Travel time variability and airport accessibility

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Abstract

This paper analyses the costs of access travel time variability for individual air travelers. Reliable access to airports is important for air travelers since it is likely that the costs of missing a flight are high. First, the determinants of the preferred arrival times at airports are analyzed, including trip purpose, type of airport, flight characteristics, travel experience, type of check-in, need to check-in luggage. Second, the willingness to pays (WTPs) for reductions in early arrival time at the airport, late arrival time, access travel time and the probability to miss a flight are estimated using a stated choice experiment. The results indicate that the WTPs are relatively high, which is partially due to the low cost sensitivity of air travelers. Third, a model is developed to calculate the costs of variable travel times for air travelers going by car, taking into account travel time costs, scheduling costs and the costs of missing a flight. In this model the value of reliability for air travelers is derived taking anticipating behavior into account. Results of the numerical exercise show that the costs of access travel time variability for business travelers are between 3-36% of access travel costs and for non-business travelers between 3-30% where these numbers strongly depend on the time of the day.

Keywords: value of reliability, scheduling, travel time variability, airport accessibility, airport choice

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1. Introduction

The accessibility of airports has been researched for a couple of decades and 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 is of vital importance for the choice of an airport by air travelers. Increasing the accessibility of an airport can therefore be one of the possible strategic actions of airports to improve their market position.

Distance can be used as a measure of accessibility. However, the distance between locations may not be a good proxy for accessibility if there is congestion on the road. Therefore access travel time is likely to be a better indicator. The analysis of Harvey (1986) already showed that travelers choose often an airport because it is close in terms of access travel time.

As indicated by Kouwenhoven (2008), a more general approach can be taken by using generalized access costs as an indicator for accessibility. In that case all the monetary costs for going to the airport such as parking costs and airport specific taxes are taken into account and non-monetary costs such as travel time are multiplied by the willingness to pay (WTP) values of a traveler. Usually these WTP are estimated using stated choice experiments (SCEs).

The WTP for a reduction in airport access travel time or value of access time (*VOAT*), has been frequently estimated in the literature. It has been found that the *VOAT* is considerably higher than the values of time for commuters. For example, Furuichi and Koppelman (1993) use RP data and find a value of 70 $/h for business travelers and 41$/h for leisure travelers but state that there may be possible collinearity between travel time and travel costs. Pels et al. (2003) find higher values of 118 $/h for non-business and 174 $/h for business travelers. Hess et al. (2007) find similar values as Furuichi and Koppelman for business and non-business travelers in a stated preference study. Hess and Polak (2005,2006), Dresner (2006) and Ishii et al. (2009) also show that there is significant heterogeneity in the WTPs for a reduction in access travel time. Furthermore, Hess and Polak (2005) suggest that a possible reason for the high estimates of the *VOAT* could be that travelers see increasing travel times as an increase in risk to miss their flight.

The main contribution of this paper is that we include the costs 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. Probably the only study that incorporates the effects of access travel time variability is a revealed preference study by Tam et al. (2008). Tam et al. (2008) estimate the disutility of a safety margin that travelers apply when traveling 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 travelers take into account because of access travel time variability. They find that both business and non-business travelers are willing to pay money to decrease the safety margin between 1 and 1.3 times the WTP for reductions in travel time. This paper extends the paper of Tam et al. (2008) by explicitly explain the determinants of the safety margin using a scheduling model. In transport economics the scheduling model has been frequently estimated for commuters (for an overview of empirical research see: Tseng 2008; Brownstone and Small 2003; Li et al., 2010). It is an intuitive model where travelers make a trade-off between the expected costs of being early and the expected costs of being late and determine the optimal departure time from home. In this paper the WTP values for reduction in schedule delay early, late and the probability to miss a flight are estimated. Second, a theoretical model for car travelers is developed to analyze the costs of access travel time variability for car travelers taking into account anticipating behavior. This step is needed to connect the estimated WTP values to real travel time data.

The resulting generalized costs can be implemented in accessibility models that analyze airport choice behaviour of travelers (see for example: Kouwenhoven 2008).

The main motivation for this paper is that the variability of travel times is important for air travelers because the costs of missing a flight are expected to be high. Therefore travelers apply large buffers to be sure that they are on time. Using a 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 included in the model.

The setup of the paper is as follows. In section 2 the scheduling model for air travelers is introduced. This model differs from the standard scheduling commuting model approaches in that travelers have large costs if they arrive later than their final check-in time. Section 3 analyzes the determinants of the preferred arrival time of airport travelers. This is necessary because the preferred arrival influences the costs of travel time variability. In Section 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 SCE. In section 5 a model is developed to derive the generalized access costs for car travelers taking into account travel time variability and anticipating behavior. These include the costs of access travel time and access travel time variability. Section 5 establishes the connection between the estimated WTPs and the observed travel time data. We use a large dataset with travel times to apply the model and to calculate the costs of access travel time variability. Section 6 concludes and discusses the results.

