in the Tseng and Verhoef (2008) model it has.
empirical research is needed to analyse which model describes the preferences of travellers in the most appropriate way.

One of the things that this thesis confirmed is that for policy evaluation, approximations of the cost of travel time variability may be available. Chapter 2, 3 and 4 show that the cost of variable arrival times is strongly related to the cost of mean travel times. This is because travel time variation increases if the mean travel time increases, and therefore the mean and the standard deviation of travel times are strongly related (Peer et al., 2010; Fosgerau, 2010).

Future large scale studies may investigate this relationship in more detail and might provide policy makers approximations that easily can be implemented in CBAs. Chapter 3 shows that at least for ex-post evaluation this is a useful approach. Applying the models using observed travel time data may also help to decide which topics are of key importance in determining the cost of travel time variability. For example, Chapter 4 shows that probability weighting is probably not that important for CBAs since it only increases the cost with 3%.

The models that are developed in this thesis have of course limitations and there are several research challenges that may be addressed in future studies. Some of these were discussed in the foregoing chapters already, but we will highlight a couple of these here.

First, it is assumed that travellers have a perfect knowledge of the empirical travel time distribution. It is likely that this knowledge is related to experience. For commuters, perfect perception may be a realistic assumption, because these travellers are experienced. But for air travellers it may well be that travellers do not know the empirical travel time distribution, and therefore make larger perception errors. Also for mode choice this may be important since the perception of travel times of the non-chosen modes may be biased.56 This may result in non-optimal behaviour, and therefore the cost of variable travel times may be higher than what was estimated in Chapter 2 and 3.

Second, we ignored trip timing decisions in transport chains. For example, Rietveld et al. (2001), De Jong et al. (2003) and Jenelius et al. (2011) study the cost of variable travel times.56 See for example, Van Exel and Rietveld (2009), for recent empirical evidence that car travellers overestimate public transport travel times.
times in trip chains and tours. Although the analysis may complicate because of waiting times at intermediate stops, the essence of the optimization problem remains similar since travellers still face stochastic arrival times (Bates et al. 2001).

A third interesting topic for further study is the definition of the travel time distribution and the role of information. Throughout this thesis it is assumed that travellers have no information about the current traffic situation. For air travellers this may be an appropriate assumption since they usually cannot reschedule easily since the ticket is booked in advance. A recent revealed preference study by Tseng et al. (2010), suggests that car travellers use information about the current traffic situation. This means that the ‘true’ variability of travel times is likely to be lower since travellers are better informed about the current traffic situation than is assumed than in this study. Future research should address in more detail what the information set of the traveller is, and base the measure of variability conditional on this information set. This is a challenging topic, not in the least place because the information set is endogenously determined by the preferences of travellers.

Fourth, most studies that estimate scheduling models heavily rely on stated preference data. Due to improvements in GPS and license-plate recognition technology, revealed preference data becomes more widely available. The validation of stated preference estimates of value of time and schedule delays is of key importance in future research because these estimates may suffer from hypothetical bias (Brownstone and Small, 2005; Börjesson, 2008; Börjesson, 2009; Hensher, 2010). The study of door-to-door travel time variability is interesting, and may be enhanced by future data availability using GPS or phone-tracking techniques.

Fifth, the theory of decision under risk and uncertainty is well developed and some topics deserve more attention in the transport literature. For example, uncertainty aversion has not been studied in detail, while this may be particularly relevant for revealed travel behaviour. Transport economists should seek a balance between developing more detailed behavioural models and the application of these models in policy analysis. More detailed models may help to understand the decision process of the traveller better, but are not necessarily needed for policy evaluation as we showed in

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57 See for an overview of recent important contributions: Abdellaoui et al. (2011).
Chapter 3, because the effects on user cost may be small. An important question that still is unanswered is if the recently found estimates for reference dependence and probability weighting are due to the artefacts of stated choice experiments, or are properly capturing the revealed behaviour of travellers (De Borger and Fosgerau, 2008; Hjorth, 2011; Hensher and Li, 2010).

