Road Traffic Congestion and Public Information: An Experimental Investigation*

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Abstract

This paper reports two laboratory studies designed to study the impact of public information about past departure rates on congestion levels and travel costs. Our experimental design is based on a discrete version of Arnott, de Palma, and Lindsey's (1990) bottleneck model where subjects have to choose their departure time in order to reach a common destination. Experimental treatments in our first study differ in terms of the level of public information on past departure rates and the relative cost of delay. In all treatments, congestion occurs and the observed total travel costs match the predicted ones. In other words, subjects' capacity to coordinate is neither affected by the availability of public information on past departure rates nor by the relative cost of delay. This absence of treatment effects is confirmed by our finding that a parameter-free reinforcement learning model best characterizes individual behavior. The number of experimental subjects taking the role of drivers is four times larger in our second study than in our first study. We observe that subjects' capacity to coordinate is not affected by the size of the population.

Keywords: Travel behavior; Congestion; Information in intelligent transportation systems; Laboratory experiments.

JEL classification codes: C91; C92; D83; R40; R41.

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1 Introduction

Information systems are often proposed to decrease congestion levels in city areas. The basic argument for providing real-time information about congestion rates is that well-informed drivers will avoid crowded routes and therefore the total traffic will be spread over the whole network, with lower congestion overall (see, e.g., Emmerink, 1998). However, Ben-Akiva, de Palma, and Kaysi (1991) argue that providing public information on road traffic congestion may exacerbate drivers' coordination problem and lead to an unpredictable outcome. In the same vein, Arnott, de Palma, and Lindsey (1999) demonstrate that better information, though valuable to users individually, can induce a welfare-decreasing adjustment in times of usage.

Most empirical results do not provide support for the adverse effect of public information which has been identified by the theoretical literature. Indeed, empirical results seem to unequivocally indicate that better information is more efficient. Numerous investigations have been conducted about the Advanced Traveler Information System (ATIS) in order to assess its impact on traffic congestion. The literature suggests that the most common response to (information about) congestion is to change departure time, although changing route also occurs frequently (see, among others, Mahmassani and Jou, 2000 and Khattak, Polydoropoulou, and Ben-Akiva, 1996). Concerning potential travel time saving through improved information, empirical studies rely on various techniques: Simulation, Stated or Revealed Preferences. Emmerink, Axhausen, Nijkamp, and Rietveld (1995) estimate that travel times savings could be around 7% whereas Al-Deek and Kanafani (1993) find, that for route incidents, such benefits could grow to 25% or 45%. By relying on simulation techniques, Levinson (2003) shows that travel time savings range from 3% to 30%, these simulation results being in line with previous studies. According to the latter results, information benefits on travel time savings are closely linked to the fraction of drivers who are informed, and increasing the share of population with information will do little to reduce travel times for informed drivers. Overall, this suggests that information not only reduces drivers travel time and cost, but also affects the travel time of other commuters. Therefore, it is essential to understand the traveler's decision-making process under past, real-time or prospective information about traffic interacting with other travelers.

More recently, laboratory experimental studies have been carried out as an attempt to better understand individual travel behavior. The interest of the laboratory experimental method is that it allows the researcher to isolate the specific impact of each variable separately by creating a controlled environment. In particular, experimental techniques allow to study the impact of information on congestion and travel costs, all other things being equal. Selten, Chmura, Pitz, Kube, and Schreckenberg (2007) reports a laboratory experiment with a two route choice scenario where the individual travel time on each route depends linearly on the actual number of subjects having chosen that route. The treatment variable is the subjects' level of information. In the first treatment, subjects only know the travel time on the route that they have chosen, and the corresponding payoff, while in the second treatment subjects also know the travel time on the non selected route. The results show that the number of subjects on each route is close to the Nash equilibrium, implying too many commuters on the fastest route. Additional information provided in the second treatment did not improve the outcome significantly in terms of efficiency. Helbing (2004) replicated this experiment, by adding new informational treatments. The new treatments provide potential payoffs for each subject and recommendations given by the experimenter about the adequate route to choose for a given period.

The results confirm earlier findings about excessive travel time incurred by experimental subjects, although additional information seems to reduce the volatility in subjects' payoffs.

This paper reports two laboratory studies designed to study the impact of public information about past departure rates on congestion levels and travel costs. Our experimental design is based on a discrete version of Arnott, de Palma, and Lindsey's (1990) bottleneck model where subjects have to choose their departure time in order to reach a common destination.[1] This model involves a single route which links the place of residence to the place of work. All drivers are located at the same point and have to reach the same point at the same time, by taking the same route. Early or late arrival generates costs in excess of the transportation costs. Transportation costs depend on travel time, which is equal to "normal time" if the driver commutes at the authorized speed, plus the time wasted in traffic jams. In an experimental session, subjects interact over many rounds, each of them choosing, in a given round, his/her departure time. While our experimental design allows us to manipulate many parameters, we focus on population size, the relative cost of delay, and the feedback provided to the subjects about congestion rates in previous rounds.

In our first experiment, which we refer to as the *small scale experiment*, subjects in groups of four take the role of drivers whose choices correspond to departure times. We consider four experimental treatments which differ in terms of the level of public information on past departure rates (information is present or not) and the relative cost of delay (in two treatments the cost is twice as large as in the other two treatments). Providing public information on past departure rates might improve subjects' capacity to coordinate their choice of departure time, resulting in a lower level of congestion. In all treatments, congestion occurs and the observed total travel costs match the predicted ones. In other words, subjects' capacity to coordinate is neither affected by the availability of public information on past departure rates nor by the relative cost of delay. This absence of treatment effects is confirmed by our finding that a parameter-free reinforcement learning model best characterizes individual behavior.

In our second experiment, which we refer to as the *large scale experiment*, subjects in groups of sixteen take the role of drivers whose choices correspond to departure times. One might conjecture that larger populations will have more difficulties to coordinate on departure times, and that information will therefore be more useful. However, we observe that subjects' capacity to coordinate is not affected by the size of the population.

The remainder of the paper is structured as follows. Section 2 presents the discrete version of Arnott, de Palma, and Lindsey's (1990) bottleneck model which we refer to as the congestion game. Nash equilibria and social optima are derived, illustrative examples are provided, and the potential effects of public information on individual behavior is discussed. Both the experimental design and the results of the *small scale experiment* are discussed in Section 3. Section 4 discusses the *large scale experiment.* Section 5 concludes.

[1]Schneider and Weimann (2004) also reports a laboratory experiment on the bottleneck model, with a single route and a choice of departure time. They find that the observed level of congestion is compatible with the Nash equilibrium prediction, implying excessive travel time for individuals. We extend this early work by varying, among other things, the level of public information on past departure rates.

2 Theoretical framework

Our theoretical framework tries to capture congestion situations that may arise for drivers who daily commute on a single road. We assume that the population of drivers is homogenous. In particular, all of them travel at the same speed, start their trip from the same place, and want to arrive at the same place at the same time. Each driver chooses his departure time in order to minimize his total travel cost, which is the cost due to transportation time plus the cost induced by a late or early arrival at place of work.

Uncoordinated decisions of departure time within the population may generate road traffic congestion. We define road congestion like in Arnott, de Palma, and Lindsey (1990, 1993)[2] as a bottleneck in the transportation infrastructure with a maximum flow capacity, which is the maximal number of drivers that can pass on in each period without congestion. In a given time slot, if the number of drivers increases beyond that capacity, a queue develops. The time it takes for a driver to pass through the bottleneck depends on the length of the queue at the time the driver joins it.

The congestion model is described more precisely as a normal form game in the next sub-section. In the second sub-section, we define the Nash equilibria (in pure and in mixed strategies) and the social optimum. An illustration with two drivers is given in the third sub-section. A characterization of equilibrium outcomes in some classes of n-player congestion games is provided in the fourth sub-section. The last sub-section discusses in a dynamic setting the possible effects of public information about past choices on adaptive behavior and convergence towards equilibrium.

2.1 The congestion game

Since the experiment is based on a finite number of drivers and a finite number of departure times, we need to derive a discrete version of Arnott, de Palma, and Lindsey's (1990) model. Let $N = \{1, ..., n\}$ be the set of drivers. A pure strategy for driver $i \in N$ is a departure time $t_i \in T = \{t_{min}, \ldots, t^* - 1, t^*, t^* + 1, \ldots, t^{max}\}$ to travel from his home to his place of work. t^* corresponds to the planned arrival time, which we assume to be the same for all drivers. t_{min} is the earliest possible departure time and t^{max} is the latest possible departure time. A pure-strategy profile, $\mathbf{t} = (t_1, \ldots, t_n) \in T^n$, is a vector of departure times, one for each driver.

To take into account the possibility that drivers can choose their departure time at random, we also need to consider mixed strategies. A mixed strategy for driver i is a probability distribution $\sigma_i \in \Delta(T)$ over the set of possible departure times T. Driver i chooses departure time $t_i \in T$ with probability $\sigma_i(t_i)$. The probability that the pure-strategy profile $\mathbf{t} = (t_1, \ldots, t_n)$ is chosen by the n drivers is denoted by $\sigma(\mathbf{t}) = \Pi_{i \in N} \sigma_i(t_i)$.

Let $r(t \mid \mathbf{t}) = |\{i \in N : t_i = t\}|$ be the number of departures in period t given the pure-strategy profile $\mathbf{t} = (t_1, \ldots, t_n)$. The *level of congestion* in period t is the number of drivers that have not been able to drive through in period t, and is defined as follows: in period t_{min} it is equal to $D(t_{min} \mid \mathbf{t}) = r(t_{min} \mid \mathbf{t})$, and for $t > t_{min}$ it is given by

$$D(t \mid \mathbf{t}) = \max\{0, D(t-1 \mid \mathbf{t}) - s\} + r(t \mid \mathbf{t}), \tag{1}$$

where $s \in \mathbb{N}^*$ is the per period *road capacity*, i.e., the number of cars that can travel on the road per

[2] Which is based on Vickrey (1969).

unit of time without building congestion.

The *transportation time* for driver $i \in N$ who leaves home in period $t \in T$ is given by

$$T(t \mid \mathbf{t}_{-i}) = \max\{1, \frac{D(t \mid \mathbf{t})}{s}\}, \tag{2}$$

where $\mathbf{t}_{-i} = (t_1, \ldots, t_{i-1}, t_{i+1}, \ldots, t_n)$.[3] If driver i leaves home in period t, his cost is

$$C(t \mid \mathbf{t}_{-i}) = T(t \mid \mathbf{t}_{-i}) + \beta \max\{0, t^* - (t + T(t \mid \mathbf{t}_{-i}))\} + \gamma \max\{0, (t + T(t \mid \mathbf{t}_{-i})) - t^*\}, \tag{3}$$

where $\gamma > 1 > \beta > 0$ are fixed unit schedule delay costs, corresponding to the unit cost of arriving after and before time, respectively. $T(t \mid \mathbf{t}_{-i})$ measures the cost of transportation time (including the opportunity cost of time), $\max\{0, t^* - (t + T(t \mid \mathbf{t}_{-i}))\}$ measures the time early and $\max\{0, t + T(t \mid \mathbf{t}_{-i})) - t^*\}$ the time late. According to the inequality $\gamma > 1 > \beta$, the time lost by arriving late induces a larger unit cost than the transportation time, and the time saved by arriving early induces a lower unit cost than the transportation time (Small, 1982 provides empirical support for this assumption). Each driver faces therefore a trade-off between transportation time and arriving on time.