2. The scheduling model for air travelers

2.1. The basic model

The scheduling model of Noland and Small (1995) has been widely accepted as the standard tool of analyzing the effects of travel time variability. The work of Noland and Small is based on earlier work of Vickrey (1969) and Small (1982). The central idea is that travelers make a trade-off between being early and late, and evaluate earliness and lateness compared to their preferred arrival time (t_{pat}). In this paper the model is extended for air travelers. The departure time (t_h) choice of air travelers is expected to strongly depend on the probability of missing a flight and the corresponding expected costs. In Fig. 1 the deterministic access cost function of an air traveler is given.

<<insert figure 1 about here>>

The x-axis of Fig. 1 indicates the time of day and the y-axis indicate the costs. Suppose an air traveler has a certain flight departure time with a corresponding final check-in time. When a traveler is later than this final check-in time he will miss his flight. The corresponding costs are likely to be high and this is the reason that travelers apply large buffers when going to the airport. In Fig 1, β is the shadow cost of being early and γ is the shadow cost, both per unit of time. The parameter θ is the discrete cost of missing a flight, which covers all the costs for waiting, rebooking and other scheduling inconveniences.

When leaving from home, an air traveler first determines what the in-airport service time and variability will be. The airport service time is defined as the time for checking in, going through the passport control, boarding and security. Based on this subjective belief the traveler determines his t_{pat}. Longer perceived in-airport service times will therefore result in an earlier t_{pat}. The t_{pat} used in this paper is defined as the time a traveler wants to arrive at the airport when access travel time is not variable. This definition is crucial since then it is possible to separate the behavioral response to airport service time variability and access travel time variability. In section 3 the determinants of the t_{pat} are analyzed.

A late arrival is defined as being later than the t_{pat}. It is likely that being late has some disutility since there will be extra stress, and therefore travelers are willing to pay money to reduce lateness. Being early also causes disutility, because of extra waiting at the airport. The *expected* costs of a traveler depend on these parameters and the arrival time distribution and are given by the cost function of Equation 1.

$$E(C) = \alpha \cdot E(T) + \beta \cdot E(SDE) + \gamma \cdot E(SDL) + \theta \cdot PMF + X \qquad (1)$$

$E(C) = access\ travel\ costs$

$E(T) = expected\ travel\ time$

$E(SDE) = expected\ schedule\ delay\ early$

$E(SDL) = expected\ schedule\ delay\ late$

$PMF = probability\ of\ missing\ the\ flight$

$X = other\ expenses\ such\ as\ parking\ costs$

In Equation 1, α is the value of airport access time (*VOAT*), β is the value of schedule delay early (*VSDE*), γ is the value of schedule delay late (*VSDL*) and θ the value of the probability to miss a flight (*VOPMF*). The expected travel costs depend on the departure time from home since the schedule delay components and the probability to miss a flight are affected by the choice of departure time. The schedule delay early (*SDE*) is given by Max$(0,t_{pat}-(t_h+T))$ and the schedule delay late (*SDL*) by Max$(0,t_h+T-t_{pat})$. The corresponding expected values can be found by taking the average over the possible travel times *T*. The *E(SDE)* increases and the *E(SDL)* decreases if travelers depart earlier from home. Furthermore, the *PMF* decreases in if travelers depart earlier from home. Since travel times are stochastic, the corresponding arrival times will also be stochastic and therefore the probability to miss a flight is included in the costs function instead of a discrete penalty if the flight is missed.

3. Determinants of the preferred arrival time

3.1. Descriptive statistics of the survey.

An internet survey was developed to collect the data that are necessary for the analysis of the access cost function. A total of 971 completed surveys have been collected in the Netherlands with 345 reporting about a business trip and 626 reporting about a non-business trip. In the survey information has been asked about the latest trip to the airport. This information has been used to customize the survey and the stated choice experiment. It was found that 1.5 % of the air travelers (0.52% of all flights) had missed a flight during the last year due to delays during their access trip. The summary statistics are given in Table 1. The share of access modes is quite similar for business and non-business travelers except that business travelers 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 travelers use Schiphol Airport as their departure airport.

