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Information Value and Sequential Decision-making in a Transport Setting: An Experimental Study

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Abstract

In economic models of dynamic choice under uncertainty, the "Information Value" is the highest price an individual is willing to pay for information. This amount usually increases as information becomes more specific. Applying experimental economics an experimental game has been constructed in which individuals choose between alternative congested transport modes to try to arrive at a destination at a specified time. To reduce the risk associated with modal choice, each subject can buy information about traffic levels. Two information messages are offered one after the other, the second giving more information. The results

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show the value individuals ascribe to information in a context of increasing information where information is not free, and the price of information price and infrastructure capacities vary. Individuals compare the utility of information to its cost and this calculation is an important part of the comparison between risk with regard to travel time and the monetary travel cost. Moreover, individuals choose to buy information when the variance of payoffs for the chosen route is sufficiently high. The paper shows that the economic model of dynamic choice seems to provide a reasonable approximation of individual values. In particular, the willingness to pay for more detailed information is higher than for more general information. Finally, it shows how an experimental economics technique can produce empirical data to test theoretical models dealing with transport behavior.

JEL: C91; D83; R41

Keywords: Dynamic Choice, Expected Utility, Information Value, Transport Congestion

1. INTRODUCTION

The provision of real-time road traffic information is an important part of present-day transport policy (Emmerink *et al.*, 1995; Mahmassani and Chang, 1985; Mahmassani and Jayakrishnan, 1991; Mahmassani and Tong, 1986). Given the growing congestion on urban and interurban roads and the difficulties in financing new facilities, better information technology may improve traffic flow, particularly as it has even been demonstrated that information provision has the potential to reduce excess travel time (Ben-Akiva, de Palma and Kaysi, 1991).

However, there have been few analytical studies of individual transport choice with changing levels of traffic information. Some of these studies have aimed to assess the welfare impact of increased knowledge about traffic (Arnott *et al*., 1991, 1996, 1999; Emmerink *et al*., 1998). Such of the models are based on rational expectations and study the impact on choice of three types of information (no information, imperfect and perfect information). Obviously, improved information increases consumer surplus, but the welfare benefit could be reduced in some cases by increased congestion, especially when there are too many informed drivers or when drivers overreact to the information they receive (Delvert, Denant-Boèmont and Petiot, 2000; Emmerink *et al.*, 1995). Note that in most of these models, information is free at all times. Furthermore individual choices are stochastic but remain static (except in Arnott *et al.* 1999) - *i.e.* once users have made their travel choice (which they may do in several stages) no more information about traffic is available for them to learn and to modify their choice. Such a model is implemented in this paper.

This paper builds an analytical model of Information Value (IV) for transport choice where decision-making is dynamic and information is not free. How do road users make use of new information about traffic levels when congestion is likely to occur on the available routes? How do they change their transport plans when they receive additional information?

An experimental economics method (Davis and Holt, 1993) has been used to test the behavioral responses of players in a transport situation. It is important to distinguish between the usual methods used to assess user preference – *i.e.* revealed and stated preference techniques - and experimental economics. As Friedman and Sunder (1994) have pointed out, the important fact is that economic experimenters try to produce laboratory experimental data, which implies a high level of control of experimental conditions and players' incentives by making payments to players which depend on their choices. There have still only been a few experimental economics studies of transport decision-making (Delvert and Petiot, 1999; Delvert, Denant-Boèmont and Petiot, 2000; Schneider and Weimann, 1997). To the best of our knowledge, this study is the first to implement a method of this type for dynamic choice[1] in the area of transport when individuals are faced with uncertainty about traffic. In the field of transport, experimental economics has only been implemented to test market efficiency (Grether, Issac and Plott, 1989 who dealt with air transport deregulation; Brewer and Plott, 1994, or Nilsson, 1997 who dealt with railway deregulation; Fischer *et al.*, 1992, who dealt with the market for taxi-cab licences).

Models Dynamic choice models with increasing information use a Bayesian learning process where the IV is the additional utility resulting from improved information about the state of nature that is to occur (see the seminal analysis of Marschak and Radner, 1972). Experimental studies that deal with individual information valuation are rare (Rauchs and Willinger, 1996) compared to dynamic choice studies, especially ones dealing with temporal inconsistency and myopic behavior (Anderhub *et al*., 1996). Our purpose is to use an experimental method to observe IV in dynamic choice settings by focusing on sequential transport choice in a context of increasing information. In forming their plans, transport users can be regarded as making

[1] We use dynamic choice as sequential choice according to *the dynamic choice theory* (Strotz, 1955-1956; Marschak and Radner, 1972).

sequential choices: to get to their destination point, they first choose a mode and then a departure time. In our experiment the amount of information available is increased as the player goes through these steps. We are thus able to study individual adaptation.