2.2 Nash equilibria and social optimum

Because we consider a discrete time model with a finite number of drivers, Nash equilibria do not exactly coincide with those characterized in Arnott, de Palma, and Lindsey (1990), where time and the number of drivers are continuous. In particular, in the continuous model, mixed and pure strategies equilibrium outcomes coincide. However, it is important to emphasize that the multiplicity of equilibrium we obtain below is not a specific feature of the discrete model: in the continuous model, while the equilibrium *outcome* (i.e., the rates of departure times) is unique, there is a continuous of coordination equilibria, depending on who departs when.

A pure strategy Nash equilibrium of the congestion game is a profile of departure times $\mathbf{t} \in T^n$ such that, given the other drivers' choice, no single driver $i \in N$ can reduce his total transportation cost by choosing another departure time $t'_i \in T$:

$$C(t_i \mid \mathbf{t}_{-i}) \leq C(t'_i \mid \mathbf{t}_{-i}), \quad \forall\, i \in N,\ \forall\, t'_i \in T. \tag{4}$$

We also consider mixed strategies equilibria because equilibria in pure strategies do not always exist, while there is always a symmetric mixed strategy equilibrium (symmetric pure strategy equilibria exist only in special cases; see Section 2.4). Furthermore, mixed strategy Nash equilibria have some interesting properties of the equilibria characterized by Arnott, de Palma, and Lindsey (1990), namely that each player is indifferent between all departure times in the equilibrium support, and is not better off outside that support. Finally, as we shall show, our experimental data is compatible with the hypothesis that subjects' decisions about the departure time is non-deterministic, and therefore varies from one round to another, all things being equal.

[3] The (variable) travel time is usually defined as $T(t \mid \mathbf{t}_{-i}) = D(t \mid \mathbf{t})/s$ instead of (2) (see, e.g., Arnott, de Palma, and Lindsey, 1993). In that way, travel time decreases when the bottleneck capacity increases, even when the queue length is lower than the capacity. With definition (2), travel time increases only when the queue length exceeds capacity, and is equal to one period otherwise. Pure strategy equilibria and the social optimum are the same for both definitions. Another similar variation has been considered, e.g., by de Palma, Ben-Akiva, Lefvre, and Litinas (1983).

We extend transportation costs to mixed-strategy profiles $\sigma = (\sigma_1, \ldots, \sigma_n) \in [\Delta(T)]^n$ with the usual abuse of notations:

$$C(t \mid \sigma_{-i}) = \sum_{\mathbf{t}_{-i} \in T^{n-1}} \sigma_{-i}(\mathbf{t}_{-i}) C(t \mid \mathbf{t}_{-i}), \tag{5}$$

where $\sigma_{-i}(\mathbf{t}_{-i}) = \prod_{j \neq i} \sigma_j(t_j)$. A mixed strategy Nash equilibrium is a mixed strategy profile $\sigma = (\sigma_1, \ldots, \sigma_n)$ such that

$$\begin{aligned} & C(t \mid \sigma_{-i}) = C(t' \mid \sigma_{-i}), \text{ for all } t, t' \in \operatorname{supp}(\sigma_i) \\ \text{and} \quad & C(t \mid \sigma_{-i}) \leq C(t' \mid \sigma_{-i}), \text{ for all } t' \notin \operatorname{supp}(\sigma_{-i}), \end{aligned} \tag{6}$$

where $\operatorname{supp}(\sigma_i) \equiv \{t \in T : \sigma_i(t) > 0\}$ is the support of σ_i.

Finally we define an efficient, or socially optimal, strategy profile as a profile of departure times that minimizes the aggregated total transportation cost of the whole population. Formally, $\mathbf{t} = (t_1, \ldots, t_n) \in T^n$ is a social optimum if for any profile $\mathbf{t}' = (t_1', \ldots, t'_n) \in T^n$, the following inequality holds:

$$\sum_{i \in N} C(t_i \mid \mathbf{t}_{-i}) \leq \sum_{i \in N} C(t_i' \mid \mathbf{t}_{-i}'). \tag{7}$$

2.3 An example with two drivers

In order to illustrate the general discrete congestion game, we present an example involving only two drivers. Assume that $s = 1$ and $T = \{t^* - 2, t^* - 1\}$. The congestion game is summarized in matrix form in Table 1. Each of the two drivers has a choice between the two departure times. The total transportation costs for each driver, induced by a given strategy profile, are indicated in the corresponding cells.

		Driver 2	
		$t^* - 2$	$t^* - 1$
Driver 1	$t^* - 2$	$(2; 2)$	$(1 + \beta; 1)$
	$t^* - 1$	$(1; 1 + \beta)$	$(2 + \gamma; 2 + \gamma)$

Table 1: The congestion game with two drivers and two possible departure times.

This game is a "chicken game". It admits two pure-strategy Nash equilibria, $(t^* - 2, t^* - 1)$ and $(t^* - 1, t^* - 2)$, and a unique mixed-strategy Nash equilibrium, given by[4]

$$\begin{aligned} \sigma_1(t^* - 2) = \sigma_2(t^* - 2) = (1 + \gamma - \beta)/(2 + \gamma - \beta), \\ \sigma_1(t^* - 1) = \sigma_2(t^* - 1) = 1/(2 + \gamma - \beta). \end{aligned} \tag{8}$$

In contrast to the pure-strategy equilibria, the mixed-strategy equilibrium is symmetric, it depends on the parameters β and γ, it involves equal costs for the two players,[5] and it is socially inefficient.[6]

[4] In this example, extending the set of departure times may modify the mixed strategy equilibria (drivers may depart before $t^* - 2$ with strictly positive probability).

[5] $C(t^* - 2 \mid \sigma_2) = C(t^* - 2 \mid \sigma_1) = C(t^* - 1 \mid \sigma_2) = C(t^* - 1 \mid \sigma_1) = (3 + 2\gamma - \beta)/(2 + \gamma - \beta)$.

[6] $1 + \beta < (3 + 2\gamma - \beta)/(2 + \gamma - \beta) \Leftrightarrow (1 - \beta)(1 + \gamma - \beta) > 0$, which is satisfied since $\gamma > 1 > \beta$ by assumption.

2.4 A qualification of pure strategy symmetric equilibria with n drivers

If $n > 2$, it is difficult, in general, to fully characterize the set of all Nash equilibria, for arbitrary sets of departure times T and cost parameters β and γ. However, under suitable restrictions on parameter values, we identify the set of pure-strategy Nash equilibria.

First note that in the trivial case in which the road capacity is larger than the size of the population, all drivers would decide to leave at $t^* - 1$ and arrive on time. If the population size is less than twice the road capacity, it is easy to show that the drivers will choose one of the two departure slots, $t^* - 1$ and $t^* - 2$, with a frequency that depends on β and γ.

Proposition 1 *If $n \leq s$ there is a unique Nash equilibrium according to which the n drivers choose departure time $t^* - 1$ and face a transportation cost equal to 1. If $s < n \leq 2s$ and $(k+1)(1+\gamma)/s > \beta > k(1+\gamma)/s, k \in \mathbb{N}^*$, the pure strategy Nash equilibria are characterized as follows : $s + k$ drivers choose departure time $t^* - 1$ and face a transportation cost equal to $1 + k(1+\gamma)/s$, and $n - s - k$ drivers choose departure time $t^* - 2$ and face a transportation cost equal to $1 + \beta$.*

We characterize below the pure strategy Nash equilibria for the case where $n/s > 2$ and the unit cost of being early is small enough. The idea underlying this result is simple. If the cost of arriving early is small the equilibrium distribution is such that s drivers choose to leave at each departure time before t^*, so that there is no congestion.

Proposition 2 *For $k \in \mathbb{N}^* \backslash \{1\}$, if $(k+1)s \geq n > ks$ and $\beta < 1/((k-1)s+1)$, the pure strategy Nash equilibria are characterized as follows : s drivers choose departure time $t^* - 1$ and face a cost equal to 1, for all $z \in \{2, \ldots, k\}$, s drivers choose departure time $t^* - z$ and face a transportation cost equal to $1 + (z-1)\beta$, and $n - ks$ drivers choose departure time $t^* - k - 1$ and face a transportation cost equal to $1 + k\beta$.*

2.5 Public information and adaptive play

If the congestion game described above is played repeatedly as in our experiment, it is theoretically unclear how agents' behavior and aggregate efficiency are affected by the fact that information about past departure times is revealed to the individuals or not. As a matter of fact, pure and mixed strategy Nash equilibrium predictions described above do *not* depend on whether or not information about past behavior is publicly revealed to the players since these predictions already apply to the one-shot game. Hence, as in Arnott, de Palma, and Lindsey (1990, 1993), there is theoretically no reason for public information to modify departure times and coordination. In particular, providing information about past departure times do *not* move equilibrium towards the social optimum.[7]

Yet, since perfect information about others' current behavior is a very strong assumption of the equilibrium prediction,[8] public information in the form of an aggregate statistics of past actions might help players to *achieve* an equilibrium of the game, because it gives them the ability to best-reply

[7]In order to provide rigorous game-theoretical predictions for our experiments, one should in principle characterize the set of equilibria of the *repeated* congestion game, depending on the information players get about their opponents' past actions. Since in our experiments subjects do not interact in the same group in each repetition of the congestion game and moreover cannot identify their opponents in a given round, we abstract from repeated game considerations by assuming that subjects' ability and incentives to alter others' future play is negligible.

[8]Of course, this assumption cannot be implemented directly in the laboratory.

much more efficiently than without such information. Indeed, by observing his own payoff only, a player is not able, in general, to know his opponents' past actions. For example, if one driver departs at $t^* - 4$ and the other drivers depart at $t^* - 1$, a given driver cannot know, being informed of his/her own transportation cost only, how to best reply. This indicates at least that efficiency, if not equilibrium play, might be easier to achieve in the treatments with information.

Related to the previous argument, in the continuous version of the congestion model, Ben-Akiva, de Palma, and Kanaroglou (1986) found particular stochastic adaptive rules, also of the types of best-reply dynamics, that converge to the equilibrium characterized by Arnott, de Palma, and Lindsey (1990, 1993). For such adaptive rules to work, agents need to observe the past distribution of plays of their opponents. Again, this might indicate that equilibrium play is more likely to be observed in experimental treatments with information than in treatments without information about past play.

With no information about others' play, drivers can adapt their decisions only according to past payoffs from actions. Hence, in this condition, a natural learning processes is reinforcement-based learning according to which a player increases the frequency of an action when this action has given him a relatively larger payoff than the other actions. On the contrary, in the treatments with information, a natural learning process is to assume that in each round each player plays a best response to the historical frequency of play, like fictitious play (see, e.g., Fudenberg and Levine, 1998). This belief based behavior is indeed possible since subjects have all the information they need to compute the best response (in particular, they know their payoff function). More details about the two types of learning models are given in Appendix B, and their predicting abilities in the experimental congestion games are compared in the next section.

3 Small scale experiment

3.1 Experimental design, theoretical predictions and procedures

In our laboratory environment, subjects in groups of 4 take the role of drivers whose choices correspond to departure times. The set of possible departure times is given by $\{t^* - 8, ..., t^* - 1, t^*, t^* + 1, ..., t^* + 8\}$ and it is large enough so that subjects' choices may lie outside the support of the equilibria (see below). By relying on a symmetric set, which allows for departure times after the objective arrival time, we also restrict from providing guidance to subjects concerning optimal play. The capacity of the road is set at $s = 1$ and the unit cost of arriving late is fixed at $\gamma = 2$.

Subjects play 40 rounds of the congestion game. By repeating the congestion game over many rounds, we give subjects the opportunity to adjust their behavior over time. To avoid repeated game effects, the experiment is based on a *strangers design*: in each round, 4 groups of 4 subjects are randomly determined by partitioning a population of 16 subjects. We believe that such a design is a more appropriate implementation of real-world congestion situations than a design where subjects would repeatedly interact with the *same* group of drivers (*partners design*).