Table 1

Summary statistics of the survey

	non-business	business
access mode		
car driver	39,6%	38,6%
car passenger[2]	25,4%	21,4%
taxi	8,9%	7,0%
train	20,1%	30,1%
other	5,9%	2,9%
total	100,0%	100,0%
characteristics of the last trip		
expected travel time (minutes)	82	79
average # of flights per year	2,66	5,84
average duration of the trip	12 days	7 days
airport chosen		
Schiphol Airport	73,5%	79,7%
small Dutch airports	8,8%	5,5%
Belgian Airports	5,8%	7,0%
German Airports	11,3%	6,1%
other	0,8%	1,7%
total	100,0%	100,0%

The mean expected travel time of non-business trips is somewhat longer than for non-business travelers. This mean expected travel time is the time from the place of departure to the check in counter. The average number of flights for business travelers is more than two times higher as the flight frequency for non-business travelers. Finally, one can see that non-business travelers are traveling less often via Schiphol Airport and more often from German airports.

Fig. 2 depicts the spatial distributions of the departure place of the respondents based on 4-digit zipcode levels. There are more departures in the western part of The Netherlands because more people live and work there.

<<insert figure 2 about here>>

[2] If travelers do not travel alone, on average there are 3 people in the car.

For 86% of the business travelers the departure place is their home location. For non-business travelers this is the case in 92% of the cases. This information is important for the analysis. The choice of departure airport of business travelers is likely to be determined on the base of the home location rather than the work location. This is an advantage for empirical analysis since residential locations are usually available in standard statistics while the work location is often unknown.

3.2. Determinants of the preferred arrival time

In this section the preferred arrival (t_{pat}) time at the airport is analyzed using a simple regression analysis. The t_{pat} is an important determinant of the costs of variable airport access time. If a traveler has a very early t_{pat}, the probability to miss a flight is lower. Therefore the impact of variable access travel times is lower if a traveler prefers to arrive earlier. The dependent variable in the regression is the flight departure time minus the preferred arrival time, so the number of minutes before the flight departure that a travelers prefers to arrive at the airport.

There are 930 observations included in the analysis. Travelers that arrive the previous day at the airport and sleep in a hotel are excluded from the analysis. Furthermore, travelers with a dependent variable lower or equal than 0 or with very extreme values are excluded from the analysis because they clearly made a mistake when filling in the questionnaire.

In Table 2 the regression results with the flight departure minus the t_{pat} as the dependent variable are shown. *E(T)* is the expected travel time of the traveler and *FTT* is the flight travel time. For both variables the log transformation is used because it is expected that the effect on the dependent variable is diminishing. Furthermore, variables for type of traveler, type of airport, 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.

Table 2

Dependent variable: flight departure time – preferred arrival time

Explanatory variables	**Coefficient**	**t-value**
Constant (min)	49.4***	5.01
LN[E(T)] (min)	3.5*	1.73
LN[FTT] (hours)	16.7***	9.43
Business (dummy)	-11.5***	-3.66
Retired (dummy)	9.3**	1.99
5-10 flights per year (dummy)	-10.0***	-2.17
More than 10 flights per year (dummy)	-20.0***	-3.34
Check in luggage (dummy)	15.9***	-3.34
Check in online (dummy)	-9.5***	-3.31
Airport large (dummy)	21.5***	5.36
Airport mid (dummy)	11.2**	1.86
Flight departure between 0:00 and 7:00 (dummy)	-11.8***	-2.71
Adjusted R^2	0.28	
Number of observations	930	

Notes: Airport large are: Schiphol Airport and Frankfurt Airport. Airport mid are Airport Dusseldorf and Airport Brussels. Significance is indicated by ***, ** and * referring to significance at the 99%, 95% and 90% level, respectively.

The results show that longer expected travel times and longer flight travel times result in an earlier t_{pat} of the traveler. Furthermore, business travelers prefer to arrive later than non-business travelers. Travelers that are retired have an earlier t_{pat}, likely because of less scheduling constraints.

Experience plays an important role. Travelers that fly between 5 and 10 times per year prefer to arrive on average 10 minutes later than travelers with less experience, and travelers that fly more than 10 times per year prefer to arrive on average 20 minutes later. This result indicates that uncertainty about in airport service times decreases when a traveler is more experienced. An experienced traveler has probably a better perception of the real in airport service time than a non-experienced traveler.

If a traveler needs to check in luggage he prefers to arrive approximately 15 minutes earlier. If a traveler 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.

The type of airport influences the decision on the t_{pat}. The larger the airport, the earlier the t_{pat} of travelers. The reason for this result is presumably that large airports are more crowded or have higher walking times to the gate. If the flight departure time is early in the morning or during the night, travelers prefer to arrive later. This could be due to the fact that airports are less crowded during this time of day.

4. Stated choice models

A stated choice experiment (SCE) has been developed to estimate the WTP values that the air travelers use in the cost function of Equation 1. An example of a choice question is given in Fig. 4. The experiment is unlabeled and respondents are asked to have their latest trip in mind when answering the questions. A ‘none’ option has not been 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, based on earlier questions about the latest trip of the respondent. The trip destination, flight departure time, access mode and final destination are provided. If respondents travel by car the parking costs are also provided. Above the choice question the final check-in time and the preferred arrival time of the respondent are shown. Before the experiment it was explained that if travelers 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.

