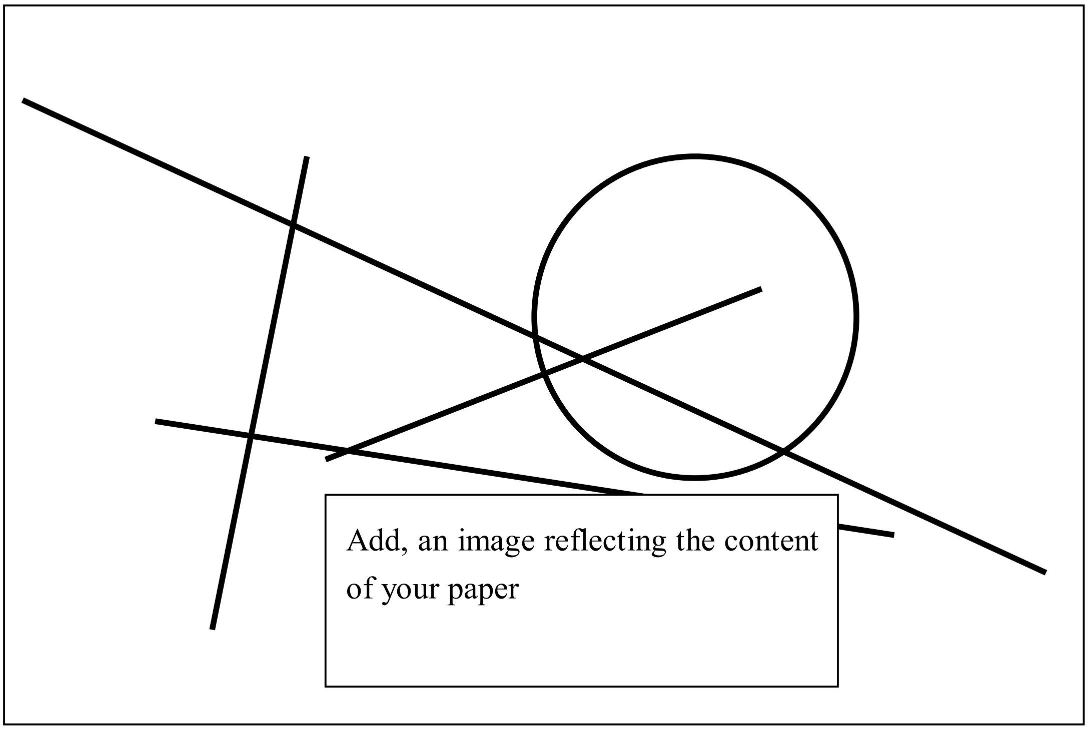

Departure time choice : estimation results and simulation to Paris area

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Abstract

The scope if this article is to develop a comprehensive study of departure time choices for Paris, Ile-de-France. For this purpose, we have proposed a computer-assisted questionnaire to generate (random) personalized tradeoffs on departure times and travel time. The data allowed us to estimate the dynamic schedule delay parameters for various groups of users and various trip purposes. We have proposed the following improvements over the standard analysis: flexible schedule delay cost functions, discrimination between free flow and congested travel time and cost for an earlier departure time (constraints at the origin).

We have shown that trips to work and for shopping or trips by car and by public transportation are described by very different cost functions and that different explanatory variables interact in the departure time choice processes. We have also demonstrated that the distribution of the dynamic parameters are better estimated with a mixed logit model and lognormal distributions. Our empirical results and our simulation results using METROPOLIS suggest for the Paris area that the schedule delay cost represents a third of the generalized cost (and half of the variable cost).

Keywords

Departure time choice, Mixed logit, value of time, dynamic traffic simulation, schedule delay cost, International Conference on Travel Behaviour Research, IATBR

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1. Introduction

Numerous time of the day dependent policies such as flexible or staggered hours, variable traffic restraints or modular road or parking pricing have been proposed to relieve congestion in private or public transportation. The impact of these policies depends on the values of the behavioral parameters to be estimated as well as on their distribution. The standard parameter to be estimated is the value of time (VOT), but other parameters also play a key role, in particular to explain the peak shift. The reason is that users change mode, but also departure time when time of the day dependant policies are implemented. In the dynamic model considered here, the user choice is based on a generalized cost function. The generalized cost, originally introduced by William Vickrey (1969) is the sum of travel time cost and schedule delay cost (corresponding to the penalties for early or late arrivals at destination). It is the scope of this paper to estimate the functional form and the parameters of the generalized cost function and to identify the other factors affecting the departure time decisions.

Numerous surveys and empirical studies have been conducted during the past 25 years in order to estimate departure time choice models. Those studies were mainly concerned with commuters and private transportation. Today, dynamic policy evaluation needs more comprehensive analysis of departure time, in particular for various groups of users and for different trip purposes.

To acquire a better knowledge of the trip time decisions, we conducted a survey in Ile-de-France. We developed a methodology based on customized scenarii in order to generate personalized and randomized tradeoffs on departure time choices. The answers to the tradeoffs proposed in the survey allow to estimate various functional forms for the schedule delay costs for various groups of users: private and public transportation users, trips to work, shopping, school; by gender, income, age, etc. Our analysis is based on binary Logit and mixed Logit choice models (for an overview of discrete choice models, see McFadden, 2000).

The study concerned Paris and its suburb. We realized a phone survey during May and June 2000. The phone calls have been processed from 5 to 8 PM by the French company SOFRES concerning the morning trips for the same day. About 4230 individuals answered the questionnaire.

The first part of the questionnaire collected all the information essential for the departure time choice model: information on the selected trip, schedule and constraints at home and destination, characteristics of the modes used (travel time, cost, time constraints, etc.), network knowledge and use of information on trip conditions. If the constraints at home are rigid, they are taken into account in the customized scenarii.

The second part of the questionnaire was concerned with the tradeoffs between two choices involving different departure times and different travel times (and thus different arrival times).

The third part is related to scenarii on modes and information (not used in this study). The fourth part concerns the characteristics of the individuals and their household.

The standard departure time model is introduced and discussed in Section 2, together with the trade-off between travel time and schedule delays. The generalized cost function is extended in Section 3 to take into account constraints at the origin and the difference between free flow and congestion travel time in the evaluation of the value of time. In this section, we also present the estimation results for different cost functions for different trip purposes and different modes. In order to take into account two sources of heterogeneity, we estimate the distribution of the dynamic parameters as well as the impact of individual characteristics on departure time choice. Section 4 concludes. In this section, we also discuss aggregate results based on our estimates. We evaluate the impact of schedule delay cost for the Paris area, and show that they account for about 50% of the variable user cost.