Our main research question concerns the effect of public information on road traffic congestion. Therefore, two information conditions are used. In the *Info = 1* condition, each subject is informed at the beginning of round $r \in \{2, \ldots, 40\}$ about the average relative frequencies of departure times based on the departure choices of all 16 subjects and averaged over previous rounds. Moreover, at any point of time during the experimental session, each subject has access to the entire history of past distributions of relative frequencies of departure times: thus, in round 4, each subject has access to the relative frequencies of departure times (derived from all 16 subjects' choices) in round 1, 2 and 3.[9] In the *Info = 0* condition, both pieces of information are missing.

We additionally investigate the impact of the relative cost of early arrival with respect to late arrival by considering two unit costs of arriving early: $\beta = 1/4$ and $\beta = 1/2$. The two information conditions are combined with the two unit costs of early arrival in a complete 2×2 factorial design. Table 2 summarizes the experimental treatments of our first experiment.

Information about congestion levels in previous rounds	Unit cost of early arrival (β)	Treatment
Yes	1/4	Info = 1, Beta = 1/4
Yes	1/2	Info = 1, Beta = 1/2
No	1/4	Info = 0, Beta = 1/4
No	1/2	Info = 0, Beta = 1/2

Table 2: Experimental treatments of the small scale experiment.

Theoretical predictions

Table 3 summarizes the theoretical predictions of the one-shot congestion game where $n = 4$, $T = \{t^* - 8, ..., t^* - 1, t^*, t^* + 1, ..., t^* + 8\}$, $s = 1$, $\gamma = 2$, and $\beta \in \{1/4, 1/2\}$.[10]

		Departure time							
		t^*-8, t^*-7	t^*-6	t^*-5	t^*-4	t^*-3	t^*-2	t^*-1	$t^*, \ldots, t^*+8$
		Number of drivers							
Pure strategy equilibrium	$\beta = 1/4$	0	0	0	1	1	1	1	0
	$\beta = 1/2$	there does not exist an equilibrium in pure strategies							
		Departure probability							
Mixed strategy equilibrium	$\beta = 1/4$	0.000	0.038	0.148	0.239	0.288	0.200	0.086	0.000
	$\beta = 1/2$	0.000	0.000	0.000	0.262	0.414	0.219	0.105	0.000
		Number of drivers							
Social optimum	$\beta = 1/4$	0	0	0	1	1	1	1	0
	$\beta = 1/2$	0	0	0	1	1	1	1	0

Table 3: Theoretical predictions of the one-shot congestion game in the small scale experiment.

[9] Instead of providing information on congestion levels in previous rounds, we could have provided subjects directly with information on transportation costs in previous rounds. We refrained from doing so as such an experimental design would have no external validity. Indeed, through the reward structure that we used in our experimental study, we have induced prescribed monetary value on choices but, in real-world congestion situations, drivers have idiosyncratic unit costs of arriving before and after their planned arrival time. It is therefore unclear how to provide information on past transportation costs in the field.

[10] The theoretical predictions have been derived with the help of *Mathematica* by Wolfram Research (2005). The codes are available from the authors upon request.

Whatever the value of β, the social optimum is such that each of the four 4 drivers chooses one of the 4 departure times, $t^* - 4$, $t^* - 3$, $t^* - 2$, and $t^* - 1$, in a coordinated way. At the social optimum, total travel costs are therefore equal to 5.5 (respectively 7) when $\beta = 1/4$ (respectively $\beta = 1/2$).

When $\beta = 1/4$, equilibria in pure strategies correspond to efficient strategy profiles. There does not exist an equilibrium in pure strategies when $\beta = 1/2$. Indeed, in this latter case, there is too much cost difference between the various departure times, so drivers' best responses never stabilize.[11]

Finally, the unique symmetric equilibrium in mixed strategies (henceforth simply symmetric equilibrium) leads to expected total travel costs of 9.36 and 11.56 when $\beta = 1/4$ and $\beta = 1/2$, respectively.

Practical procedures

The experiment was run on a computer network using 128 inexperienced students at the BETA laboratory of experimental economics (LEES) at the University of Strasbourg. Eight sessions were organized, with 16 subjects per session. A total of 2 independent observations per treatment was collected. Subjects were randomly assigned to a computer terminal, which was physically isolated from other terminals. Communication, other than through the decisions made, was not allowed.

The subjects were instructed about the rules of the game and the use of the computer program through written instructions, which were read aloud by an experimenter. We decided to make the context clear in the instructions, by telling the subjects that the aim of the experiment was to study travel decision making. In particular, the instructions made clear that "*... each member of your group has to choose a departure time in order to go to a meeting. All members of your group (including yourself) have their meeting time at 8:00 am at the same place. Furthermore, all members of your group (including yourself) must drive on the same road in order to reach the meeting place. Finally, all members of your group (including yourself) depart from the same location.*" [12] In each round each subject had to choose among 17 possible departure times in the set $\{7:20, 7:25, 7:30, ..., 8:30, 8:35, 8:40\}$.

We made clear in the instructions how the level of congestion and the travel times were computed. The instructions also contained three tables explaining how the total cost is computed as a function of the travel time and a penalty either for early or late arrival. The computation rules were illustrated with the help of examples and subjects had to answer a control questionnaire in order to check their understanding of the instructions..

As the congestion game involves only costs for the participants, we endowed subjects with a starting cash balance of 250 points at the beginning of the experimental session. Points which were saved in each round accumulated throughout the experiment and were converted into local currency at the end of the experiment (at a predefined rate of 1 euro for 10 points). On average, each subject earned approximately 15 euros and each session took between $1\frac{1}{4}$ and $1\frac{3}{4}$ hours.

At the end of a given round in the Info = 1 condition, each subject was informed about his number of remaining points at the beginning of the round, his departure choice, his arrival time, his travel costs, his number of remaining points at the end of the round and the departure choices of the 3 other subjects he interacted with. At the end of a given round in the Info = 0 condition, we did

[11] An efficient strategy profile cannot be an equilibrium when $\beta = 1/2$ because the driver that should depart in period $t^* - 4$ is better off by deviating and choosing departure time $t^* - 2$ instead, since his cost will be equal to 2 which is smaller than $1 + 3\beta = 2.5$.

[12] Original instructions in French as well as a translated version in English are available from the authors upon request.

not provide subjects with the choices of their interacting partners.

3.2 Results

Analyses at the aggregate level

As already mentioned, socially optimal total travel costs equal 5.5 (respectively 7) when $\beta = 1/4$ (respectively $\beta = 1/2$). In round $t \in \{1, \ldots, 40\}$ of a given session, we define the efficiency rate as $88/\sum_i C_i$ (respectively $112/\sum_i C_i$) when $\beta = 1/4$ (respectively $\beta = 1/2$) where C_i is the actual travel cost of subject $i \in \{1, \ldots, 16\}$. Our first result shows that none of the two treatment variables has a significant impact on the efficiency rate whose average matches the efficiency rate of the symmetric equilibrium.

Result 1. Neither the level of information on past congestion levels nor the magnitude of the marginal cost of early arrival has a significant impact on the efficiency rate. In each treatment, the average efficiency level corresponds approximately to the efficiency level achieved under the assumption that each subject behaves according to the symmetric equilibrium.

Support. Figure 1 shows the temporal dynamics of the efficiency rate in each treatment. Neither the level of information on past congestion levels nor the magnitude of the marginal cost of early arrival seems to have a systematic impact on the efficiency rate. Moreover, the efficiency rate exhibits no clear temporal pattern.

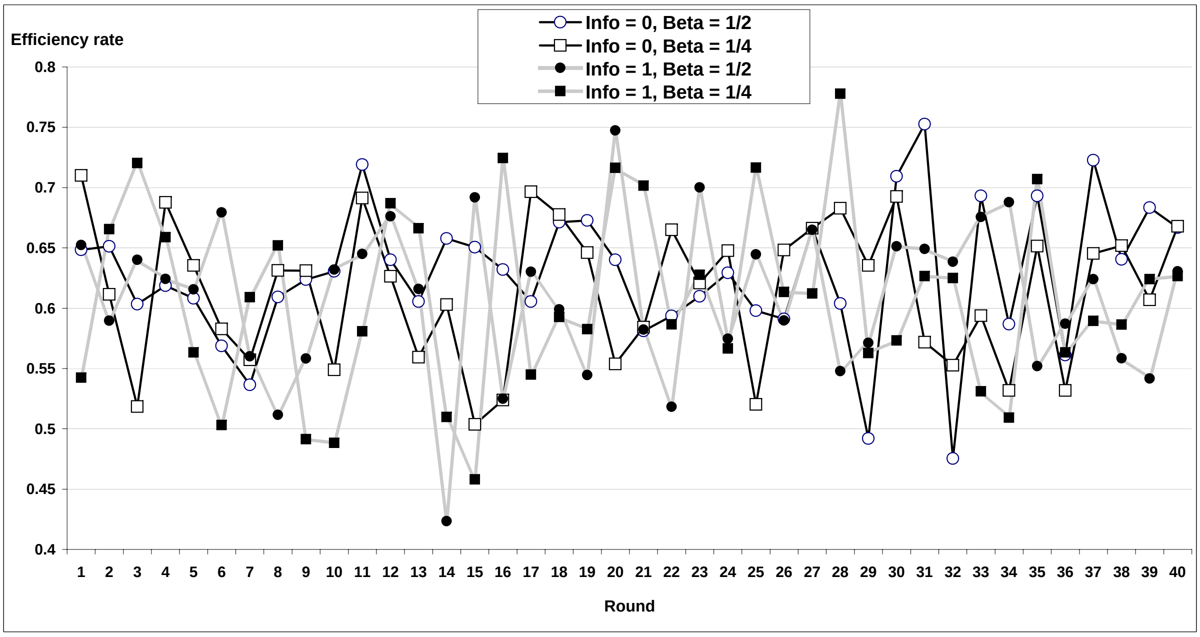


Figure 1: Temporal dynamics of the efficiency rate in each treatment.

To test for potential treatment effects and time trends more rigorously, we ran the regression reported in table 4. According to the high p-value (0.852) of the F-statistic, we fail to reject the null hypothesis that only the intercept is useful in predicting the efficiency rate. The efficiency rate averaged over all rounds and all sessions equals 61.46%.[13] The average efficiency rate translates into an efficiency level of 8.94 (respectively 11.39) in both treatments where $\beta = 1/4$ (respectively $\beta = 1/2$) which is very close to 9.36 (respectively 11.56), the efficiency level achieved under the symmetric equilibrium.

Dependent variable: Efficiency rate				
	Estimate	Std.Error	t-statistic	p-value
Intercept	0.6118	0.0213	28.656	<0.01
Info = 1	-0.0117	0.0302	-0.388	0.698
Beta = 1/2	0.0025	0.0302	0.084	0.933
Round	0.0001	0.0009	0.121	0.903
Info = 1 * Beta = 1/2	0.0062	0.0427	0.145	0.885
Info = 1 * Round	0.0002	0.0013	0.180	0.857
Beta = 1/2 * Round	0.0006	0.0013	0.453	0.651
Info = 1 * Beta = 1/2 * Round	-0.0009	0.0018	-0.510	0.611
Residual standard error: 0.0937 on 312 degrees of freedom				
R-Squared: 0.0106, Adjusted R-squared: -0.0116				
F-statistic: 0.4758 on 7 and 312 degrees of freedom, p-value: 0.852				

Note: OLS estimates. We denote an interaction between two predictors by '*'.

Table 4: Results of the estimation of the efficiency rate.