The first attribute of an alternative is the monetary travel cost which is based on the reference travel time of the respondent. The second and the third attribute are the departure time from home and the usual travel time. The usual arrival time is defined by these two attributes. Finally, the probability of missing a flight is given as a percentage. Within a choice, the latest arrival will have a higher probability of missing a flight because from the pilot study it was found that respondents find it very unrealistic when a later arrival will result in a lower probability of missing a flight. Respondents can ask additional explanation about percentages if they do not understand what percentages are. Only 6% of the respondents asked for additional explanation and only 1 respondent did not understand what a percentage is after the explanation.[3] It was explained that if a travelers arrives too late, he arrives 15 minutes after the final check-in time. Table 3 summarizes the possible attribute levels.

Table 3

Design attributes

Design Attribute	**Levels[4]**	**Remarks**
Costs	0.15,0.2,0.25,0.3,0.4,0.45	multiplied with reference travel time in minutes to obtain costs in euros
Travel time	-15%,-5%,0%,10%,20%	deviation from reference travel time
Arrival	5,10,35,50,90,110,120,170	minutes before final check-in time
Probability to miss the flight	0, 0.5%, 1%, 1.5%, 2%, 3%	

The possible arrival times are based on the observed arrivals in a pilot study. In the choice experiment every respondent receives 10 choices with 2 alternatives. The design has 13 blocks and is almost balanced for every respondent, meaning that every respondent receives the attribute levels of Table 3, 3 or 4 times in the choice experiment.

[3] However, this respondent is included in the analysis because it is unknown if the perception is also biased in a revealed preference situation.
[4] If taxi is the access mode the levels of the cost attribute is 0.3 higher.

After the experiment, additional questions were asked about how the choices were made. Some respondents (5%) are not used in the analysis of the choice responses because they made mistakes in the questions about the reference trip or they indicated that they choose randomly between the alternatives. Almost 70% of the respondents indicate that they find the trade-offs realistic, which indicates that the attributes are likely to capture most important aspects of the airport access utility function.

4.1 Econometric setup

For the estimation of the model a slightly generalized version of the mixed logit is used. The basic mixed logit model is not capable of capturing scale heterogeneity. Recently, Fiebig et al. (2009) showed that scale heterogeneity might be an issue, while the results of Green and Hensher (2010) suggest that it is not of major importance for estimating the mean WTP values. In the notation we follow Fiebig et al. (2009) who define the utility of person *n* for alternative *j* for choice *t* as:[5]

$$U_{njt} = \sigma_n \cdot (\boldsymbol{\beta} + \eta_n) \cdot x_{njt} + \varepsilon_{njt} \qquad (2)$$

In equation 2 the vector $\boldsymbol{\beta}$ is homogeneous over the population while η_n captures the individual specific component of the marginal utility. The parameter σ_n captures the scale which is different over individuals. Fiebig et al. (2009) show that when η_n=0 and σ_n=1 the model reduces to a standard binary logit model with a scale parameter set to 1. In the estimation we use a lognormal distribution for the scale, so σ_n is defined by:

$$\sigma_n = \exp(z), \text{ where } z \sim N(\lambda_0, \lambda_1) \qquad (3)$$

[5] Fiebig et al. (2009) call this model GMNL-II. They also introduced GMNL-I where the scale only affects the vector $\boldsymbol{\beta}$, but not η_n.

To estimate the model we constrain λ_0=0 because the standard deviation of the scale can be estimated but the mean is not identified. If λ_1=0, the formulation is exactly similar to the standard mixed logit model where the scale is usually normalized to 1. The deterministic part of the utility is given by equation 4 (where the subscripts are omitted).

$$V = (\beta_C + \beta_{DBC} \cdot DBC) \cdot C + \beta_T \cdot E(T) + \beta_{ESDE} \cdot E(SDE) + \beta_{ESDL} \cdot E(SDL) + \beta_{PMF} \cdot PMF \quad (4)$$

In Equation (4), C is the travel cost, $E(T)$ is the expected travel time, SDE = max(0,H-T) is the schedule delay early , and SDL = max(0,T-H) is the schedule delay late, where H is the headstart defined as $t_{pat} – t_h$. The schedule delay variables capture the extra disutility of being early or late and do not capture the (dis)utility of having a shorter or longer trip. This (dis)utility is already captured by the travel time variable T. A separate cost coeffient for business travelers is estimated by including a dummy DBC, which is equal to 1 if the traveler is a buniess traveler and 0 otherwise. Finally, PMF is the probability to miss a flight expressed as a percentage. In the estimated it is assumed that the cost coefficient is non-random and that the others are normally distributed. Since the utility is linear in the parameters, WTP values can be derived by taking the ratio of the mean coefficient with the cost coefficient. The distribution of the scale cancels out. The models are estimated in Biogeme (Bierlaire 2005, 2008) using maximum simulated likelihood (Train 2003). For the approximation of the integral 25000 Halton draws are used (Halton 1960).