2. The departure time choice model

2.1 The standard model

The choice of departure time involves the tradeoff between travel time and schedule delay. For most trip purposes, the traveler has a preferred arrival time at destination, but usually arrives at destination either too early (and incurs an early schedule delay cost) or too late (and incurs a late schedule delay cost). Usually, the travel time is the largest when the arrival time at destination is the preferred arrival time, since congestion is then maximum. The analysis of departure time choice is based on the idea that there is a tradeoff between travel time cost and schedule delay cost. This idea was initially introduced by Vickrey (1969) and it is currently at the basis of many studies of dynamic travel behavior.

The standard model analyzes the choice of arrival time at work. Let t_d denote the departure time, t^* denote the preferred arrival time or the official work start time[1] and let $tt(t_d)$ be the

[1] See below for a detailed definition of t*.

travel time. The generalized cost function $C(t_d)$ depends on the travel time $tt(t_d)$, the early schedule delay $[t^* - t_d - tt(t_d)]^+$ and the late schedule delay $[t_d + tt(t_d) - t^*]^+$, where $[x]^+$ denotes $\max(x,0)$. Three dynamic parameters reflect the marginal costs : α denotes the value of time, β the cost of being one additional minute early at destination and γ the cost of being one additional minute late at destination. With a linear specification, the cost function $C(t_d)$ is:

$$C(t_d) = \alpha tt(t_d) + \beta[t^* - t_d - tt(t_d)]^+ + \gamma[t_d + tt(t_d) - t^*]^+ . \quad (1)$$

The econometric approach envisaged in Section 3 is based on non-normalized costs $C(t_d)$ described by equation (1) and involves the normalization of the variance of the residuals. Another normalization is used in Section 2 since the formulation envisaged in this section involves the comparison of cost functions and does not include random terms. In this case, the cost function is normalized by the value of time, α and is denoted by $C_0(t_d)$, with

$$C_0(t_d) = tt(t_d) + \frac{\beta}{\alpha}[t^* - t_d - tt(t_d)]^+ + \frac{\gamma}{\alpha}[t_d + tt(t_d) - t^*]^+ . \quad (2)$$

Alternative specifications for $C(t_d)$ have been proposed by various authors and will be envisaged in Section 3. For example, a discontinuous piecewise linear cost function was introduced by Small (1982). Hendrickson and Plank (1984) tested a quadratic form. Noland et al. (1998) introduced a planning cost defined as a function of the standard error of travel time.

Vickrey's model has been widely used for car trips from home to work and has recently been extended to transit trips from home to school (Nuzzolo and Russo, 1998). In this paper, we extend Vickrey's model to other trip purposes. Since there is congestion in private and public transportation during the morning peak hours, trip timing for other purposes than commuting is also determined by a tradeoff between travel time and schedule delay. We show that the numerical values of dynamic parameters depend on the purpose of the trip. For example, consider a trip to work with an important meeting at the arrival time. For this trip, the late schedule delay cost is intuitively higher than the early schedule delay cost. If we consider another trip between the same origin and the same destination, but for a shopping purpose, there is no reason for the late schedule delay cost to be higher than the early schedule delay cost. In this last example, the early schedule delay cost could be higher than the late schedule delay cost, because an early arrival induces a waiting time if the shop is closed.

A schedule delay appears when the arrival time does not coincide with the "individual reference time", usually referred to as the preferred arrival time. These concepts are defined in the next section.

2.2 The preferred arrival time

The schedule delay is defined as the difference between the actual and the preferred arrival times. Various definitions have been proposed for this time difference. The first application (Cosslett, 1977) used "latest arrival time without penalty", but the word penalty is not clearly defined. The "official work start time" proposed by Abkowitz (1980) and Small (1982) entails different flaws. First, this definition is limited to work related trips with fixed hours. Second, this definition does not include the preferences to arrive before the official work start time (for example to drink a coffee, read a newspaper, etc.). It therefore induces a bias in the computation of the delay.

Mannering (1989) and Noland and Small (1995) used the "usual arrival time". However, in numerous cases the usual arrival time does not correspond to the individual preferences. For example, transit users cannot choose exactly their arrival time, so their usual arrival time does not correspond to the arrival time they would prefer. Wang (1996) used "planned hours" and arrival time which are fixed in a schedule activity pattern defined at the beginning of the day. However, the planned arrival time is not more representative of the preferences of transit users than is the usual arrival time. Other studies (Hendrickson and Plank 1984, Mahmassani and Chang 1986, Abu-Eisheh and Mannering 1988, Cascetta *et al.* 1992, de Palma and Rochat 1996, de Palma *et al.* 1997), defined the schedule delay as the difference between the real arrival time and the "preferred" or the "desired" arrival time.

The two latter variables are sometimes used without distinction. Ben-Akiva (1999) notes that the desired arrival time is the outcome of a choice (depending on travel time variability and on the penalties for late or early arrivals) and does not necessarily correspond to the preferred arrival time. For this reason we use the "preferred" arrival time terminology. The preferred arrival time should be included in the "tolerable" arrival time window. For example, consider a worker traveling from home to work with the following two characteristics:

- He cannot arrive before 8 AM (the opening hour of the building he works in)
- He cannot arrive after 9 AM (a very important meeting starts at 9 AM)

To the question : *What is your preferred arrival time* ?, the respondent could reply 10 AM because she/he does not consider her/his constraints at destination. Therefore, if we use the "preferred" terminology, we have to limit the time interval to the constrained context: *Between 8 AM and 9 AM, what is your preferred arrival time* ? Note that the preferred arrival time could be an interval, Δ, in which the individual could arrive without supporting any penalty. If it is the case, we keep the information on Δ. In the following section, we discuss the methodology used to generate personalized tradeoffs.

2.3 The tradeoff principle

As the time variable is continuous, each user faces a continuum of departure time alternatives included in an interval of acceptable departure/arrival times[2]. Following Vickrey's model, the simplest departure time choice is binary. In the survey, each respondent was proposed pairs of departure times associated with pairs of travel times (i.e. pairs of arrival times).