□

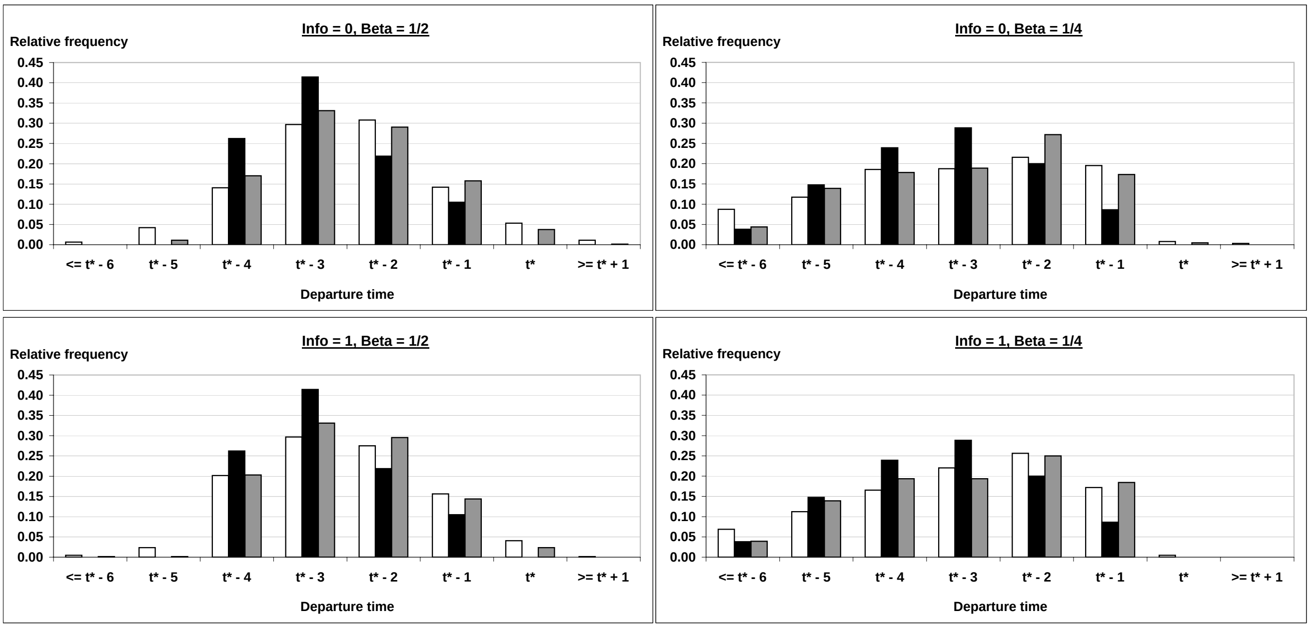
It seems that, at least at the aggregate level, subjects' behavior is well in line with the symmetric equilibrium. Our second result confirms this intuition.

Result 2. In each treatment, the distribution of average relative frequencies of departure times is slightly more skewed to the right than the distribution of departure probabilities predicted by the symmetric equilibrium. Average travel costs are close to the predicted ones for most departure times but at departure time $t^* - 1$ they are substantially larger. In most treatments the variation in travel costs per departure time decreases over time but providing information on past congestion levels does not systematically reduce the volatility of travel costs.

Support. Figure 2 on the following page shows the average relative frequencies of departure times in each treatment for both the first and the second half of the 40 rounds. In all cases, the observed distribution of departure times is quite similar to the one predicted by the symmetric equilibrium which implies that the level of information on past congestion levels does not have a systematic impact on the observed distribution contrary to the magnitude of the unit cost of early arrival. Subjects' behavior differs depending on the cost of being early and, over time, the relative frequencies of departure times get slightly closer to the departure probabilities predicted by the symmetric equilibrium. Under the assumption that the treatment variable information has no effect on the

[13] According to a quantile-comparison plot of the studentized residuals against the t distribution, we find reasonable to assume that errors are normally distributed. Additionally, according to a plot of the studentized residuals against the fitted values, assuming a constant variance for the errors seems reasonable. Finally, according to a Durbin-Watson test, the null hypothesis of no autocorrelation in the errors is not rejected (D-W statistic = 2.04, p-value = 0.97).

frequencies of departure times, we cannot reject the null hypothesis that the distribution of average relative frequencies of departure times follows the predictions of the symmetric equilibrium for both values of β (Kolmogorov-Smirnov one-sample tests, p-values > 0.1).[14] Still, even in the second half of the sessions, the observed distributions of departure times are more skewed to the right than the theoretical distributions, subjects choosing too often the departure times $t^* - 2$ and $t^* - 1$.



Note: White bars correspond to the actual relative frequencies averaged over the first 20 rounds.
Black bars correspond to the probabilities predicted by the symmetric equilibrium.
Grey bars correspond to the actual relative frequencies averaged over the last 20 rounds.

Figure 2: Average relative frequencies of departure times in each treatment.

According to the symmetric equilibrium, departure times which are chosen with positive probability have identical travel costs. We now investigate whether the departure times which belong to the support of this equilibrium have identical average travel costs in the different treatments. Table 5 summarizes the average travel costs per departure time in the support of the symmetric equilibrium in each treatment.

At the symmetric equilibrium, each departure time which is chosen with positive probability leads to an expected travel cost of 2.34 (respectively 2.89) when $\beta = 1/4$ (respectively $\beta = 1/2$). In the second half of the experimental sessions where $\beta = 1/4$, average travel costs for departure times before $t^* - 1$ are slightly smaller than the predicted travel costs whereas the average travel costs at $t^* - 1$ is substantially larger. In the second half of the experimental sessions where $\beta = 1/2$, average travel costs for departure times $t^* - 4$ and $t^* - 3$ are slightly smaller than the predicted travel costs whereas the average travel costs at $t^* - 2$ and $t^* - 1$ are slightly larger. Overall, the standard deviations of the average travel costs per departure time are quite small and, in three out of four treatments, they

[14]Both conclusions hold whether the first or the second half of the experimental sessions is considered. Needless to say, given the few independent observations, the power of the nonparametric test is rather low.

Treatment		Departure time t^*-6	t^*-5	t^*-4	t^*-3	t^*-2	t^*-1	Standard deviation
Info = 0,	First 20 rounds	—	—	2.68	2.44	2.66	3.34	0.39
Beta = 1/2	Last 20 rounds	—	—	2.67	2.71	3.00	2.96	0.17
Info = 0,	First 20 rounds	2.42	2.18	2.12	2.00	2.00	3.06	0.51
Beta = 1/4	Last 20 rounds	2.25	2.24	2.10	1.98	1.98	3.16	0.57
Info = 1,	First 20 rounds	—	—	2.81	2.59	3.11	3.40	0.35
Beta = 1/2	Last 20 rounds	—	—	2.82	2.66	3.16	3.25	0.28
Info = 1,	First 20 rounds	2.42	2.27	2.18	2.03	2.19	3.26	0.57
Beta = 1/4	Last 20 rounds	2.25	2.32	2.19	1.96	2.24	2.88	0.40

Note: Only the departure times which belong to the support of the symmetric equilibrium are considered.

Table 5: Average travel costs per departure time in each treatment.

decrease over time. Not surprisingly, providing information on past congestion levels does not reduce the volatility of travel costs as this information does not affect the distribution of average relative frequencies of departure times in a systematic way. □

Analyses at the individual level

Our previous analyses have shown that, in each treatment, the aggregate pattern of play is reasonably well characterized by the symmetric equilibrium. Needless to say, the relative frequency distributions that are observed in the aggregate could be an artifact of aggregation of subjects, each of whom is playing in a way that deviates significantly from the symmetric equilibrium. For example, it could well be that most subjects play pure strategies, i.e. choose the same departure time from one round to the next. We now show that this is not the case, the pattern of choices made by most subjects being broadly consistent with individual play of mixed strategies.

Result 3. In each treatment, a large majority of the subjects choose at least three different departure times in the last 20 rounds and the observed patterns of choices are broadly consistent with individual play of mixed strategies. Neither the level of information on past congestion levels nor the magnitude of the marginal cost of early arrival has a systematic impact on the number of departure times chosen.

Support. Figures 4–7 in Appendix A shows the relative frequencies of departure times in the first and second half of the session for each of the 128 subjects. Even in the last 20 rounds of the session, very few subjects choose the same departure time from one round to the next (2, 5, 2 and 2 subjects in treatment (Info = 0, Beta = 1/2), (Info = 0, Beta = 1/4), (Info = 1, Beta = 1/2), and (Info = 1, Beta = 1/4), respectively). Instead, most subjects choose at least three different departure times and the variability in the choice frequencies is rather low (see table 6). The average number of different departure times chosen in the last 20 rounds equals 3.19, 2.88, 2.94 and 3.22 in treatment (Info = 0, Beta = 1/2), (Info = 0, Beta = 1/4), (Info = 1, Beta = 1/2), and (Info = 1, Beta = 1/4), respectively. Contrary to the prediction of the symmetric equilibrium, the relative cost of early arrival has no systematic impact on the average number of departure times chosen. The same is true for the information on past congestion levels.

Treatment	Number of departure times chosen 1	2	3	4	5	6	7
Info = 0,	2	6	13	7	3	1	0
Beta = 1/2	(0.00)	(9.43)	(5.78)	(4.01)	(3.23)	(1.63)	(—)
Info = 0,	5	9	9	5	2	2	0
Beta = 1/4	(0.00)	(6.84)	(7.14)	(4.48)	(3.97)	(2.30)	(—)
Info = 1,	2	8	15	6	0	0	1
Beta = 1/2	(0.00)	(8.13)	(6.04)	(3.86)	(—)	(—)	(2.91)
Info = 1,	2	7	10	8	5	0	0
Beta = 1/4	(0.00)	(7.68)	(5.61)	(3.25)	(2.37)	(—)	(—)

Note: Average standard deviations of choice frequencies are in brackets.

Table 6: Frequency of subjects per number of departure times chosen in each treatment (rounds 21-40).

□

Finally, we thoroughly examine the ability of the symmetric equilibrium to characterize the play of subjects in our first experiment. To do so, we compare the actual *individual* decisions in each round with the distribution of predicted probabilities by relying on mean squared deviation (MSD) as a measure of closeness of predictions to actual decisions. Additionally, we compare the observed individual decisions with the predictions of two types of learning model: a reinforcement-based model similar to that used by Roth and Erev (1995),[15] and a two-parameter family of belief-based models similar to the "cautious fictitious play" of Fudenberg and Levine (1998). Both learning models can be considered as forecast rules that, given information from previous rounds, predict probabilistically a subject's choices in the current round. A number of researchers have presented results demonstrating that, in many cases, learning models are better able to describe and predict experimental results than static Nash equilibrium. It seems therefore appropriate to compare the predictive success of the stationary symmetric equilibrium with the ones of the two types of learning model.

Roughly speaking, reinforcement-based models assume that individuals make decisions according only to past payoffs from decisions: decisions receive reinforcement related to the payoffs they earn, and over time individuals adjust their play so that decisions leading to higher payoffs become more likely. Taken literally, this means that decisions are made without regard to the other individuals' payoffs or their history of play. The Info = 0 condition seems therefore tailor-made for reinforcement learning (even though the "payoff matrix" of the one-shot congestion game is public knowledge). On the contrary, as already mentioned in subsection 2.5, the Info = 1 condition gives subjects enough information for belief learning. Indeed, according to belief-based models, individuals hold beliefs concerning the likely play of their opponents, and they choose strategies based on their expected payoffs given these beliefs. The chosen belief-based models are characterized by two parameters: λ which determines the extent to which the individual responds optimally to his beliefs and δ which determines the relative amount of bearing given to past outcomes relative to current outcomes in forming beliefs. All details concerning both types of learning model are provided in Appendix B.[16]

[15] We rely on a parameter-free version of reinforcement learning. For more general versions, see Erev and Roth (1998).
[16] Our exposition follows closely Feltovich (2000).