4.2 Estimation results

The estimation results for the binary logit (BL), binary panel mixed logit (BPML) and the generalized binary panel mixed logit (GBPML) model are given in Table 4. The income level of a traveler does not affect the sensitivity to costs and is therefore not included. The BPML model and the GBPML model give comparable results in terms of WTP values. Although the standard deviation of the scale parameter is significant and the loglikelihood improves, this does not seem to affect the mean and standard deviation parameters that much. This is in line with the findings of Greene and Hensher (2010).

Table 4

		BL		BPML		GBPML	
Variable description	Symbol	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
mean costs coefficient	μ_C	-0.02**	-9.24	-0.04**	-7.67	-0.04**	-7.91
dummy business * costs	DBC	0.01**	3.45	0.02**	2.64	0.02**	2.85
mean travel time coefficient	$\mu_{E(T)}$	-1.09**	-9.67	-1.41**	-8.96	-1.44**	-9.04
mean expected schedule delay early coefficient	$\mu_{E(SDE)}$	-0.69**	-22.02	-1.19**	-15.57	-1.32**	-14.25
mean expected schedule delay late coefficient	$\mu_{E(SDL)}$	-1.22**	-26.93	-2.53**	-14.44	-2.59**	-12.56
mean probability to miss a flight coefficient	μ_{PMF}	-0.38**	-15.15	-0.55**	-11.94	-0.54**	-11.80
Standard deviations	Symbol	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
standard deviation of travel time coefficient	$\sigma_{E(T)}$	-	-	1.01**	4.90	0.98**	3.03
standard deviation expected schedule delay early coefficient	$\sigma_{E(SDE)}$	-	-	-1.10**	-13.22	-1.31**	-13.01
standard deviation expected schedule delay late coefficient	$\sigma_{E(SDL)}$	-	-	1.95**	11.83	2.08**	9.18
standard deviation probability to miss a flight coefficient	σ_{PMF}	-	-	0.30**	3.96	0.19**	2.17
Scale	Symbol	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
mean scale parameter	λ_0	--fixed--		--fixed--		--fixed--	
standard deviation of scale parameter	λ_1	-	-	-	-	0.33**	-3.10
Mean WTP values business	Symbol	mean		mean		mean	
Value of access time (€/hour)	VOAT	90.08		69.80		71.29	
Value of schedule delay early (€/hour)	VSDE	56.94		58.91		65.35	
Value of schedule delay late (€/hour)	VSDL	100.83		125.25		128.22	
Value of the probability to miss a flight (€/%)	VOPMF	31.49		26.98		26.68	
Mean WTP values non-business	Symbol	mean		mean		mean	
Value of access time (€/hour)	VOAT	45.80		36.91		35.82	
Value of schedule delay early (€/hour)	VSDE	28.95		31.15		32.84	
Value of schedule delay late (€/hour)	VSDL	51.26		66.23		64.43	
Value of the probability to miss a flight (€/%)	VOPMF	16.01		14.27		13.41	
Model characteristics							
Loglikelihood		-5187.62		-4580.24		-4575.90	
Pseudo-R^2		0.18		0.28		0.28	
Number of Observations		9168		9168		9168	
Number of Halton draws		-		25000		25000	

Note: ** indicates significance at the 95% level. The t-values reported are robust t-values.

Controlling for unobserved heterogeneity in the marginal utilities is important. The model improvement is significant and the mean *VOAT* and *VSDL* do significantly change. The resulting mean *VOAT* is in line with earlier estimations in the literature. The estimated values are lower than the values found by Pels (2003) and comparable to the values found by Furuichi and Koppelman (1993) and Hess and Polak (2006). From additional questions in the survey about which factors travelers find important in the choice experiment, it was found that the high values of the WTPs are mainly the result of a low sensitivity to travel costs. The reason for this is that travelers do not travel very often to the airport and therefore the costs for this trip are less important compared to the case of commuting, where the trip is made several times per week. Another issue is that business travelers receive often cost compensation for their trip and therefore are less sensitive to travel costs.