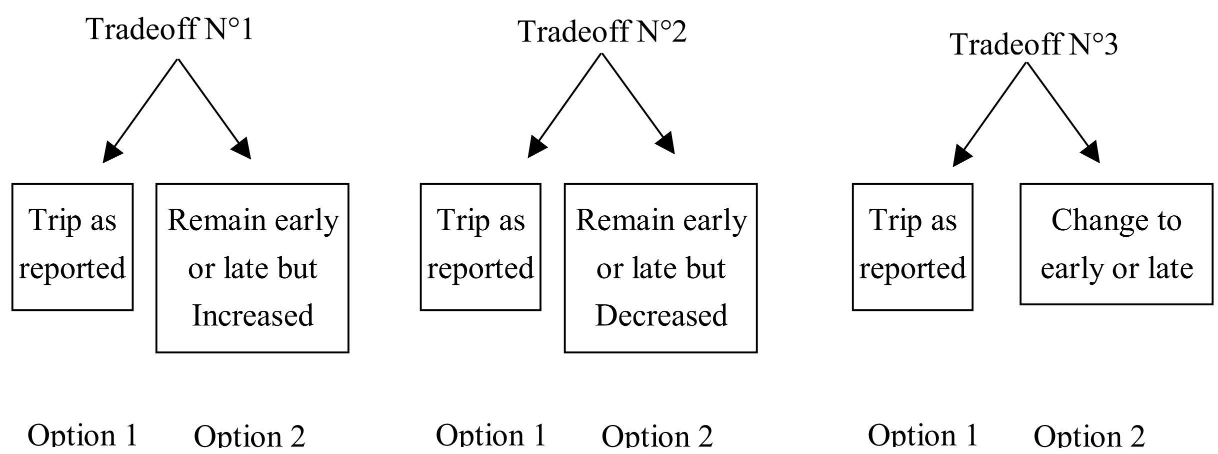
A question involves the following two options:

- **Option 1.** The same trip as the one observed (with the "*R*" index corresponding to **R**eported), characterized by the reported departure time, t_d^R, the reported travel time, tt^R, and the reported arrival time, t_a^R.
- **Option 2.** An hypothetical (randomly generated) trip (with the "*S*" index corresponding to **S**imulated), characterized by the departure time, t_d^S, the travel time, tt^S, and the arrival time, t_a^S.

Three tradeoffs were proposed to each respondent (see Figure 1). The simulated options are respectively characterized by the following schedule delays:

- A delay of the same nature than the reported trip (early or late) but **increased**,
- A delay of the same nature than the reported trip (early or late) but **decreased**,
- A delay with a nature **opposed** to the one of the reported trip.

Figure 1 Binary tradeoffs



[2] See below for a definition of "acceptable".

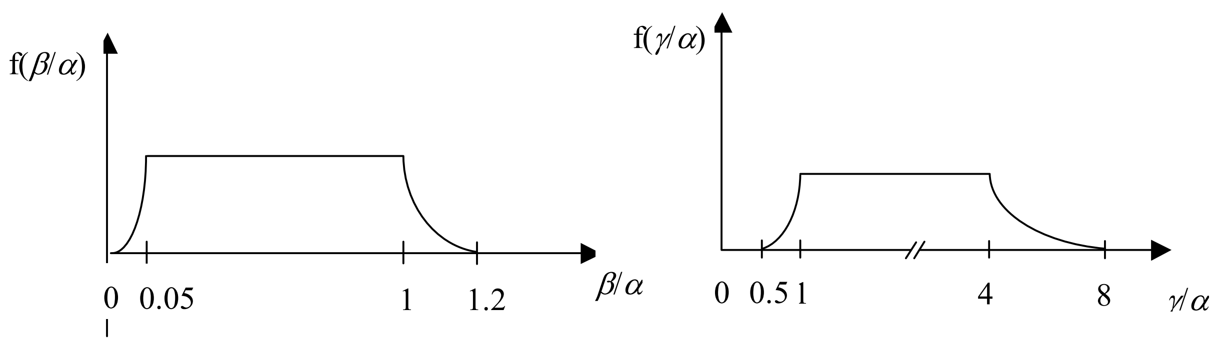
In the case the arrival time of the reported trip is on time, a late scenario and an early scenario are proposed.

For each tradeoff, option 2 is based on the utility equivalence between reported and simulated options (see Figure 1). The procedure used to generate option 2, entails four steps that are detailed now.

STEP 1. Random draws of the dynamic parameters

The distribution of the dynamic randomly simulated parameters is based on uniform distributions. The means are chosen consistently with previous empirical studies on work trips: 0.5 for $\frac{\beta}{\alpha}$ and 2.5 for $\frac{\gamma}{\alpha}$ (see Small, 1982). The interval bounds of the distributions were chosen to be consistent with our *a priori* for all trip purposes. The tails of the distributions have been modified to take into account behaviours that would not be consistent with the theoretical model (that is $\beta/\alpha > 1$ and $\gamma/\alpha < 1$, see Arnott *et al.*, 1993). We set to 1% the probability of the following events: $1 < \beta/\alpha < 1.2$, $0.5 < \gamma/\alpha < 1$. The two resulting distributions (including tails on the other side) are presented in Figure 2.

Figure 2 Distributions of the simulated schedule delay costs parameters



Random draws of the dynamic parameters, denoted by $\frac{\hat{\beta}}{\alpha}$ and $\frac{\hat{\gamma}}{\alpha}$, are used to compute the level of the schedule delay cost $\hat{C}(t_d^R)$ corresponding to the reported travel time:

$$\hat{C}(t_d^R) = tt^R + \frac{\hat{\beta}}{\alpha}[t^* - t_d^R - tt^R]^+ + \frac{\hat{\gamma}}{\alpha}[t_d^R + tt^R - t^*]^+$$

The variables tt^R and t_d^R are observed, so $\hat{C}^R$ can be computed.

STEP 2 . Computation of intervals for arrival times subject to the following restrictions

- 2.1 The values of the dynamic parameters $\frac{\hat{\beta}}{\alpha}$ and $\frac{\hat{\gamma}}{\alpha}$ are the same in the reported and the simulated case.
- 2.2 The level of the schedule delay cost is the same in the reported and the simulated option : $\hat{C}(t_d^R) = \hat{C}(t_d^S)$.
- 2.3 Two constraints on departure time, travel time and arrival time are imposed:
  - *Tolerance on departure time*: the time constraints at home reported by the respondent have to be respected.
  - *Exclusion of arrival times close to the reported arrival time* (plus or minus 5 minutes) to ensure a minimum difference between the two options.

The result of this step is an interval of arrival times (i.e. a set of possible arrival times for the simulated option). If this interval is empty (for example because the time constraints are too tight) other dynamic parameters are drawn[3].

STEP 3 . Simulated arrival time t_a^S

The simulated arrival time t_a^S is drawn in the feasible interval computed in STEP 2 using a uniform distribution.