Sixth, it is worth studying the effect of omitting scheduling cost in simple time/money trade-offs in stated preference analysis. If rescheduling is not accounted for, it is likely that the value of travel time savings in these experiments is upward biased.

These and other topics deserve attention and hopefully this thesis inspires future researchers to study the cost of travel time variability with better models and better data. This to provide policy makers a convincing economic perspective on the value of reliable transport systems. This thesis is a small step forward, but probably we need another decade to arrive at a consensus about empirical values of the cost of travel time variability. That is not a problem, but a great challenge.


Samenvatting

Reizigers willen meestal op een bepaalde tijd aankomen op hun bestemming. Variatie in reistijden leidt tot variatie in aankomsttijden. Deze studie onderzoekt hoeveel euro luchtreizigers en autoreizigers ervoor over hebben om de reistijdvariatie te verminderen en ontwikkelt nieuwe methoden om de kosten van reistijdvariatie te berekenen. Dit is een belangrijke vraag omdat investeringen in infrastructuur kunnen leiden tot een lagere variatie in reistijden. Daarom is het van belang dat naast de maatschappelijke baten van reistijdwinsten ook de maatschappelijke baten van reducties in de variatie van reistijden worden meegenomen in kosten-batenanalyses (KBAs).

De studie ontwikkelt economische gedragsmodellen en analyseert de kosten van reistijdvariatie door gebruik te maken van gemeten reistijddata.

In het standaard tijdstipkeuzemodel voor autoreizigers kiest een reiziger zijn optimale vertrektijd van huis gegeven zijn gewenste aankomsttijd, de verdeling van reistijden, de kosten van reistijd (VOT), de kosten van te vroeg aankomen (VSDE) en de kosten van te laat aankomen (VSDL).

Het eerste deel van deze studie (hoofdstukken 2 en 3) analyseert de kosten van reistijdvariatie voor reizigers die een vliegreis gaan maken. Hoofdstuk 2 ontwikkelt een gedragsmodel voor reizigers die naar de luchthaven gaan. Omdat het missen van een vlucht hoge kosten met zich meebrengt verschilt het tijdstipkeuzegedrag van deze reizigers met het gedrag van woon-werkreizigers. Met behulp van een keuze-experiment worden de waarden voor reistijd naar de luchthaven (29 euro/uur), te vroeg aankomen op de luchthaven (23 euro/uur), te laat aankomen op de luchthaven (34 euro/uur) en het reduceren van de kans op het missen van een vlucht geanalyseerd (6 euro/%). De bovenstaande waarden zijn ongeveer 30% hoger voor zakenreizigers en zijn hoger voor reizigers met een hoger inkomen. De waarden zijn gebruikt in een tijdstipkeuzemodel voor reizigers die met de auto naar de luchthaven gaan. In dit model kiezen reizigers hun optimale vertrektijd gegeven de reistijdverdeling en de geschatte parameters. De reistijdverdeling verandert over de dag en wordt geschat op basis van empirische reistijddata, gebruik makend van nonparametrische schattingstechnieken zodat er geen
aannames nodig zijn voor de vorm van de reistijdverdeling. Het hoofdstuk laat zien dat de kosten van reistijdvariatie sterk afhangen van de tijd van de dag en dat deze liggen tussen 0 en 30% van de totale gegeneraliseerde kosten (zonder benzine- en parkeerkosten) voor een reis naar de luchthaven.

Hoofdstuk 3 analyseert het keuzegedrag voor luchtreizigers in de Verenigde Staten wanneer er sprake is van variatie in aankomstvertragingen van vluchten. Omdat er sprake is van een dienstregeling kunnen reizigers kiezen uit een beperkt aantal vertrektijden. Eerdere studies naar de kosten van vertragingen namen alleen de kosten van de gemiddelde vertraging mee en lieten de kosten van te laat of te vroeg komen buiten beschouwing. Hoofdstuk 3 laat zien dat de kosten van vertraging ongeveer 27% hoger zijn als ook deze kosten meegenomen worden. Verder laat het hoofdstuk zien dat de kosten van onbetrouwbaarheid goed benaderd kunnen worden met een lineaire functie van de gemiddelde vertraging. Dit vergemakkelijkt de toepassing van het model voor KBAs van beleidsmaatregelen waarbij deze relatie intact blijft. Het model in dit hoofdstuk is generiek en kan ook gebruikt worden voor de analyse van andere vervoersmodi zoals bus, tram, metro of trein, zolang aangenomen wordt dat reizigers hun reis plannen.