For business and non-business travelers it was found that the typical pattern *VSDE*<*VOAT*<*VSDL* appears. The ratio between the *VOAT* and *VSDE* is close to 1, and therefore higher than for commuters (Small 1982). Travelers are sensitive for reductions in the probability to miss their flight. The estimated WTP for a reduction in this probability is around 13 €/% for non-business travelers and 27€/% for business travelers. If utility is linear in the probability to miss a flight, the cost of missing a flight are around € 1341 and € 2668 respectively, which is higher than the average reported ticket price in our sample because of the extra disutility of rebooking flights, rescheduling appointments, loss of holidays and stress.[6]

5. Calculation of the costs of airport access travel time variability for car users

In this section the model is developed to calculate the costs of airport access travel time variability for car travelers. This is a crucial step in the analysis, because the connection is made between the estimated WTP values of the previous section and the observed travel time

[6] The linearity assumption has been tested by estimating a model with dummies for each level of the probability to miss a flight. The utility appears to be almost linear for both business and non-business travelers for values of the probability to miss a flight between 0 and 3%.

distribution taking into account anticipating behavior. It is assumed travelers optimize their departure time from home according to this travel time distribution and the mean estimated WTPs of section 4. Furthermore it is assumed that the behavior of air travelers does not significantly change the behavior of other travelers because air travelers are only a very small fraction of the total traffic. Therefore the travel time distribution is assumed to be exogenous and it does not change if a traveler chooses his departure time.

In this section a model is developed to calculate the costs of airport access travel time variability for car travelers. This is a crucial step in the analysis, because the connection is made between the estimated WTP values of the previous section and the observed travel time distribution taking into account anticipating behavior. Furthermore it is assumed that the behavior of air travelers does not significantly change the behavior of other travelers because air travelers are only a very small fraction of the total traffic. Therefore the travel time distribution is assumed to be exogenous and it does not change if a traveler chooses his departure time.

One could argue that t_{pat} is also a choice variable in the model because it depends on the WTP values as well. For example, travelers with a higher *VOPMF* are likely to have an earlier preferred arrival time. We control for the in-airport service time variability by assuming that t_{pat} is explained by the regression results of section 3. Given their preferred arrival time travelers choose their optimal departure time from home. This enables us to derive the expected scheduling costs due to access travel time variability without knowing the distribution of the in-airport service time for which there is no data available.

The difference between the final check-in time and the preferred arrival time is denoted by $T_{airport}$. Since the final check-in time is usually fixed (around 45 minutes before the flight departure time) for an airport, the regression results of section 3 can be used to obtain empirical values for $T_{airport}$.

The results for the optimal costs given by Noland and Small (1995) and Fosgerau and Karlström (2010) cannot be used in our case since there is a kink after the preferred arrival time (t_{pat}) as shown in Fig. 1. Define the headstart H as t_{pat}-t_h. A traveler faces a time-of-day dependent cumulative distribution of travel times, $F(T;H)$ and corresponding probability density function $f(T;H)$ with mean $\mu[H]$ and standard deviation $\sigma[H]$. The expected travel time for an air traveler is given by Equation 5 and is simply the time-of-day dependent mean travel time.

$$E(T;H) = \int T \cdot f(T;H)\,\mathrm{d}T = \mu[H] \tag{5}$$

The expected schedule delay early is given by Equation 6 by integration over all possible early arrivals. The integral starts at T=0 and ends at $T = H$, because then a travelers arrives exactly on time and the schedule delay early will be 0.

$$E(SDE;H) = \int_0^H (H-T) \cdot f(T;H)\,dT \tag{6}$$

Similarly the expected schedule delay late can be derived by integrating from $T = H$ where the schedule delay late is 0, to the final check-in time $H + T_{airport}$, since it was assumed that other schedule disutility after the flight is missed will be captured by the discrete variable θ.

$$E(SDL;H) = \int_H^{H+T_{airport}} (T-H) \cdot f(T;H)\,dT \tag{7}$$

The probability of missing a flight (PMF) depends on the variable $T_{airport}$. If a traveler arrives earlier at the airport because of his beliefs that there will be a long in-airport service time, the traveler will have an earlier preferred arrival time and therefore $T_{airport}$ will be higher.

$$PMF(H) = \int_{H+T_{airport}}^{\infty} f(T;H)\,dT \qquad (8)$$

In Equation 8 the integral starts at the delay when the flight will be missed ($T = H + T_{airport}$). For all delays higher than this delay travelers will miss their flight. The probability to miss a flight is decreasing in $T_{airport}$. The optimization problem is given in Equation 9, where Equations 5-8 are multiplied with the corresponding WTP values that were estimated in section 4.

$$\min_H E(C) = \alpha \cdot E(T) + \beta \cdot E(SDE) + \gamma \cdot E(SDL) + \theta \cdot PMF \qquad (9)$$

The decision of the traveler is to determine the optimal H that minimizes the expected travel costs based on the travel time distribution and his WTP values. There is no closed-form solution for this minimization problem. Therefore we empirically illustrate the model by taking a typical business and a non-business traveler going to Schiphol Airport with mean WTP values estimated in the GBPML model. For this analysis loop detector data is used where the origins are the highway ramps in The Netherlands and the destination is a highway ramp close to Schiphol Airport. In total 581 highway ramps are used. The data we use is measured by loop detectors with observations for every 15 minute time-of-day interval. The data is interpolated to obtain 1-minute interval data and fitted with a kernel smooth density function because travel time distributions vary strongly over time-of-day[7]. Figure 5a and 5b plot the value of reliability as a function of the costs of mean travel time. In total there are 581•1440 observations. In figure 4 we report the average percentage of the costs of travel time variability in the total expected travel costs.