STEP 4 . Simulated travel times tt^S

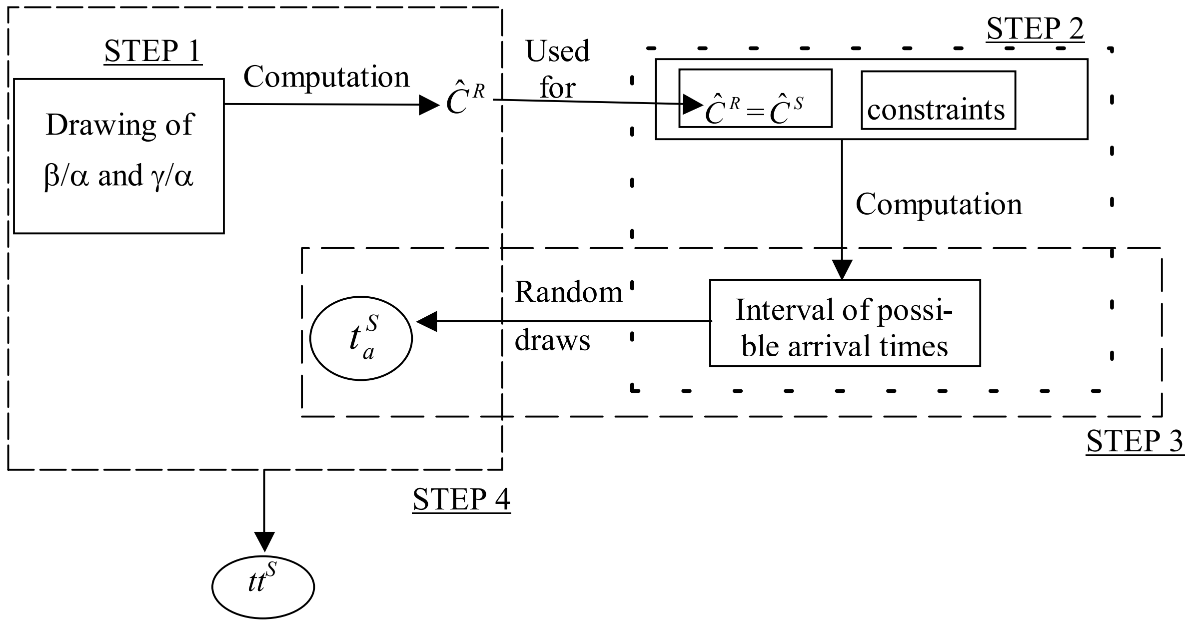
We use the simulated values $\frac{\hat{\beta}}{\alpha}$ and $\frac{\hat{\gamma}}{\alpha}$ of the dynamic parameters and t_a^S to compute the simulated travel times tt^S. Using the equivalence principle (STEP 2.2), we compute tt^S as the unique solution to:

$$tt^R + \frac{\hat{\beta}}{\alpha}[t^* - t_d^R - tt^R]^+ + \frac{\hat{\gamma}}{\alpha}[t_d^R + tt^R - t^*]^+ = tt^S + \frac{\hat{\beta}}{\alpha}[t^* - t_d^S - tt^S]^+ + \frac{\hat{\gamma}}{\alpha}[t_d^S + tt^S - t^*]^+ .$$

Figure 3 describes the four steps.

[3] Since the redraws and the computations during STEP 2 are time consuming, we set to 10 the maximal number of redraws.

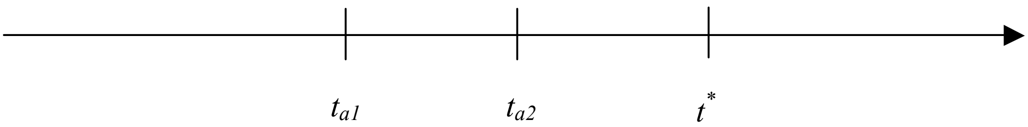
Figure 3 Procedure used to compute option 2



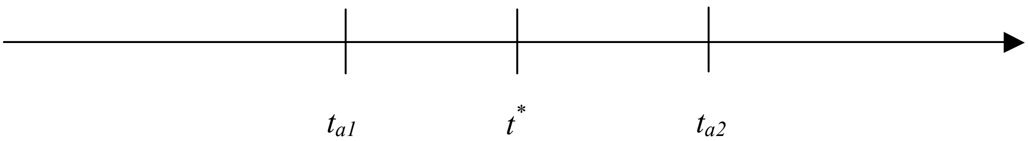
The previous procedure generates a simulated option defined by tt^S and t_a^S (and $t_d^S = t_a^S - tt^S$). The respondent is required to choose between the simulated option and the reported option. The answers to this binary choices are used in Section 3 to estimate the dynamic parameters for different groups of users.

Each of the three binary tradeoffs studied in Figure 1 is between the revealed arrival time t_a^R and travel time tt^R, and a simulated arrival time t_a^S that may be either earlier or later and travel time tt^S. Min(t_a^R ,t_a^S) is denoted t_{a1} and Max(t_a^R ,t_a^S)is denoted t_{a2}. The different cases are:

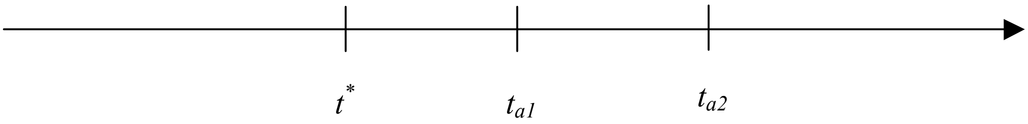
- Tradeoff 1 or 2 with $t_a^R < t^*$: arrive very early (t_{a1}) or early (t_{a2})



- Tradeoff 3: arrive early (t_{a1}) or late (t_{a2})



- Tradeoff 1 or 2 with $t_a^R > t^*$: arrive late (t_{a1}) or very late (t_{a2})



We use the sub-sample of individuals that revealed their preferred arrival time. In this sub-sample, some users only answered one or two scenarii because they lack flexibility at the origin or at the destination (see Section 2.2). The answers to the tradeoffs (3195) are pooled to estimate binary departure time choice models.

In the estimated models, the utility function, $U(t)$, has two components : the schedule delay cost function, $C(t)$, and a vector of individual characteristics, X :

$$U(t) \;=\; -C(t) \;+\; \theta(t)X, t = t_{a1}, t_{a2}\,. \tag{3}$$

This binary choice model explains the utility difference $U(t_{a1}) - U(t_{a2})$. Individual characteristics have the same value in the two alternatives, so they do not affect the choice except if they are valued differently in the two alternatives: in this case, the vector of parameters $\theta(t)$ associated to characteristics X is alternative dependent. The estimated parameter corresponds to $\theta(t_{a1}) - \theta(t_{a2})$.