Result 4. A parameter-free reinforcement learning model best characterizes the play of subjects. Its improvement over stationary (symmetric) equilibrium play is substantial but the latter one still fares better than a two-parameter belief learning model.

Support. Because predictions of early-round play according to the learning models depend heavily on unknown initial conditions (propensities or beliefs), we look only at the models' predictions of behavior in the last ten rounds where the initial conditions are derived from the experimental data of the first thirty rounds. MSD is obtained by pairing the predicted probability of departure time $t \in T = \{t^* - 8, ..., t^* - 1, t^*, t^* + 1, ..., t^* + 8\}$ being chosen (denoted $p^{\text{PRED}}(t)$) according to the behavioral model being considered and the actual probability that t was chosen (denoted $p^{\text{ACT}}(t)$)—which is either zero or one—for each choice made by each subject in each of the last ten rounds. Hence, for a given treatment,

$$MSD = \left(\frac{1}{320} \sum_{r=31}^{40} \sum_{s=1}^{32} \sum_{t \in T} \left(p_{r,s}^{\text{PRED}}(t) - p_{r,s}^{\text{ACT}}(t) \right)^2 \right)^{1/2},$$

where r indexes the last ten rounds and s indexes the 32 subjects of the given treatment. Table 7 summarizes the predictive abilities of the models. In addition to the reinforcement model, the symmetric equilibrium, and fictitious play, we show the MSD of the "best" belief-based learning model in terms of this criterion.[17] Keeping in mind that better predictive power is implied by lower MSD, we can see that the parameter-free reinforcement learning model is best and it is the only model that performs better than stationary symmetric equilibrium play. Indeed, even though the best belief learning model does slightly better than equilibrium play in the treatment (Info = 1, Beta = 1/2) it does much worse in the treatment (Info = 1, Beta = 1/4) and, as a result, the sum of the two MSDs is lower for symmetric equilibrium than for best belief learning. Moreover, the MSDs of the belief learning model should be penalized as two parameters were fitted to minimize them. Given that subject behavior is not adequately described by belief learning, it is not surprising that providing subjects with the choices of their interacting partners at the end of each round does not affect their behavior.

	Treatment			
Behavioral Model	(Info = 0, Beta = 1/2)	(Info = 0, Beta = 1/4)	(Info = 1, Beta = 1/2)	(Info = 1, Beta = 1/4)
Reinforcement learning	0.734	0.687	0.726	0.783
Fictitious play	—	—	1.146	1.259
Best belief learning	—	—	0.866	0.925
Symmetric equilibrium	0.888	0.918	0.871	0.915

Note: Fictitious play is characterized by $\lambda = \infty$ and $\delta = 0$.
Best belief learning is characterized by $\lambda = 2.492$ and $\delta = -0.145$.

Table 7: MSDs of behavioral models in rounds 31-40.

□

[17] The best belief-based learning model minimizes the sum of the MSDs in the two treatments with Info = 1. It was found by a grid search over values of λ and δ to three significant digits.

4 Large scale experiment

Real-world congestion situations usually involve a large number of drivers. The number of subjects who participated in any of the experimental sessions of our first experiment is arguably small (16). In order to address this concern, we decided to run a second experiment with 64 subjects being involved. This large scale experiment was run in a different environment since the capacity of the LEES (experimental laboratory at the University of Strasbourg) is limited to 16 subjects. Subjects were randomly assigned to one of three computer rooms and were told that they would be interacting within a population of 64 subjects, split into 4 groups of 16 players in each round, and randomly rematched after each round. Given the absence of impact of the treatment variables considered in the small scale experiment and also because of the large monetary costs, only one experimental session was implemented: the road capacity was scaled up to 4 ($s = 4$), β was set equal to 0.5, and subjects were provided with information on past congestion levels. Moreover, due to time constraints, subjects only played 25 rounds of the congestion game.[18] Like in the first experiment, γ was set equal to 2, the set of possible departure times was $\{t^* - 8, ..., t^* - 1, t^*, t^* + 1, ..., t^* + 8\}$, each subject was endowed with 250 points at the beginning of the session, and the conversion rate was 10 points = 1 euro. Instructions were similar to those used in the small scale experiment except that they incorporated more details since more outcomes were possible.[19]

Given the chosen parametrization, the strategic considerations for the one-shot congestion game are similar to those applying in treatment (Info = 1, Beta = 1/2) of the small scale experiment. Indeed, the fact that the population has been multiplied by four is compensated by the fact that the capacity of the road has been multiplied by four. There does not exist an equilibrium in pure strategies but, due to computational problems, we are unable to compute the mixed strategy equilibrium. The social optimum is such that 4 drivers leave in each of the periods $\{t^* - 4, t^* - 3, t^* - 2, t^* - 1\}$ which leads to total travel costs being equal to 28. This is exactly four times the total travel costs at the social optimum of the congestion game with 4 drivers ($\beta = 1/2$).

Consequently, and under the assumption that subjects' capacity to coordinate in the congestion game is independent of the size of the population, we would expect the efficiency rate observed in the large scale experiment to be similar to the efficiency rate observed in treatment (Info = 1, Beta = 1/2) of the small scale experiment. Our fifth result confirms that coordination failures in the congestion game are not more severe the larger the population of drivers.

Result 5. Subjects' capacity to coordinate in the congestion game seems independent of the size of the population.

Support. Figure 3 on the next page shows the temporal dynamics of the efficiency rate in the large scale experiment and in treatment (Info = 1, Beta = 1/2) of the small scale experiment.

In all rounds except one, the efficiency rate observed in the large scale experiment is larger or

[18]Clearly, more time is needed to complete a round when 64 subjects have to take a decision. Therefore, we had to stop the experimental session after $2\frac{1}{2}$ hours, although the subjects had completed only 25 rounds out of the announced 40 rounds.

[19]In the small scale experiment, depending on the level of congestion, there are 4 possible transportation durations (with a minimum of 5 minutes and a maximum of 20 minutes). In contrast, in the large scale experiment, there are 13 possible transportation durations.

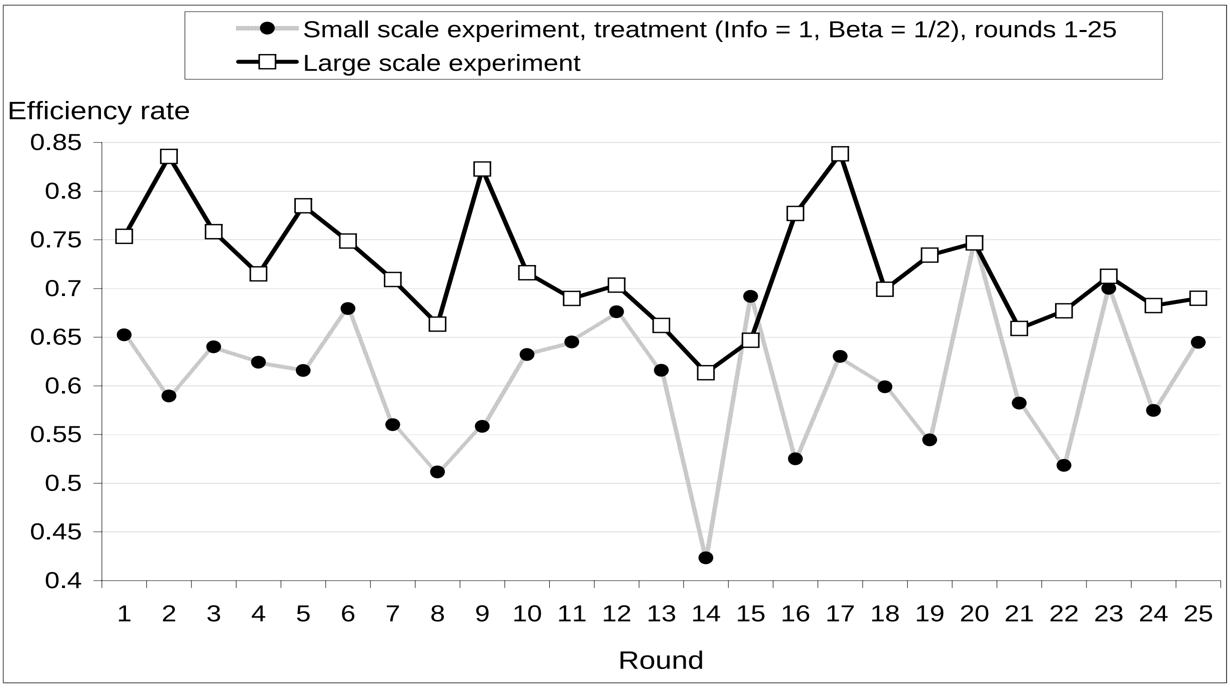


Figure 3: Temporal dynamics of the efficiency rate in the large scale experiment.

equal to the efficiency rate observed in treatment (Info = 1, Beta = 1/2) of the small scale experiment. The efficiency rate in the large scale experiment is decreasing over the rounds and seems to converge to the efficiency rate in treatment (Info = 1, Beta = 1/2) of the small scale experiment. If anything, subjects' capacity to coordinate in the congestion game seems to be positively affected by the size of the population at least in the initial rounds of play. □

5 Conclusion

The objective of this paper was to develop a discrete version of Arnott, de Palma, and Lindsey's (1990, 1993) bottleneck model and to test its descriptive accuracy by running laboratory experimental studies. To this end, we built a game theoretical model in which drivers have to reach a common destination at the same time by choosing departure times. Drivers could suffer from congestion, which increases travel time cost, but they could also suffer from delays by arriving too early or too late to destination. Basically, individuals are confronted with a coordination problem, and equilibria depend on the relative cost of delays. Two laboratory studies were conducted in order to mainly assess the impact of public information about past departure rates on congestion levels and travel costs.

As expected, congestion occurs, leading to excessive travel time cost for commuters. More interestingly, observed departure times are very close to the symmetric mixed strategy Nash equilibrium predictions and increasing the group size or providing more information to drivers about past congestion levels do not significantly decrease congestion levels and social inefficiency.

Travel information can be classified into a number of classes, depending on the time at which it is provided and the nature and objective of the information (see Khattak, Polydoropoulou, and

Ben-Akiva, 1996 and van Berkum and van der Mede, 1993). Our public information was retrospective information. One might think that current and predictive information could have more significant effect on behavior, because these kinds of information might actually decrease uncertainty on travel times, as noticed by Ettema and Timmermans (2006). That being said, inducing optimal outcomes in congestion problems seems to require the combination of infrastructure marginal cost pricing and information (see Anderson, Holt, and Reiley, 2006). Further research in this area could be important in order to estimate costs and benefits of transport policies concerning information technologies, and more precisely public investments in ATIS.

References

Al-Deek, H., and A. Kanafani (1993): "Modeling the benefits of advanced traveler information systems in corridors with incidents," *Transportation Research C*, 1(4), 303–324.

Anderson, L., C. Holt, and D. Reiley (2006): "Congestion pricing and welfare: An entry experiment," Discussion Paper, College of William and Mary.

Arnott, R., A. de Palma, and R. Lindsey (1990): "Economics of a bottleneck," *Journal of Urban Economics*, 27, 111–130.

——— (1993): "A structural model of peak-period congestion: a traffic bottleneck with elastic demand," *American Economic Review*, 83, 161–179.

——— (1999): "Information and time-of-usage decisions in the bottleneck model with stochastic capacity and demand," *European Economic Review*, 43, 525–548.

Ben-Akiva, M., A. de Palma, and P. Kanaroglou (1986): "Dynamic model of peak period traffic congestion with elastic arrival rates," *Transportation Science*, 20(2), 164–181.