More specifically, two kinds of information are offered at different prices: the second message is more precise than the first, but is provided later in the sequence of decisions - *i.e.* when the route has already been chosen. In most cases, the individual should be willing to pay more for the second message than for the first.

Two components of our experiment are quite new considering how information learning is implemented and how choices are dynamic, especially by comparison with the papers dealing with information and road transport cited above. First, decision-making is sequential - *i.e.* (a) the individual is able to reconsider his or her choice as regards information acquisition and (b) the level of available information increases as the decision sequence progresses, which implies Bayesian process for the individual. Second, the information messages are not free of charge.

Section 2 briefly defines the expected utility of increasing information - *i.e.* the Information Value - and then describes the dynamic transport choice experiment. The third section derives the theoretical results stemming from the model. Lastly, the fourth section gives the experimental results and compares them with theoretical predictions.

2. AN EXPERIMENT TO INVESTIGATE DYNAMIC TRANSPORT CHOICE WITH INCREASING INFORMATION

How much is a decision-maker willing to pay for additional information before he or she makes his or her decision? *The Information Value (IV)*[2] *is defined as the maximum amount a player is willing to pay in order to obtain a given item of information*. In more precise terms, what is involved is an information partition under expected utility maximizing assumption.

2.1. Information Value in Expected Utility

A basic theoretical model of Information Value in Expected Utility describes a two-period choice (t = 1, 2) under uncertainty. Let D be the set of possible choices at the beginning of the first period ($d_i \in D$; $i = 1,..., I$ for t = 1), S the set of states (s_j the state j, j = 1 to J) and Y a set of messages/observations with elements y (y_k the signal k). By definition, an *Information Set* is the set of different states that the agent is unable to discern[3]. An *Information Partition* (IP) is therefore a collection of information sets, the information sets being themselves subsets of S which are mutually exclusive and for all incompatible. In Von Neumann-Morgenstern (VNM) Expected Utility, an IP(A) is more informative than an IP(B) if IP(A) is more detailed than IP(B). Moreover, an IP(A) is better than an IP(B) if

$$U\left[IP(A)\,;\,\pi(.),u(.)\right] \quad \geq \quad U\left[IP(B)\,;\,\pi(.),u(.)\right]$$

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[2] The following definitions are taken from Willinger (1989). For more details about the axioms which underline the Bayesian information structure, see Laffont (1991) or Jones and Ostroy (1984).

[3] For instance, if an individual makes an experiment by throwing a dice and announces to an hooded individual that the result is “an even number”, this individual is not able to say if the result is “2”, “4” or “6” but knows that “1”, “3”, “5” are impossible states. Then, he or she is not able to discern among states “2”, “4”, “6” because the experiment do not enable to discriminate between these three states. The information partition associated to this experiment is the union of information sets IP(A)=({1,3,5},{2,4,6}), each set being attached to an experiment ({1,2,3} is attached to “the number is uneven”, {2,4,6} is attached to “the number is even”), whereas before throwing the dice, the information partition was IP(B)=({1,2,3,4,5,6}).

where $\pi(.)$ is the probability function on *S before any message is observed, and u(.)* is the utility function attached to states s_j.

"Increasing information" means that the agent moves from IP1 (a particular collection of subsets of *S* at *t = 1*) to IP2 (a collection of subsets of *S* at *t = 2)* which is more detailed than IP1[4]. For example, if we assume that a driver goes from A to B via the same road every morning and that four states of traffic are possible: "very light", "light", "medium" and "heavy". These states are all equally probable. Each level gives a certain level of transport cost for the driver. Before leaving A, he or she could obtain more information about the traffic level, for example by means of a radio-message saying "the traffic between A and B is not heavy". This is one possible message *y* among other possible messages, and enables the driver to revise his or her probabilities. Here, the state "heavy" becomes impossible, and the probabilities have changed (now 1/3 per possible traffic state). Thus, three kinds of situation have to be considered:

(i) No information (incomplete IP): the decision-maker is not able to to improve his or her information - *i.e.* is unable to refine his or her information via the set of *S* and the IP does not change over time. The driver receives no more information before leaving A or receives a message that is of no use.