3. Estimation of the dynamic parameters

3.1 Additional components of the cost function

We decompose the travel time variable in two components: the free flow and the congested travel time (for both public and private transportation). For private modes, the difference between the two components is due to congestion, and for public modes it is due to waiting time (and delays). Each individual reveals his free flow travel time. This information may be biased, but was validated with aggregate data. The simulated travel time can be larger or lower than the revealed free flow travel time. The simulated free flow travel time then corresponds to minimum of the revealed free flow travel time and the simulated travel time. In our experiment, in 30% of cases, the simulated travel time is lower than the revealed free flow travel time. To the best of our knowledge, this analysis is the first one to estimate separately the value of time for free flow and congested regimes.[4].

We also improved the standard model by introducing constraints at origin. In particular, we introduce the cost of leaving home earlier (since early departure implies less time for sleeping or getting prepared, stress, etc.).

3.2 Estimates for work purposes with equal dynamic parameters

Following Hendrickson and Plank (1985) who envisaged quadratic cost functions, we further explore non-linear cost functions and test different functional forms. The basic objective is to determine the best fitting functional form.

The best estimates combine a concave cost function for the early schedule delay and a piece-wise linear function for late schedule delay (with two regimes: one from 5 to 30 minutes and one from 30 to 60 minutes. It is possible to interpret the kinks in the piecewise linear function as psychological levels (tolerance to delay). For all functional forms tested, it was found that the cost for less than five 5 minutes late delay is negligible (five minutes indifference bands). A similar kind of indifference region is also observed for the early schedule delay since the marginal cost is zero at the origin with a quadratic cost.

The best estimates are described below. Let $\boldsymbol{\alpha_0}$, $\boldsymbol{\alpha_c}$, δ, β_2, γ_1 and γ_2 denote the dynamic parameters for, respectively, free flow travel time tt_{free}, congested travel time $tt_{congested}$, early departure delay tt_{earlyD}, early arrival schedule delay (in quadratic form) $(tt_{earlyS})^2$, late arrival schedule delay tt_{lateS} when tt_{lateS} is less than λ and late schedule delay when tt_{lateS} is more than λ, where λ denotes the breaking level (fixed to λ=30). The cost function is now written as:

$$C(t)= \alpha_0 tt_{free} + \alpha_c tt_{congested} + \delta\ tt_{earlyD} + \beta_2 (tt_{earlyS})^2 + \gamma_1 tt_{lateS} I(tt_{lateS \leq \lambda}) + \gamma_2 tt_{lateS} I(tt_{lateS > \lambda}), \quad (4)$$

where *I(condition)* is a dummy variable equal to *1* when condition is met and *0* else. The results presented in Table (1) correspond to the parameters of the utility function in equation (3)

[4] Hendrickson and Plank (1985) use a different component, as it is include in the mode choice model jointly estimated with a departure time choice model.

Table 1 Work purpose - Logit model

Parameter	Estimate	Standard error
α_0	0.0325***	0.013
α_c	0.0459***	0.010
δ	0.0472***	0.006
β_2 (5-60 min)	0.00042*	0.0001
Mean cost (1 hour)	*0.0252*	
γ_1 (5-30 min)	0.0786***	0.016
γ_2 (30-60 min)	0.0997***	0.027
Constant	-0.1986**	0.107
I(constraint at home)	0.7145***	0.157
I(official arrival time)	-0.5121***	0.099
Observations		1988
Pseudo R^2		0.112
Log Likelihood		-1207

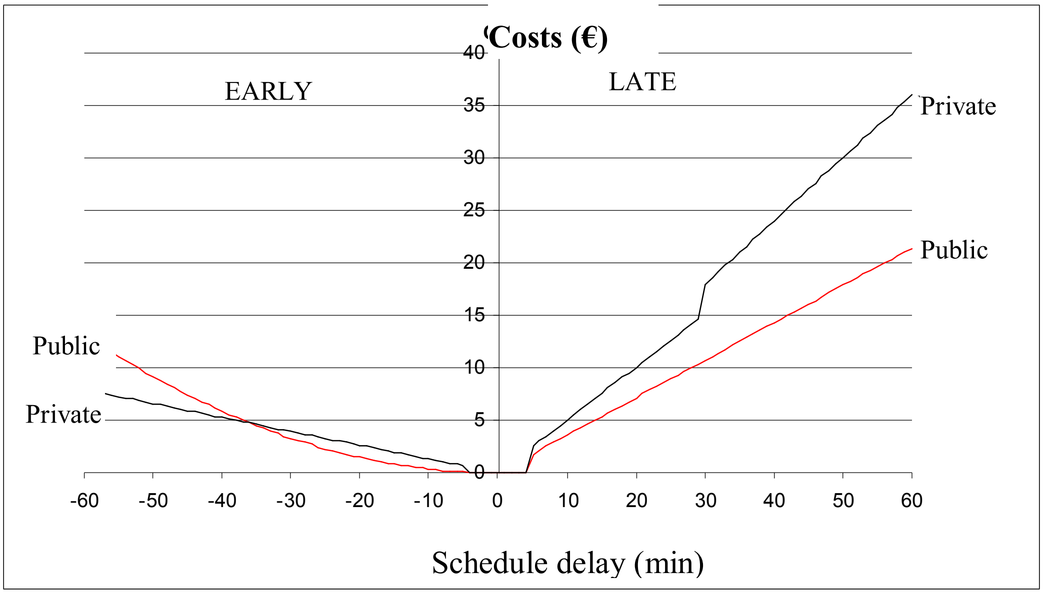
* : 10% singif., ** : 5% singif. *** : 1% singif.

In order to make the coefficient β_2 directly comparable to the other VOT coefficients, we evaluated the mean cost of early schedule delay for the maximum delay considered, that is 1 hour. It simply corresponds to $\beta_2*60^2/60=\beta_2*60=0.0252$. Evaluated at the sample average delay early (24 minutes), the mean cost of early schedule delay would be $\beta_2*24=0.0101$.

As expected, the VOT associated to the congested travel time is larger than the VOT for the free flow travel time and both values of travel time are larger than the VOT for early schedule delay, and lower than the VOT for late schedule delay ($\beta<\alpha<\gamma$). The cost of earlier departure is highly significant. We also estimated the model without this component and observed that the introduction of an early departure cost implies a significant decrease of the estimated early schedule delay cost (at destination). This suggests that the usual estimates in the literature mix two different components that we were able to discriminate.