Hoofdstuk 4 en 5 analyseren de kosten van reistijdvariatie voor autoreizigers. Hoofdstuk 4 gebruikt nieuwe inzichten in de literatuur over keuzegedrag waar er sprake is van risico’s en ontwikkelt een model dat rekening houdt met het feit dat reizigers kansen niet zo goed begrijpen of optimistisch of pessimistisch van aard zijn. Vele studies laten zien dat kansen worden gewogen, waarbij vaak gevonden wordt dat kansen op hele slechte en hele goede uitkomsten overschat worden. Het hoofdstuk bestudeert hoe de tijdstipkeuze van reizigers beïnvloed wordt en laat zien dat voor plausibele parameterwaarden het wegen van kansen geen groot effect heeft (ongeveer 3% hogere reiskosten). Dit effect is relatief klein omdat zowel de kansen op hele lange reistijden als op hele korte reistijden worden overschat, waardoor de reiziger ondanks het wegen van de kansen alsnog dicht in de buurt van de optimale vertrektijd vertrekt.

Hoofdstuk 5 is een econometrische bijdrage aan de literatuur over heterogene preferenties, en schat de parameters van het standaard tijdstipkeuzemodel voor autoreizigers. De meest gebruikte econometrische schattingsmethode om
(ongeobserveerde) heterogeniteit te analyseren in de literatuur is het mixed logit model, waarbij een verdeling van de preferentieparameters, zoals de waarde van tijd en de waarde van te vroeg of te laat aankomen, geschat wordt. Eén van de problemen van het mixed logit model voor toepassing in transportmodellen is dat het onbekend is hoe de verdeling van preferenties er in de toekomst uitziet. Gegeven de langetermijnhorizon voor infrastructuurinvesteringen is het van belang om rekening te houden met het feit dat de karakteristieken van een populatie veranderen en daarmee de verdeling van de preferenties. Daarom is het nuttig om zoveel mogelijk heterogeniteit te verklaren met geobserveerde karakteristieken, omdat deze meestal beschikbaar zijn in statistieken van de toekomstige populatie. Hoofdstuk 5 maakt gebruik van semiparametrische schattingsmethodes en laat zien hoe de verdeling van preferenties geschat kan worden onder de aanname dat meer gelijke individuen (in termen van geobserveerde karakteristieken zoals bijvoorbeeld inkomen en leeftijd), meer gelijke preferenties hebben. De econometrische techniek wordt gebruikt om een tijdstipkeuzemodel te schatten voor woon-werkreizigers, waarbij er significante heterogeniteit in preferenties wordt gevonden. Bijvoorbeeld mensen met een hoog inkomen zijn bereid meer te betalen voor reducties in reistijd en hebben hogere kosten voor te vroeg of te laat komen. Het hebben van jonge kinderen leidt tot een 50% hogere waarde van reistijd en tot een 20-30% hogere waarde van niet op tijd aankomen.

Deze studie laat zien dat het weglaten van gebruikersbaten van reducties in reistijdvariatie in KBAs leidt tot een significante onderschatting van de baten van investeringen in de infrastructuur. Daarom is het goed als er indicatoren voor de kosten van reistijdvariatie in KBAs worden opgenomen. De kosten van reistijdvariatie lijken sterk gerelateerd aan de gemiddelde reistijdvertraging en hangen af van het tijdstip van de dag. Voor beleidsmaatregelen lijkt de gemiddelde vertraging vermenigvuldigd met een vaste factor dus een goede benadering voor de kosten van onbetrouwbaarheid. Dit is een nuttig resultaat aangezien de implementatie van tijdstipkeuze in netwerkmodellen zeer complex is.
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