Ben-Akiva, M., A. de Palma, and I. Kaysi (1991): "Dynamic network models and driver information systems," *Transportation Research A*, 25, 251–266.

de Palma, A., M. Ben-Akiva, C. Lefvre, and N. Litinas (1983): "Stochastic equilibrium model of peak period traffic congestion," *Transportation Science*, 17(4), 430–453.

Emmerink, R. (1998): *Information and pricing in road transportation*. Berlin: Springer.

Emmerink, R., K. Axhausen, P. Nijkamp, and P. Rietveld (1995): "Effect of information in road transport networks with recurrent congestion," *Transportation*, 22(1), 21–53.

Erev, I., and A. E. Roth (1998): "Predicting how people play games: Reinforcement learning in experimental games with unique, mixed strategy equilibria," *American Economic Review*, 88, 848–881.

Ettema, D., and H. Timmermans (2006): "Cost of travel time uncertainty and benefits of travel time information: Conceptual model and numerical examples," *Transportation Research C*, 14, 335–350.

Feltovich, N. (2000): "Reinforcement-based vs. belief-based learning models in experimental asymmetric-information games," *Econometrica*, 68(3), 605–641.

Fudenberg, D., and D. K. Levine (1998): *The theory of learning in games*. MIT Press.

Helbing, D. (2004): "Dynamic decision behaviour and optimal guidance through information services: models and experiments," in *Human Behaviour and Traffic Networks*, ed. by M. Schreckenberg, and R. Selten, pp. 47–97. Berlin: Springer.

Khattak, A., A. Polydoropoulou, and M. Ben-Akiva (1996): "Modeling revealed and stated pretrip travel response to advanced traveller information systems," *Transportation Research Record*, 1537, 46–54.

Levinson, D. (2003): "The value of advanced traveler information systems for route choice," *Transportation Research C*, 11, 75–87.

Mahmassani, H., and R.-C. Jou (2000): "Transferring insights into commuter behavior dynamics from laboratory experiments to field surveys," *Transportation Research A*, 34(4), 243–260.

Roth, A. E., and I. Erev (1995): "Learning in extensive-form games: Experimental data and simple dynamic models in the intermediate term," *Games and Economic Behavior*, 8, 164–212.

Schneider, K., and J. Weimann (2004): "Against all odds: Nash equilibria in a road pricing experiment," in *Human Behaviour and Traffic Networks*, ed. by M. Schreckenberg, and R. Selten, pp. 133–155. Berlin: Springer.

Selten, R., T. Chmura, T. Pitz, S. Kube, and M. Schreckenberg (2007): "Commuters route choice behaviour," *Games and Economic Behavior*, 58(2), 394–406.

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

van Berkum, E., and P. van der Mede (1993): "The impact of traffic information: dynamics in route and departure time choice," Delft University of Technology.

Vickrey, W. (1969): "Congestion theory and transport investment," *American Economic Review*, 59, 251–260.

Wolfram Research, I. (2005): *Mathematica Edition: Version 5.2*. Wolfram Research, Inc., Champaign, Illinois.

Appendix A. Additional figures

These figures are not necessarily meant for publication but could be made available on a webpage.

White bars correspond to the actual relative frequencies averaged over the first 20 rounds, black bars correspond to the probabilities predicted by the symmetric equilibrium, and grey bars correspond to the actual relative frequencies averaged over the last 20 rounds.

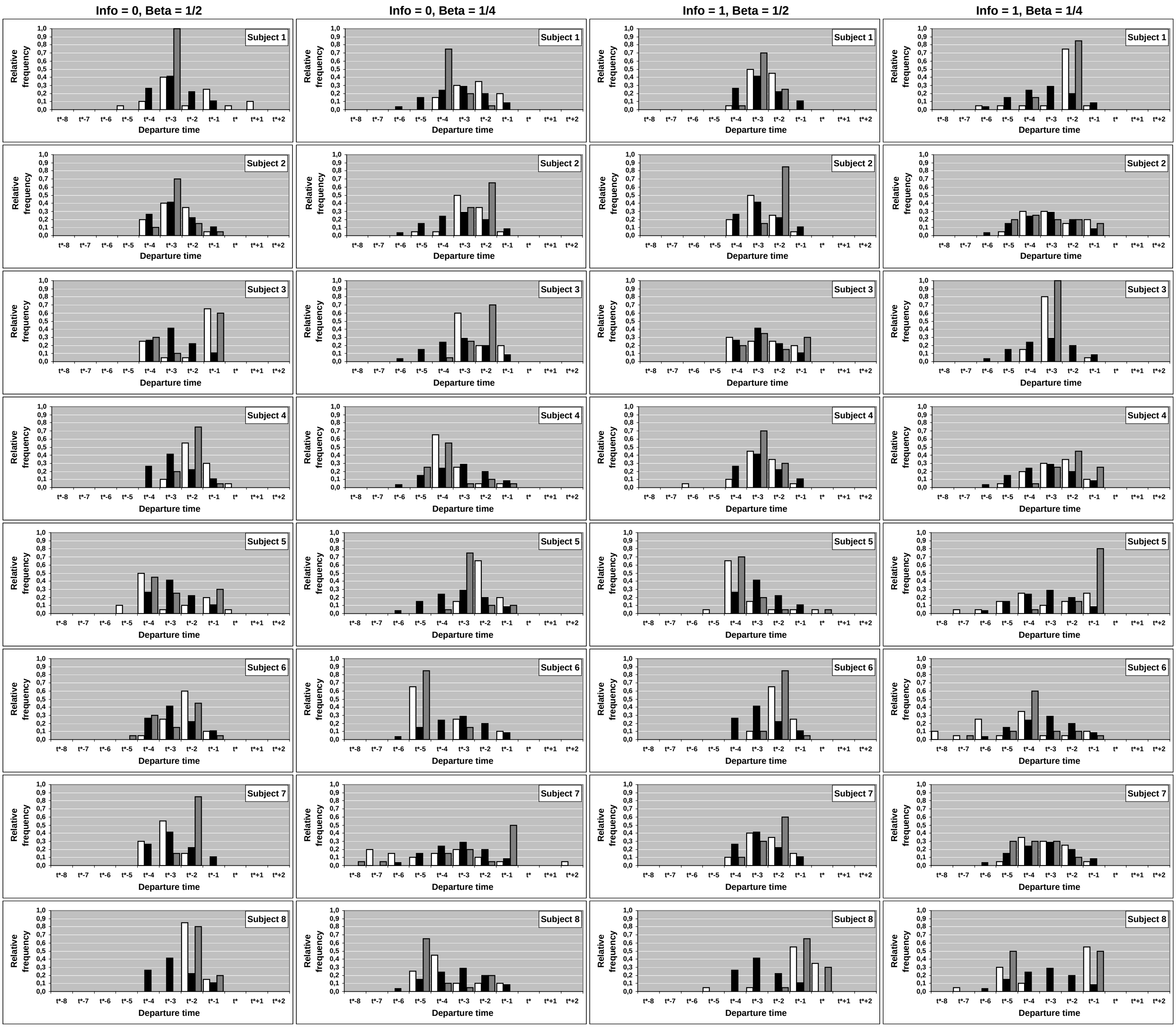


Figure 4: Individual relative frequencies of departure times in each treatment (Part 1).

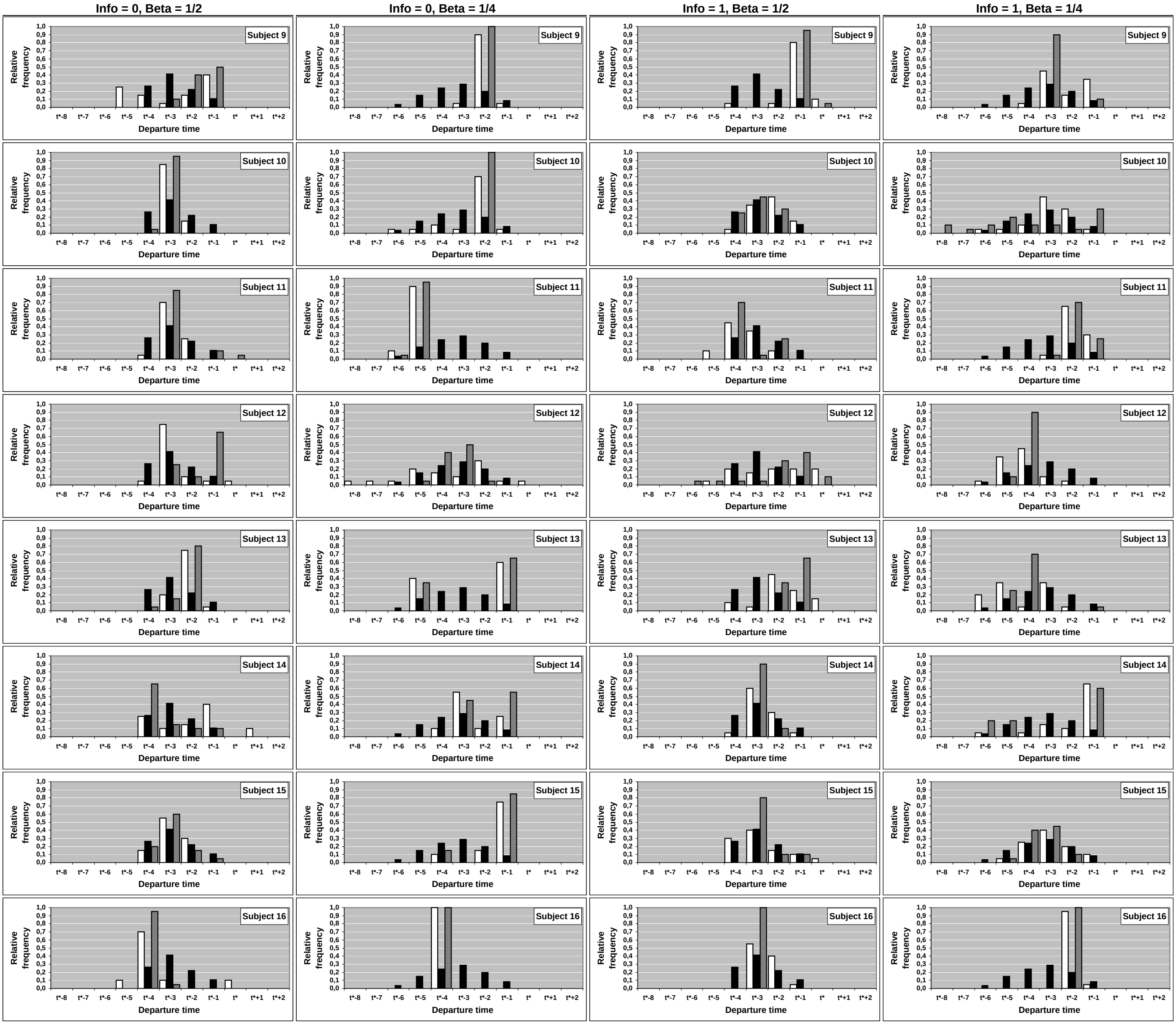


Figure 5: Individual relative frequencies of departure times in each treatment (Part 2).