The results of separate estimates by mode used (private/public) are reported in Annex Table A1 and represented on Figure 3.

Figure 2 The cost function by mode – Work purpose – Logit model



3.3 Estimates for work purposes - random dynamic parameters

We used the procedure proposed by Mc Fadden and Train (2000) to test the Logit model against the Mixed Logit model. This test was applied to the simple standard cost model and to the proposed specification of cost. In both models, the Logit was rejected at the 1% level.

Different distributions for the dynamic parameters of the mixed logit model were tested[5] (see Hensher and Green (2002) for a discussion on the number of draws for the mixed Logit) and presented in Table 2. We tested the different methods they propose, and obtained the same econometric results. Our model was estimated with 10 000 draws.

We initially tried to estimate a lognormal distribution for the three dynamic parameters, but as it is common in studies using mixed logit (Johansson 2000, Egert et Tveteras 2001, Chung et Alcacer 2002), the standard deviations were hardly significantly different from zero. Accord-

[5] We used the SAS 8.2 Proc MDC.

ing to Hensher and Greene (2002), this problem comes from a lack of variability in the scenarii. In our case, variability is limited by the constraints imposed on step 2. Fontan (2003) showed how important these limitations are. Another explanation to this lack of significance is linked to the normalization. Considering a distribution for α is equivalent to assuming heteroskedasticity when cost is normalized as in equation (2) (the estimation procedure assumes that residuals are homoskedastic with the non normalized cost of equation (1)). After testing many distributions, we found that the best fitting model is obtained with deterministic VOT for travel time (α) and lognormal distributions for early and late schedule delay (β and γ). Our results can therefore be interpreted as an indication that residuals are still homoskedastic in the normalized cost formulation.

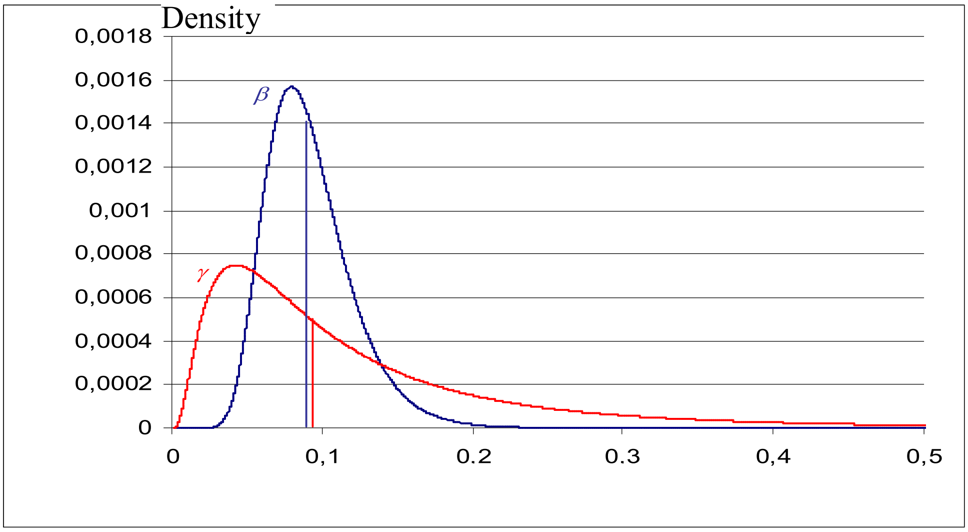
Table 2 Work purpose – Mixed Logit with Log normal distributions

Parameter	Estimate	Standard error[a]
α_0	0.0921***	0.017
α_c	0.1313***	0.019
$\bar{\beta}$ Lognormal	-2.4369***	0.133
σ_β	0.3047 [b]	0.206
E(β) and std(β)	0.0915	0.0285
$\bar{\gamma}$ Lognormal	-2.4127***	0.246
σ_γ	0.8626***	0.203
E(γ) and std(γ)	0.1299	0.1365
Constant	-0.4870***	0.146
I(constraint at home)	0,7079***	0.172
I(official arrival time)	-0,5484***	0.111
Observations	*1941*	
Pseudo R²	*0.14*	
Log Likelihood	*-1178*	

[a] *Standard deviation for the random dynamic parameters β and γ*
b« s14 » : significant at the 14% level

The marginal distributions of the parameters are displayed in Figure 2. The distribution of the parameters plays an important role both for theoretical work and for simulation results (briefly presented in Section 4).

Figure 3 Lognormal distributions of the two key parameters β and γ



Using the expectation and the standard deviation of a lognormal distribution, the mean values of the VOT for early and late schedule delay are $E(\beta)=\exp\left(\bar{\beta}+\sigma_\beta^2/2\right)$=0.0915 and $E(\gamma)=\exp\left(\bar{\gamma}+\sigma_\gamma^2/2\right)$=0.1299, respectively. The inequalities ($\beta<\alpha<\gamma$) are respected for the average values (0.0915<0.0921<0.1299), at least for free flow travel time. Although the point estimate for the value of congested travel time (α=0.1313) is larger than the mean value of time for late delay, the difference is not significant and the null hypothesis that γ>α cannot be rejected at the 5% level. Standard deviations for early and late schedule delay are $std(\beta)=\sqrt{\exp\left(2\bar{\beta}+\sigma_\beta^2\right)\left[\exp\left(\sigma_\beta^2\right)-1\right]}$ and $std(\gamma)=\sqrt{\exp\left(2\bar{\gamma}+\sigma_\gamma^2\right)\left[\exp\left(\sigma_\gamma^2\right)-1\right]}$. Note that the standard deviation of γ is highly significant, whereas the standard deviation of β is significant only at the 14% level.

3.4 Estimates for other purposes

For purposes other than work, the largest data set concerns shopping (227 scenarii), followed by schooling (171 scenarii). Because of the small sample sizes, the other purposes (leisure, medical care, administrative task, etc.) had to be grouped in the "other purpose" category. (328 scenarii).

Since the complete forms would require a large number of observations, we only proposed simple models for each of these three trip purposes. Intuition suggests a different functional form for each purpose, which was confirmed by the lack of significance of additional coefficients in more comprehensive specifications. See Fontan (2003) for exhaustive results, not reported here.

Note that the numerical values of VOT are not directly comparable between the three purposes because of the normalization of the variance of the residuals. Assume that the VOT are the same for the three models with the normalized cost of equation (2) but the variances of the residuals differ for the three trip purposes. Then the coefficients estimated with the non normalized cost of equation (1) would differ.