<<insert figure 4 about here>>

[7] For each time period, we use an optimal bandwidth for a normal kernel and use 100 equally spaced points. All programming has been done in Matlab 7.6.0.

Policy makers can use these numbers as a rule of thumb to calculate the generalized access costs to analyze how access travel time variability affects the choice of airports. We report the percentages as a function of time of day. For business travelers, the morning peak costs of travel time variability raise up to 36% and for the evening peak around 27%. During daytime this number is between 10 and 20% and during night time it drops to 3% because the variation in travel times is lower. The results are intuitive since the morning peak in The Netherlands has usually more severe congestion than the evening peak. Earlier work in the context of commuting already showed that the costs of travel time variability are strongly related to the costs of expected travel time because the mean and the variance of travel time are strongly related (Fosgerau 2009).

6. Conclusions and discussion

In this paper the effect of airport access travel time variability on travel costs has been analyzed. The binary logit and binary mixed logit estimations show that scheduling plays an important role in departure time decisions of travelers going to the airport. For both business and non-business travelers there is heterogeneity in the scheduling parameters and controlling for heterogeneity results in a lower mean value of access time. Finally, a connection is made between the estimated shadow costs of scheduling taking into account anticipating behavior of air travelers. Using a large dataset of Dutch travel times we show that for business travelers the costs of variability are in between 3-36% depending on the time of day. For non-business travelers this number is in between 3-30%.

The models that are developed in section 5 have some limitations. To calculate the generalized costs, it is assumed that air travelers have a perfect perception of the travel time distribution and that utility is linear in its arguments. In the case of commuters perfect perception may be a realistic assumption because these travelers are experienced. For air travelers it may well be that travelers do not know the travel time distribution and therefore make larger perception errors. This may result in non-optimal behavior and therefore the costs of variable travel times may be higher than estimated in the model of section 5. Therefore extension to a rank-dependent scheduling model as proposed by Koster and Verhoef (2010) may be a direction for future work.

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Fig. 1 Deterministic access costs function of an air traveler