(ii) Perfect information (Perfect IP): the agent goes from IP(A) to IP(B) the later being singletons. The agent then combines a signal y_k and a state s_j - if an agent receives the signal y_k, he or she knows that state s_j will occur in the coming period. In our example, a driver who gets a radio message saying "the traffic is heavy" will be able to change his or her departure

[4] It is possible to say that IP2 is a refinement of IP1 if in IP2, (i) the number of information sets is greater than in IP1 *and* (ii) if every information set belonging to IP2 is a collection of subsets of any information set belonging to IP1. See Rasmusen (1989) for further details.

time for instance. He or she knows with certainty that the probability is 1 for “heavy” and 0 for the other states;

(iii) Imperfect information (Partial IP): the agent improves his or her information - *i.e.* refines his or her IP, but remains unable to combine any y_k with a single s_j. For instance, if the radio message says “The traffic level is changing from very light to light at the moment”, the driver will know that the probability of having medium or heavy traffic is 0, but not know with certainty from the message which state will occur.

The IV is the difference between the expected utility with the more detailed IP and the expected utility with the less detailed IP. In VNM expected utility, IV is always positive or equal to zero. Obviously, the imperfect information cases are the most interesting, because it is unusual for the driver to have perfect knowledge about the states which will occur in the coming period.

2.2. A dynamic transport choice experiment with increasing information about traffic

The experiment deals with a sequential transport choice and observes how transport choices change when individuals are offered traffic information which is not free of charge. First, if the IV theory is right, subjects should be willing to pay more for the most accurate information. Second, subjects should only buy the information in the case where IV - *i.e.* Expected Utility with the information minus Expected Utility without information - exceeds the information price.

(a) Design[5]

In the experiment[6], 3 groups of 10 subjects[7] play 10 rounds. During each round, each of the subjects plans their travel from point *A* to point *B*. The arrival time t^* at *B* is constrained (fixed at 5 pm)[8]. In each round, players are first informed about road capacities. In this experiment the capacity is the number of players who can take a given route without incurring congestion (*L* = 1 means that if 2 or more players choose *L* the travel time on *L* will increase). First, players choose their transport mode – either Train (*T*) or Road (*R*). If they choose *T*, they are sure of getting *B* at 5 pm. All players have the opportunity to purchase information about traffic level on *R*, I_R giving *nR*, the actual number of players who has chosen *R*. All the players know the price of this information, which is different for each round. They can either purchase I_R or refuse to do so. The players are unaware of whether the others have purchased I_R.

Players who choose *R* will then select their route – either a Local road route (*L*) or a free Highway (*H*). The capacity on *L* route is always lower than on *H* route. All players have the opportunity to purchase information about the actual traffic on *H* (I_H gives *nH*) and the price is different during each round. The players do not know who has purchased the information.

At the end of each round, the players have to choose their departure time t_d from among a set of possible departure times. The amount paid to each player depends both on his arrival time

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[5] The design of the experiment stems from a discussion with Professor Werner Güth, who suggested a design to investigate transport choice. His initial idea has only been implemented in part, the emphasis being placed on information value.

[6] Full instructions are available from the authors on request.

[7] Students taking economics and the management courses. There is no difference between the 3 groups.

[8] The paper does not directly deal with the morning commute problem. We do not refer explicitly to the morning rush in such a way that in the experiment the subjects only concentrate on the information impact on their own modal and time decision in front of a constraint arrival time whenever during the day.

t_a, which may differ from the constrained arrival time t^*, and on his or her travel time t. The travel time t is a function of the traffic level on each route - *i.e.* the number of players who have chosen *L* or *H*. In the experiment, the travel time without congestion is 40 minutes on route *L* and 30 minutes on route *H*. The travel times with congestion are shown in the table of payments given to the players.

Each player's monetary endowment for the first round is 60 ECUs (1 ECU for 1 FF or 6.55957 €). The endowment for each of the following rounds is the sum of the player's payments for the previous rounds added to the initial endowment. Any communication between players is forbidden during the experiment.

(b) The payoff function

The payoff function is based on a transport cost function (Vickrey, 1969). It takes into account both the cost of the journey time and the cost of the difference between the actual and target arrival times. Such a function is widely used in transport economics, in the context of both analytical studies and experimental work.

For any departure time t_d, in the event of early arrival $\left(t_a(t_d) < t^*\right)$, the total travel cost is

$$C(t_d) = \alpha t(t_d) + \beta\left[t^* - t_a(t_d)\right] \tag{1}$$

where α is the cost of a unit of transport time and β is the cost per time unit of being early.

For any t_d, in the event of late arrival $\left(t_a(t_d) > t^*\right)$, the total travel cost is

$$C(t_d) = \alpha t(t_d) + \gamma\left[t_a(t_d) - t^*\right] \tag{2}$$

where γ is the cost per time unit of being late.