Children are an incentive for an earlier departure in the context of shopping, maybe because parents have a constraint to be back on time in order to take care of their children.

Concerning the VOT for delay at destination, only the early delay should matter for shopping (an early arrival delay may imply time spent waiting for the opening of the shop and/or a cost of early departure), whereas only late delay should matter for schooling (a natural official arrival time corresponding to the preferred arrival time implies that students should have a significant schedule delay cost).

The early schedule delay cost is very significant and relatively high in the context of shopping (1 hour of early delay is 10% more expensive than 1 hour spent in congestion)[6]. It is also highly significant for the "other" trip category, but three times less expensive than congested time. This low value is not surprising since a majority of individuals in the third sample do not work, so waiting time should be less expensive for them. The early schedule delay cost is not significant for schooling trips. Note that 80% of the scenarii have an early delay, so this result does not come from a data problem. A careful reading of the answers to the open question on the preferred arrival time reveals that the students wish to arrive early in order to chat with their friends. So is not surprisingly that the VOT for early arrival is not significant (it may even be negative since those users seem to enjoy early arrival).

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[6] With the quadratic form, 1 hour too early costs $0.00106*60^2=3.816$, whereas 1 hour congested time costs $0.0569*60=3.414$.

Table 3 Estimation results for the three other purposes

Parameter	Shopping		Schooling		Other	
	Estimate	Std error	Estimate	Std error	Estimate	Std error
α_c	0.0569*	0.024	0.0694**	0.029	0.1123***	0.028
β (5-60 min)			0.0251	0.019	0.0469***	0.015
β_2 (5-60 min)	0.00106***	0.0003				
VOT(1 hour)/60	0.0636					
γ (5-60 min)	0.0580	0.046	0.164***	0.062	0.1094***	0.042
Constant	1.1833**	0.500	-0.839***	0.320	0.1011	0.283
Number of children	0.3346***	0.141				
Age	-0.3954***	0.183				
I(constraint at home)					0.9056**	0.408
I(no correction on arrival time)					-0.678***	0.257
Error on arrival time			0.1401***	0.044		
Observations		227		171		328
Pseudo-R^2		0.10		0.105		0.104
Log Likelihood		-139		-100		-197

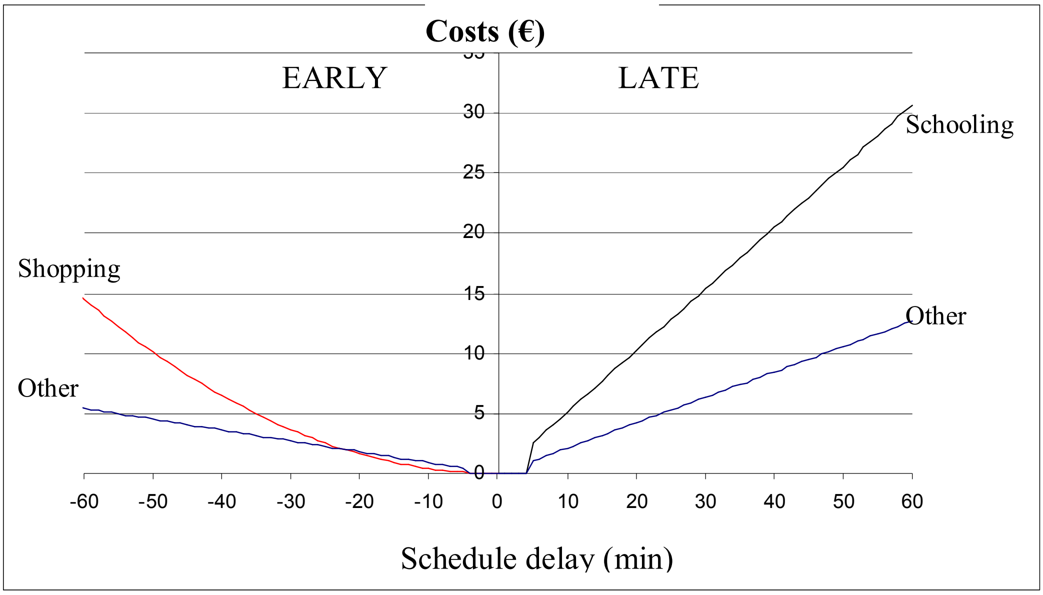
The coefficient of late schedule delay is very high (2.35 times more expensive than congestion time) and highly significant for students, in spite of the small sample size (173 obs). It is very high and significant for "other" trip purposes, which is not surprising in the context of a medical appointment, for example. As expected, it is low and not significant for shopping.

The value of congested time is not very significant in the shopping sample. This may mean that travelers are not stressed by the time spent in the mode when they go shopping.

In the third sample, the late schedule delay cost is not significantly different from the cost of time spent in congestion. However, the grouping of relatively different trip purposes gives averaged results that are difficult to interpret.

These results appear clearly on Figure 4.

Figure 4 Title



The estimated parameters can now be used to evaluate aggregate costs and can be introduced as inputs in the simulation model METROPOLIS.

4. Concluding comments

The scope if this article was to develop a comprehensive study of departure time choices for Paris, Ile-de-France. For this purpose, we have proposed a computer-assisted questionnaire to generate (random) personalized tradeoffs on departure times and travel time. The data allowed us to estimate the cost function, including dynamic schedule delay parameters for various groups of users and various trip purposes. We have proposed the following improvements over the standard analysis: flexible schedule delay cost functions, discrimination between free flow and congested travel time and cost for an earlier departure time (constraints at the origin). The new parameters we introduced proved to play a significant role in the estimated cost functions and to affect significantly the aggregate results.

We have shown that trips to work and for shopping or trips by car and by public transportation are described by very different cost functions and that different explanatory variables interact in the departure time choice processes. We have also demonstrated that the distribution of the dynamic parameters are better estimated with a mixed logit model and lognormal distributions.

Our parameters were estimated up to a multiplicative constant (normalization of the variances). In order to recover the true values of the parameters, we used values of time previously estimated (and currently used in the cost benefit analysis in France), together with the distribution of trip purposes and delays. The values of travel time we use are 21.03€/h for private mode and 13.24€/h for public mode. Using the estimated ratios for $\frac{\beta}{\alpha}$ and $\frac{\gamma}{\alpha}$ (see Annex Table A1), we obtained the following VOT for private mode commuters: 7.91€/h for early schedule delay, 30.21€/h for late schedule delay less than half an hour and 36.02€/h for late schedule delay more than half an hour. Similarly, for public mode commuters, we obtain 13.20€ for one hour early schedule delay and 21.45€/h for late schedule delay. For all the other trip purposes, we chose a value of travel time of 7.17€:h, representing 55% of the value of travel time for public mode commuters. This gives 8.01€/h for early schedule delay when shopping, 16.90€/h for late schedule delay for schooling, 2.99€/h for early schedule delay and 6.98€/h for late schedule delay for other purposes.