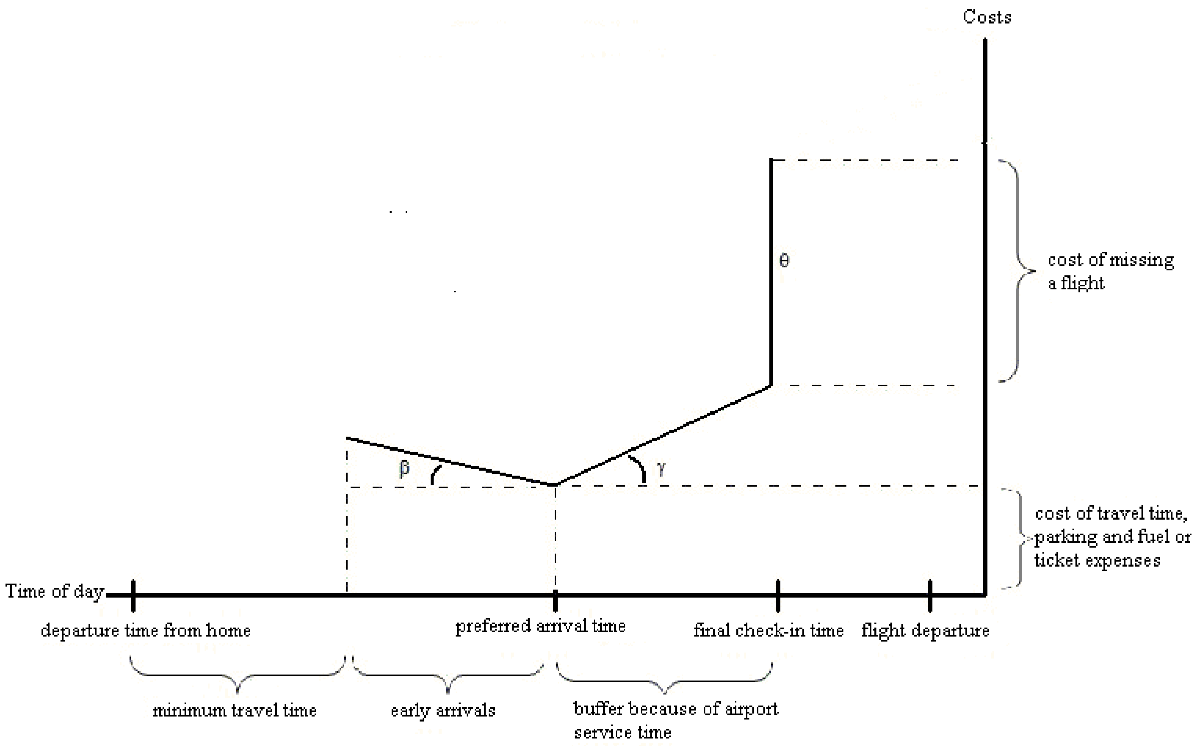

Fig. 2 Spatial distribution of the departure place for business and non-business (personal) trips.

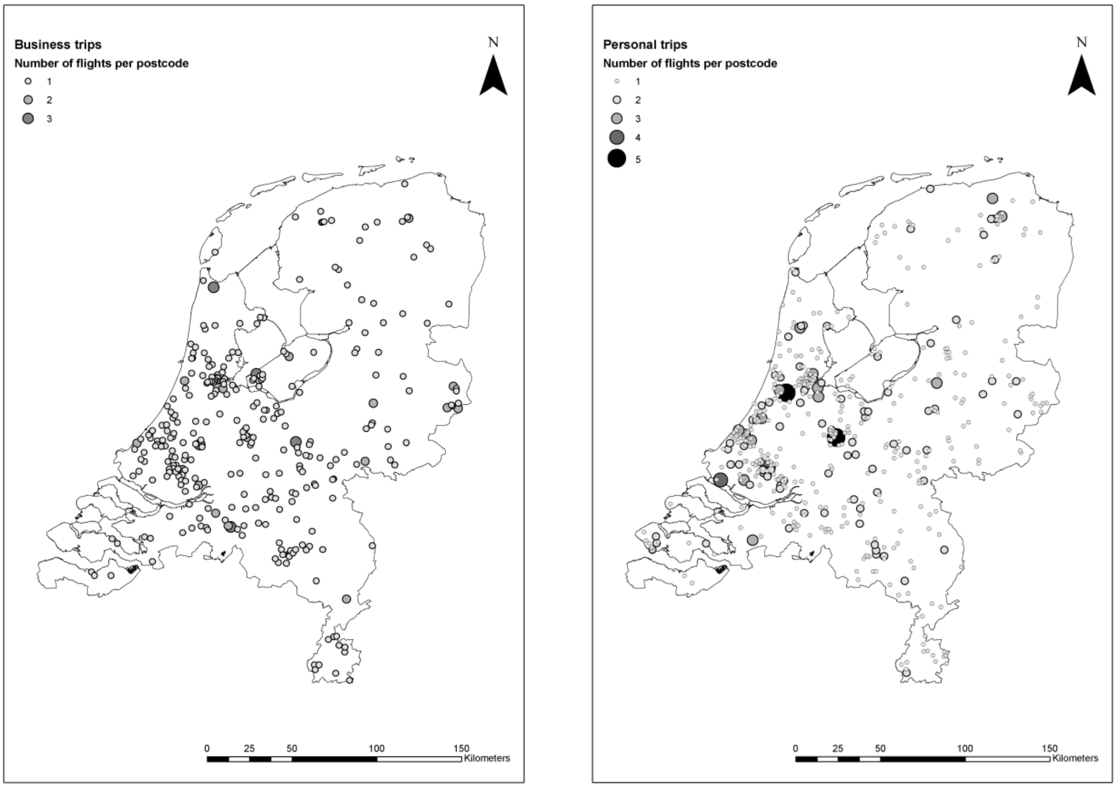

Fig. 3 Example of a stated choice question.

You make a flight to Washington via London Heathrow with departure time 16:20.
You travel in the same way to the airport as your last trip, so by train and you arrive at the check-in counter.
You have only these two possibilities to travel to the airport,alternative A and alternative B.
Which alternative do you prefer?

Your final check-in time is 15:50.
If there are no delays your preferred arrival time at the check-in counter is 15:00.

Travel costs: 24 euros
Departure time: 14:10
Usual travel time: 1 hour and 35 minutes
Usual arrival time: 15:45
Probability to miss your flight: 1%

Travel costs: 38 euros
Departure time: 12:25
Usual travel time: 1 hour and 35 minutes
Usual arrival time: 14:00
Probability to miss your flight: 0.5%

Alternative A ○ **Alternative B** ○

Fig. 4: Average percentage of the costs of access travel time variability in total access travel costs as a function of time-of-day.