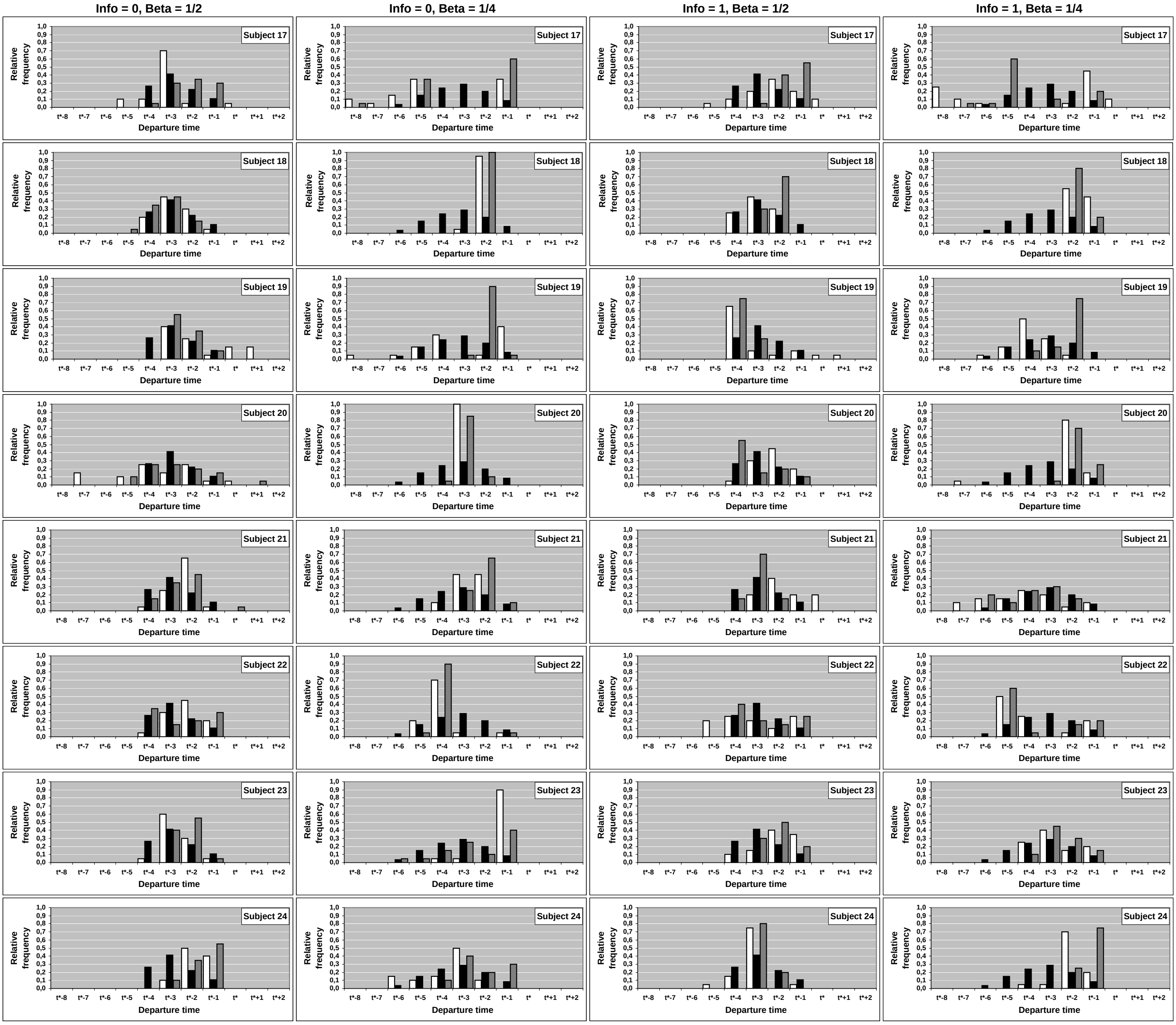


Figure 6: Individual relative frequencies of departure times in each treatment (Part 3).

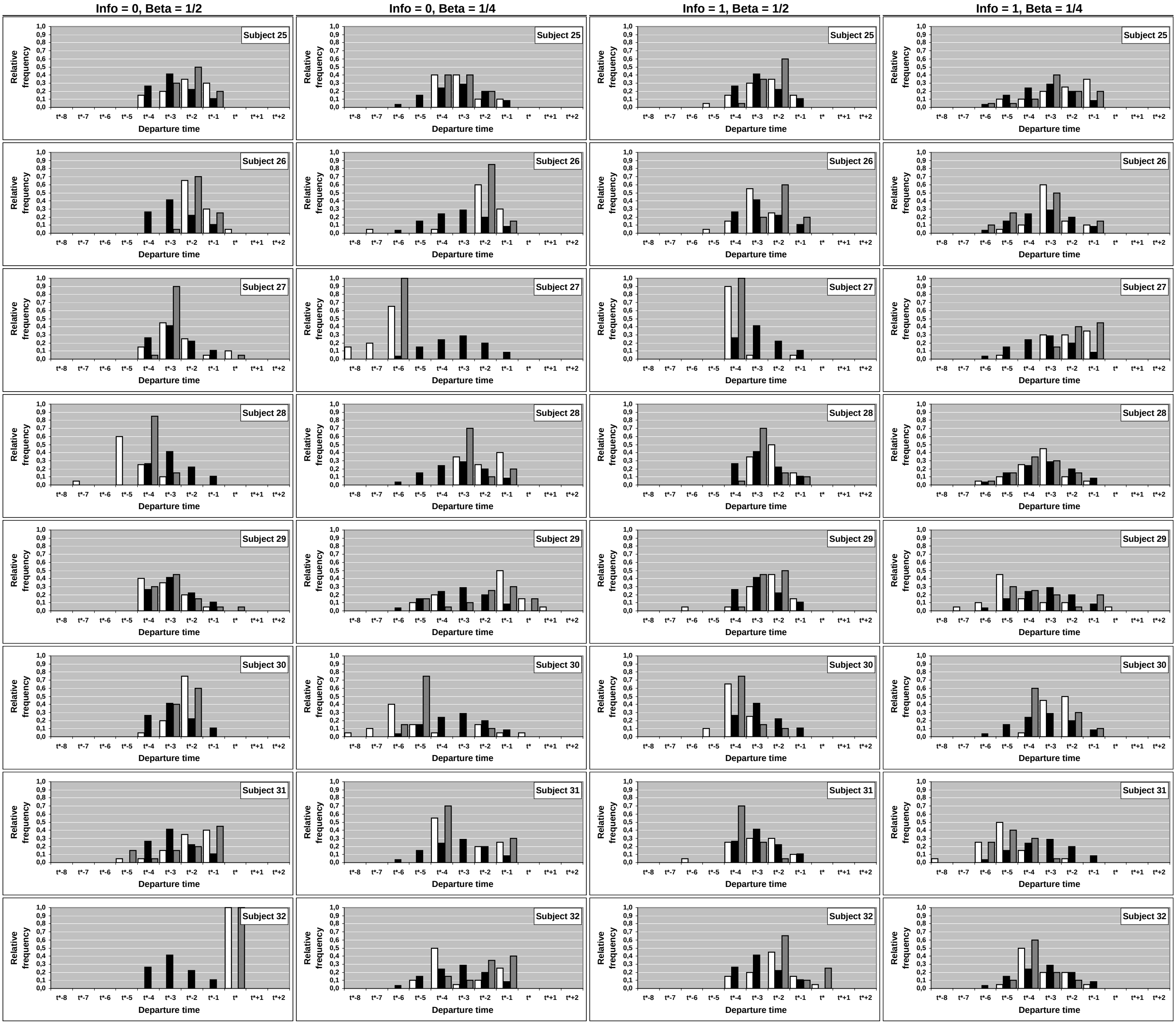


Figure 7: Individual relative frequencies of departure times in each treatment (Part 4).

Appendix B. Learning models

The Reinforcement-Based Model

Rather than endowing drivers with the high degree of cognitive sophistication implicit in equilibrium predictions, the reinforcement model posits that drivers merely learn, over time, to make better decisions (decisions leading to lower realized travel costs) more often and worse decisions less often.

Specifically, in round r, drivers have a nonnegative initial propensity $q_r(t)$ for choosing departure time t, $t \in T$. The *strength of propensities* (Q_r) in round r is the sum of the propensities for choosing all departure times: $Q_r = \sum_{t \in T} q_r(t)$. For any $r \geq 1$, if departure time t was chosen in round r and the corresponding travel costs were $C_r(t)$ then $q_{r+1}(t) = q_r(t) + \exp(-C_r(t))$ and $q_{r+1}(t') = q_r(t')$ for any $t' \neq t$.

Initial (round-1) propensities are exogenous. The probability of choosing departure time t in round r is the corresponding propensity, divided by the strength of propensities in round r: $p_r^{RL}(t) = q_r(t)/Q_r$ where RL stands for reinforcement learning.

The Belief-Based Models

According to belief-based models, drivers hold beliefs concerning the likely play of the other drivers, and they choose departure times based on their expected travel costs given these beliefs. Specifically, drivers' beliefs are characterized by nonnegative *belief weights* over other drivers' departure times. The weight on an other driver choosing departure time $t \in T$ in round r is $\omega_r(t)$. The *strength of beliefs* (Ω_r) is the sum of the weights: $\Omega_r = \sum_{t \in T} \omega_r(t)$. For any $r \geq 1$, weights for round $r+1$ are found by increasing the weight of each departure time that was observed in round r: $\omega_{r+1}(t) = (1-\delta)\omega_r(t) + k$ where $k \in \{1, \ldots, 15\}$ is the number of the other drivers who chose departure time t. The parameter δ determines the relative amount of bearing given to past outcomes relative to current outcomes in forming beliefs. If $\delta = 0$, outcomes in all rounds have equal import, while if $\delta = 1$, only the most recent outcome is considered. If $\delta \in (0, 1)$, more recent outcomes are more important than previous outcomes, while if $\delta < 0$, the opposite is true. Initial belief weights are exogenous. The assessed probability of each other driver's choosing departure time t in round r is the corresponding belief weight, divided by the strength of beliefs in round r: $\mu_r(t) = \omega_r(t)/\Omega_r$.[20]

Given these assessed probabilities, a driver's perceived expected travel costs $C^e(t \mid \mu_r)$ to each available departure time t can be calculated. The driver's chosen departure time in round r is determined from these expected travel costs; the probability of a driver choosing departure time t in round r given beliefs μ_r is

$$p_r^{BL}(t) = \frac{\exp(-\lambda \cdot C^e(t \mid \mu_r))}{\sum_{t \in T} \exp(-\lambda \cdot C^e(t \mid \mu_r))},$$

where BL stands for belief learning. The parameter λ determines the extent to which the driver responds optimally to his beliefs. If $\lambda = 0$, the driver chooses any departure time with equal likelihood irrespective of expected travel costs, while as λ gets large, his behavior approaches best-response play.

[20] We assume that an assessment always corresponds to a mixed strategy profile, i.e., we exclude correlated probability distributions over other drivers' play. See Fudenberg and Levine (1998, chap. 2, sect. 5) for a discussion of this modeling issue in multi-player fictitious play.

Appendix C. Translated instructions

The original instructions were written in French. Here we include only the translation of the instructions used in treatment (Info = 1, Beta = 1/2) of the small scale experiment. The instructions for the other small scale treatments or the large scale experiment involve only minor changes from those reprinted here. These translated instructions are not necessarily meant for publication but could be made available on a webpage.

Welcome

This is an experiment about travel decision making in which you will serve as a driver. You will have to choose a departure time in order to go to a meeting. You will drive on a road on which there is a chance of traffic jam. The instructions are simple. If you follow them and make good decisions, you may earn a significant amount of money. All of your decisions will be treated in an anonymous manner and they will be gathered across a computer network. You will input your choices on the computer you are seated in front of and the computer will indicate your earnings to you as the experiment proceeds.

The total amount of money that you earn in the experiment will be given to you in cash at the end of the experiment.

General setting of the experiment

16 people will participate in the experiment. The experiment will consist of **40 periods**. **In each of the 40 periods**, 4 groups of 4 people will be formed at random. So, in each period, you will be **a member of a group of 4 people** who will be randomly chosen among the 16 people participating in the experiment. **The composition of your group will change after each period**. There will be no way for you to identify which of the other participants are in your group in a given period, because they can be seated anywhere in the room.