The resulting aggregate cost is provided in Table 4.

Table 4 Aggregate costs

Trip purpose / mode	Late schedule delay		Early schedule delay		Total schedule cost		Agg. Cost (1000€)	Travel time		share of schedule delay cost (%)
	% users late	Avg. delay	% users early	Avg. delay	Cost / user	Nb. users (1000)		Avg travel time	Avg. travel cost	
Work / private	21.10	22.57	47.68	22.05	5.92	799	4 728	35	12.27	48.3
Work / public	23.89	25.66	43.66	20.83	4.60	603	2 772	51	11.25	40.9
Shopping	27.09	17.56	40.89	17.15	1.98	804	542	43	5.14	38.4
Schooling	13.89	22.20	52.78	48.52	0.41	48	601	30	3.59	11.5
Other	20.95	24.73	43.48	21.54	1.35	151	370	38	4.54	29.7
Total						2 404	9 013			

The average schedule delay cost per user early (resp. late) is the product of the above values for early schedule delay early (resp. late) by the average delay early (resp. late). The average schedule delay cost is then computed as the sum of the average schedule delay cost early or late, weighted by the fraction of users early or late (users on time, that is less than 5 minutes early or late, have a zero schedule delay cost). The average travel cost is simply the product of the chosen values of time by the average travel time.

Trips to work represent the largest part of the aggregate schedule delay cost (more than 80%). The total schedule delay cost for Paris area is equal to 9,013 Millions € per day, so for 5 days (Monday to Friday) the cost goes up to 2,343 Millions € per year. Since the Paris GIP (global intern product) in 1998 was 364,369 Millions €, the schedule delay cost represents 6,4 % of the regional GIP.

Based on the answers to open questions (see Fontan 2003), we found that 37,8% of the delays were volunteer and for involuntary delays, half were due to network under-functioning. So this network weakness is evaluated here to 2,8 Millions € per day and 728 Millions € per year.

These figures reveal the importance of schedule delay costs but, since they are based on average results, they only give an approximation of the real regional costs. We now turn to a more accurate evaluation for the dynamic simulations results. The estimated distribution of the parameters is introduced in the simulation model METROPOLIS. This model is based on a network with 20,000 links and an origin-destination matrix. The results based on the lognormal distribution of the parameters α, β and γ are as follows. The free flow travel time is 5.93 €, the waiting time cost is 2.05 € and the average schedule delay cost is 2.20€. The total cost is then 10.18 € and the variable cost (schedule delay cost plus congestion cost) is 4.25€. Therefore, the schedule delay cost represents 51.8 % of the variable cost. It should be mentioned that these figures fluctuate according to the trip purpose.

Our empirical results and our simulation results using METROPOLIS suggest for the Paris area that the schedule delay cost represents one third of the generalized cost (and half of the variable cost).

We have proposed the first monetary evaluation of the schedule delay costs. We observed that the total area cost of the delays is large (6,4% of the regional PIB) so the delay costs should not be neglected when evaluating policies that may impact the schedules or the travel times. We have also proved that the use of specific estimates of the dynamic parameters for the Paris area was important for dynamic simulation results.

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Appendix A: Tables

A 1: Work Trips for private and public transportation, Logit models

	Private		Public	
Parameters	**Estimates**	**Std**	**Estimates**	**Std**
α_c	0.0749***	0.017	0.0427***	0.016
α_0			0.0388***	0.018
β (5-60 mn)	0,0282*	0.015		
β^2 (5-60 mn)			0.0007***	0.0002
γ_1 (5-30 mn)	0.1076***	0.026		
γ_2 (30-60 mn)	0.1283***	0.042		
γ (5-60 mn)			0.0692***	0.023
δ	0.0365***	0.012	0.0445***	0.011
C	0.2183	0.168	0.3558*	0.175
I(constraint at home)	0,6463***	0.206	0,6126**	0.258
I(official arrival time)	-0,4049***	0.140	-0,6709***	0.157
Observations	987		835	
Percent concordant	71,6		74,4	
Pseudo R^2	0,11		0,13	
Log Likelihood	-603		-477	

A 2: Work Trips for private and public transportation, Mixed Logit

	Private		Public	
Parameters	**Estimates**	**Std**	**Estimates**	**Std**
α_c	0.1629***	0.042		
α *Lognormal*			-2,2853***	0.174
σ_α *Lognormal*			0,5386**	0.279
β *Lognormal*	-2,2493***	0.287		
σ_β *Lognormal*	0,6929***	0.274		
β^2			0,0018***	0.0002
γ *Lognormal*			-2.0661***	0.284
σ_γ *Lognormal*			0.6859*	0.395
γ_1 *(5-30 mn) Lognormal*	-2.2221***	0.393		
$\sigma_{\gamma 1}$ *(5-30 mn) Lognormal*	0.6813**	0.329		
γ_2 *(30-60 mn)*	0.1455***	0.055		
C	0.5754*	0.297	0.1560	0.174
I(constraint at home)	0,8189***	0.299	0,7314***	0.274
I(official arrival time)	-0,4222**	0.174	-0,6782***	0.169
Observations	987		835	
Pseudo R²	0,14		0,15	
Log Likelihood	-615		-540	
Parameters means and standard errors				
Average = $\text{Exp}(\alpha+\sigma_\alpha^2/2)$			0,1176	
Std = $\sqrt{(\text{Exp}(2\alpha+\sigma_\alpha^2)\,[\text{Exp}(\sigma_\alpha^2)-1])}$			0,0682	
Average = $\text{Exp}(\beta+\sigma_\beta^2/2)$	0,1340			
Std = $\sqrt{(\text{Exp}(2\beta+\sigma_\beta^2)\,[\text{Exp}(\sigma_\beta^2)-1])}$	0,1052			
Average = $\text{Exp}(\gamma+\sigma_\gamma^2/2)$	0,1366		0,1602	
Std = $\sqrt{(\text{Exp}(2\gamma+\sigma_\gamma^2)\,[\text{Exp}(\sigma_\gamma^2)-1])}$	0,1050		0,1242	