The maximum gain G is fixed. If $Arg\min C(t_d)$ is the lowest possible travel cost for all departure time t_d, the payoff function is

$$P(t_d) = G + \frac{Arg\min C(t_d) - C(t_d)}{2}. \quad (3)$$

The payoff for choice T is 1 ECU.

In the experiment[9], G = 20 ECUs, $\alpha = 1$ ECU, $\beta = 2$ ECUs, $\gamma = 3$ ECUs. We have also implemented a bonus of 20 ECUs in the case of $t_a = t^*$.

To illustrate, let us fix the constrained arrival time t^* at 17:00. Assume the player's chosen route is L and the player's chosen departure time t_d is 16:15 and that in view of congestion the actual arrival time $t_a(t_d)$ is 17:15 in the case where $L = 1$, $H = 2$ and $nL = 10$. The minimum among all possible costs is always 30 (in the case of a choice H with low traffic levels on H (1 or 2 users), and a 16:30 departure time choice). Then, if the player has chosen L and nL being equal to 10, then his or her travel time is 60 minutes and his or her travel cost is 60 ECUs (60 minutes *1 ECU). Moreover, he or she has chosen 16:15 as a departure time, and then he or she arrived at B 60 minutes later – *i.e.* at 17:15, being late for 15 minutes. His or her schedule delay cost is then equal to 15 minutes * 3 ECUs = 45 ECUs. His or her total travel time cost is then 60 ECUs + 45 ECUs = 105 ECUs. The corresponding payoff is equal to 20 + (30-105)/2 = -17.5 ECUs (see the Tables of payoffs used in the experiment in Appendix A).

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9 The values taken for the cost of travel time and schedule delay are not typical of those found in the standard literature (Arnott *et al.*, 1990). However, in our experiment, the idea was to give a high value for schedule delay cost in order to encourage players to make an intelligent choice of departure time.

3. THEORETICAL RESULTS AND MODEL

3.1. Basic assumptions

The main assumption is that individuals are Expected Utility maximizers. Thus, when individuals receive perfect information about traffic levels they choose the departure time that maximizes the payment. Moreover, the IVs are determined with respect to the payoff function. We assume, as do most experimenters in decision-making games, that this payoff function represents the utility function of any player, and that all players are risk-neutral – *i.e.* that expected utility is equivalent to expected payoff. Information Value is in this case equivalent to the gain in expected payoff enabled by increasing information. We have assumed, however, that we could use an uniform probability function. Note that the model implemented here differs from classical discrete choice models (Ben-Akiva and Lerman, 1985) in that we have assumed that neither the decision rules nor the utility function are probabilistic. The utility function is assumed to be known and the choice process is deterministic. Only the traffic levels are uncertain.

In the experimental design, all the subjects know they are playing against the (n-1) other subjects in the group, and this knowledge affects their choice. Then, if the experiment implements a game situation, why not use game theory tools in order to determine the equilibrium instead of decision theory? There seems to be no reason that decision theory does not apply to decision-making in game theory situations, as has been pointed out by Broome

(1990). This author describes the traditional "twin prisoners' dilemma"[10] (*i.e.* situations where the players are entirely self-interested, but think very much alike), where "you and your twin can act nice or nasty". Acting nasty is a dominant strategy, so both players will choose it. What would be the outcome if decision theory were used? Broome says (1990, p. 487): "Faced with the twin prisoners dilemma, a follower of Savage has two alternatives. She may decline to apply the theory at all, perhaps taking the general view that decision theory does not apply to games. Or she may pick some things to serve as states of nature. She may, for instance, take your twin's acts as states of nature from your point of view. They will then have to be assigned probabilities independent of your own acts. And whatever probabilities they are assigned, acting nasty will come out with a higher expected utility for you".

Broome then goes on to argue that in numerous game situations, using decision theory could give the same result as game theory. For example, in Public Good Games, the best theoretical solution is not to contribute. There is no doubt that in many of the experimental settings associated with such games, the best choice according to expected utility theory is also not to contribute. We have assumed here that the best choice given by decision theory is the same as that given by game theory.