At the beginning of the experiment, you will receive an **endowment of 250 points**. In each period, you will loose a certain amount of points. In a given period, your loss will depend on your own choice of departure time as well as on the choices of the three other members of your group. Your remaining amount of points available at the end of the experiment will be converted into euros. The conversion procedure of points into euros will be explained at the end of the instructions.

The meeting

In each of the 40 periods, each member of your group has to choose a departure time in order to go to a meeting. All members of your group (including yourself) have their **meeting time at 8:00 am at the same place**. Furthermore, all members of your group (including yourself) must **drive on the same road** in order to reach the meeting place. Finally, all members of your group (including yourself) depart from the same location.

Choice of departure time

The time at which you depart for the meeting must be one of the 17 possible departure times indicated below:

7:20 am	7:25 am	7:30 am	7:35 am	7:40 am	7:45 am	7:50 am	7:55 am	8:00 am	8:05 am	8:10 am	8:15 am	8:20 am	8:25 am	8:30 am	8:35 am	8:40 am
								↓ meeting time								

At the earliest, you can depart at 7:20 am. At the latest, you can depart at 8:40 am. Departure times therefore range from 7:20 am to 8:40 am, and two departure times are separated by 5 minutes. We remind you that the meeting time is at 8:00 am for you as well as for the other members of your group.

Since all members of your group (including yourself) drive on the same road, starting from the same location and going to the same destination, there might be a traffic jam. If there is a traffic jam we say that there is road congestion.

Road congestion and travel time

If the departure time you choose is such that you are the only member of your group driving on the common road at the present time then your travel time equals 5 minutes. On the other hand, if another member of your group chooses the same departure time as you then your travel time is doubled, meaning that your travel time equals 10 minutes. If two other members of your group choose the same departure time as you then your travel time is tripled, meaning that your travel time equals 15 minutes. If all three other members of your group choose the same departure time as you then your travel time is quadrupled, meaning that your travel time equals 20 minutes.

Besides, it might be that you are the only member of your group choosing a certain departure time but that you are driving on a road with some congestion, so that your travel time is increased. Indeed, the three other members of your group might chose departure times which result in a traffic jam and when you choose to depart there is still road congestion. The road congestion evolves dynamically depending on the departure times chosen by all members of your group. We provide details below about possible road congestion levels, for any given departure time.

In the remainder of the instructions, we denote by "t" one of the 17 possible departure times introduced above. Departure time t is therefore greater or equal to 7:20 am, and it is lower or equal to 8:40 am. Let us first define the notion of frequency of departure time for a given departure time.

> **The frequency of departure time for departure time t is equal to the number of members of your group who choose t as a departure time**. For example, if two members of your group choose t then the frequency of departure time for t equals 2. Of course, if none of the members of your group (including yourself) chooses t as a departure time then the frequency of departure time for t equals zero.

The congestion level associated with departure time t depends both on the congestion levels associated with past departure times and on t's frequency of departure time. Let us start with the definition of the congestion level associated with departure time 7:20 am.

> **The congestion level associated with departure time 7:20 am is equal to the frequency of departure time for departure time 7:20 am.** For example, if you are the only member of your group who chooses to depart at 7:20 am then the congestion level associated with 7:20 am equals 1.

Let us explain now how we define the congestion level associated with a departure time that is strictly greater than 7:20 am. In the following, departure time t refers to a departure time that is greater than or equal to 7:25 am and is lower than or equal to 8:40 am. We denote by "$t-5$" the departure time just before departure time t. For example, if departure time t equals 7:55 am then departure time $t-5$ equals 7:50 am.

> **If the congestion level associated with departure time $t-5$ equals zero then the congestion level associated with departure time t is equal to t's frequency of departure time**.
> Similarly, **if the congestion level associated with departure time $t-5$ equals 1 then the congestion level associated with departure time t is equal to t's frequency of departure time**.
>
> **If the congestion level associated with departure time $t-5$ equals 2 then the congestion level associated with departure time t is equal to t's frequency of departure time plus 1**.
> **If the congestion level associated with departure time $t-5$ equals 3 then the congestion level associated with departure time t is equal to t's frequency of departure time plus 2**.
> **If the congestion level associated with departure time $t-5$ equals 4 then the congestion level associated with departure time t is equal to t's frequency of departure time plus 3**.

Your travel time depends on the congestion level associated with the departure time you choose. More precisely, **you travel time, measured in minutes, is equal to 5 times the congestion level associated with the departure time you choose**. Let us illustrate the relation between the departure times chosen by all members of your group and your travel time with the help of two examples.

Example 1: Assume that the other three members of your group choose to depart at 7:30 am. In this case, the congestion level associated with departure time 7:30 am, which is due to the choices of the three other members of your group, is equal to 3.

- Whether you choose to depart at 7:20 am or at 7:25 am, your travel time is equal to 5 minutes as the congestion level associated with your chosen departure time equals 1 (you are the only driver on the road given the departure time you chose).

- If you choose to depart at 7:30 am then your travel time is equal to 20 minutes as the congestion level associated with your chosen departure time equals 4 (there are four drivers on the road given the departure time you chose).
- If you choose to depart at 7:35 am then your travel time is equal to 15 minutes as the congestion level associated with your chosen departure time equals 3.
- If you choose to depart at 7:40 am then your travel time is equal to 10 minutes as the congestion level associated with your chosen departure time equals 2.
- Finally, if you choose to depart at 7:45 am or later then your travel time is equal to 5 minutes as the congestion level associated with your chosen departure time equals 1 (at the time you choose to depart there is no road congestion anymore).

Example 2: Assume that two members of your group choose to depart at 8:15 am and that the other member of your group chooses to depart at 8:20 am.

- If you choose to depart at 8:10 am or earlier then your travel time is equal to 5 minutes as the congestion level associated with your chosen departure time equals 1 (you are the only driver on the road given the departure time you chose).
- If you choose to depart at 8:15 am then your travel time is equal to 15 minutes as the congestion level associated with your chosen departure time equals 3 (two other members of your group have chosen the same departure time you chose).
- If you choose to depart at 8:20 am then your travel time is equal to 15 minutes as the congestion level associated with your chosen departure time equals 3.
- If you choose to depart at 8:25 am then your travel time is equal to 10 minutes as the congestion level associated with your chosen departure time equals 2.
- Finally, if you choose to depart at 8:30 am or later then your travel time is equal to 5 minutes as the congestion level associated with your chosen departure time equals 1 (at the time you choose to depart there is no road congestion anymore).

Your earnings

At the beginning of the experiment, your will receive **250 points**. In each of the 40 periods of the experiment, you will loose a certain amount of points, i.e., your initial endowment will be reduced. Therefore, in a given period, your available amount of points will be lower than your available amount of points in the previous period. Your loss in each period is determined as follows.

In each period, each member of your group will choose a departure time. **When choosing your departure time you will not know the departure times chosen by the three other members of your group**. Once all four departure times have been chosen, the computer in front of which you are seated will compute your travel time according to the congestion level associated with your departure time. Given your travel time and your departure time, the computer will compute your arrival time. **In a given period, your loss depends both on your travel time and on your arrival time**. Let us provide now more details concerning the computation of your loss in a given period.

In each period, once your travel time has been computed, the computer subtracts from your available amount of points a “travel time penalty”. Note that, whatever the departure times chosen by the four members of your group, your travel time is at least 5 minutes and it cannot exceed 20 minutes. The table below shows your time penalty as a function of your travel time:

Travel time	**Travel time penalty (travel time / 5)**
5 minutes	1 point
10 minutes	2 points
15 minutes	3 points
20 minutes	4 points

Moreover, if you do not reach the meeting place exactly at the meeting time (we remind you that the meeting takes place at 8:00 am) then you will get an additional penalty.

If you arrive at the meeting place earlier than 8:00 am then you will get an “advance penalty”. Note that, whatever the departure times chosen by the four members of your group, your arrival time will be at least 7:25 am. The table below shows your advance penalty as a function of your arrival time in case your arrival time is lower than or equal to 8:00 am:

Arrival time	**Advance time**	**Advance penalty (advance time / 10)**
7:25 am	35 minutes	3.5 points
7:30 am	30 minutes	3 points
7:35 am	25 minutes	2.5 points
7:40 am	20 minutes	2 points
7:45 am	15 minutes	1.5 points
7:50 am	10 minutes	1 point
7:55 am	5 minutes	0.5 point
8:00 am	0 minute	0 point

On the other hand, if you arrive at the meeting place later than 8:00 am then you will get a “delay penalty”. Note that, whatever the departure times chosen by the four members of your group, your arrival time will be at most 9:00 am. The table below shows your delay penalty as a function of your arrival time in case your arrival time is greater than or equal to 8:00 am:

Arrival time	Time delay	Delay penalty (time delay / 2.5)
8:00 am	0 minute	0 point
8:05 am	5 minutes	2 points
8:10 am	10 minutes	4 points
8:15 am	15 minutes	6 points
8:20 am	20 minutes	8 points
8:25 am	25 minutes	10 points
8:30 am	30 minutes	12 points
8:35 am	35 minutes	14 points
8:40 am	40 minutes	16 points
8:45 am	45 minutes	18 points
8:50 am	50 minutes	20 points
8:55 am	55 minutes	22 points
9:00 am	60 minutes	24 points

To summarize, **if you arrive early at the meeting** then **your loss in points** for the current period is equal to **your travel time penalty + your advance penalty**.

If your arrival time is 8:00 am, i.e., if **you arrive exactly on time at the meeting**, then **your loss in points** for the current period is equal to **your travel time penalty**.

If you arrive late at the meeting then **your loss in points** for the current period is equal to **your travel time penalty + your delay penalty**.

Summary

You will participate in an experiment that consists of 40 periods. In each of the 40 periods, you will be a member of a group of 4 people who will be randomly chosen among the 16 people participating in the experiment and the composition of your group will change after each period. At the beginning of the experiment, you will receive an endowment of 250 points. In each of the 40 periods, each member of your group has to choose a departure time in order to go to a meeting. Departure times are chosen simultaneously and all members of your group (including yourself) have their meeting time at 8:00 am at the same place. **At the beginning of each period**, the computer will provide you with the **average relative frequencies of departure times deduced from the choices made by the 16 people participating in the experiment (including yourself) in the previous periods**. So, in the first period, you will have no information about past relative frequencies of departure times, since no choice has been made yet. At the beginning of the second period, you will be informed about the relative frequencies of departure times deduced from the choices made by the 16 people participating in the experiment in the first period. At the beginning of the third period, you will be informed about the average relative frequencies of departure times deduced from the choices made by the 16 people participating in the experiment in the first and second periods. And so on. Once all four departure times have been chosen, the computer computes your travel time, your arrival time and your loss in points for the current period. At the end of each period, you will see on the screen of the computer the amount of points which were available at the beginning of the period, the departure time you chose, your arrival time, the departure times the three other members of your group chose, your loss in points for the current period and the amount of points remaining at the end of the period. Then the next period begins. At the beginning of each period, your available amount of points is reminded to you.

When the 40th period is over, the computer shows your available amount of points at the end of the experiment. This amount of points will be converted into euros according to the following conversion rate: 100 points = 10 euros. For example, if at the end of the experiment you have 150 points left then you will receive 15 euros in cash.

In the upper left corner of the screen you will see a button called "**History**". If you click on this button, you will see for **any of the previous periods, the frequencies of departure times deduced from the choices made by the 16 people participating in the experiment (including yourself)**.

Before starting the experiment, the instructions will be read aloud, and you will have to answer a control questionnaire in order to check your understanding of the instructions. If you make too many mistakes when answering the control questionnaire then you will not be able to participate in the experiment.

Good luck!