So, for routes *H* and *L*, the individual will have to choose the departure time t_d. We have assumed that the driver will choose the best t_d for route *L* or route *H* if he or she have received

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[10] Two people are arrested for the same crime. The police lack evidence to convict either suspect and consequently need them to give testimony against each other. They are placed in separate rooms and given the opportunity to confess. If only one of them confesses, he or she serves one year and the other receives a ten-year sentence. If both confess, they each serve five-year terms. If neither confesses, each receives a maximum two-year penalty. Thus, both would be better off if neither confesses, but each, aware of each other's incentives to confess in any case, will probably confess. This game, called a "coordination game" by game theorists, demonstrates the failure of spontaneous coordination between non-cooperative players, according to the Pareto-optimality criterion.

perfect information about the traffic level on the route. The information alternatives available to the individual are: “purchase no information” or, “purchase I_R giving *nR*” or, “purchase I_H giving *nH*” or, “purchase both I_R and I_H”. It might be thought that the last case need not be considered, but it may be of value to purchase I_H if the individual has already purchased I_R (for example, individuals who have purchased I_R and choose *R* would get perfect information with I_H).

3.2. Expected gains and information value

We have to calculate how the expected gains are increased if the individuals purchase I_R or I_H, or I_R *and* I_H. We shall first of all compute the expected gains without any information purchase.

(a) The expected gains without any information

The expected gains without any information are as follows :

$$E(T) = 1 \tag{4}$$

$$E(R) = Max\left[E(L); E(H)\right] \tag{5}$$

with

$$E(L) = Max\left[e_{td_i}\right] \; ; \; e_{td_i} = \sum_{x=1}^{10} \pi(nL = x) U\left(td_i\right); \tag{6}$$

$$E(H) = Max\left[e_{td_{i'}}\right] \; ; \; e_{td_{i'}} = \sum_{y=1}^{10} \pi(nH = y) U\left(td_{i'}\right) \tag{7}$$

where:

td_i is the departure time *i* for choice *L* (*i* = 1 to 5);

$td_{i'}$ is the departure time *i’* for choice *H* (*i’* = 1 to 9);

$U(td_i)$ is the utility attached to td_i at each traffic level for *L* - *i.e.* the payoff defined in (3);

$U(td_{i'})$ is the utility attached to td_i' at each traffic level for *H;*

$\pi(nL = x)$ is the probability of the number of players on *L* (*nL*) being equal to *x* (the traffic level on *L* is *x*);

$\pi(nH = y)$ is the probability of the number of players on *H* (*nH*) being equal to *y*.

Let us now explain equations (5), (6) and (7). In equation (6), a player who chooses *L* can choose a departure time of 16:00. The expected utility of this departure time given his or her choice *L* is then the expected payoff of a 16:00 departure time choice. This is the probability of *x* of players choosing *L* multiplied by the payoff for every possible level of traffic. Here, the possible states for traffic are *nL* = 1,…,10 therefore $\pi(nL = x) = 0.1$. Equation (7) gives the expected utility – in the experiment, the expected payoff – for the choice *H*. Finally, equation (5) means that, if the player is an expected utility maximizer, he or she should choose between *L* or *H* by comparing the values he or she expects.

Given the payoff structure, a player who has chosen *R* has to choose between *L* and *H* before choosing a departure time. The payoff of *L* or *H* will then depend upon the departure time. For instance, in one of our experiments (where the capacity of *L* was 2 and the capacity of *H* was 4), the expected payoff of a 16:00 departure time on *L* was +13.75, -0.75 for 16:05, *etc.* (expected payoff declines with a later departure time). A rational player should choose 16:00 if *L* has been chosen so, the expected payoff for *L* is +13.75. For *H*, the expected payoff is given by the best choice from among the possible departure times on that route. For example, the highest expected payoff on *H* in this case was –7 ECUs with a departure time of 16:00 on *H*. So, a rational player having chosen mode *R* should choose route *L* and a departure time of 16:00, because, *without any information*, this is the best choice with regard to the expected payoff.

(b) The expected gains with I_H – The Information Value for I_H

The expected gains with I_H are as follows :

$\forall nH = \bar{y}\ ;\ \bar{y} = 0,\ldots,10 \Leftrightarrow nL = x\ ;\ x \in [0\ ,(10-\bar{y})]$,

$$E(R/I_H \,|\, nH = \bar{y}) = Max\left(E(L/I_H \,|\, nH = \bar{y}); E(H/I_H \,|\, nH = \bar{y})\right) \tag{8}$$

where I_H gives the number of players *y* who have chosen *H* (*nH*) and

$$E(R/I_H) = \sum_{y=0}^{y=10} \pi(nH = y)\, E\left(R/I_H \,|\, nH = \bar{y}\right) \tag{9}$$

and the IV for I_H is

$$IV(I_H) = E(R/I_H) - E(R) \geq 0\,. \tag{10}$$

(c) The expected gains with I_R – The Information Value of I_R

The expected gains with I_R are as follows :

$$\forall nR = \bar{z}\ ;\ (\bar{z} = 0,\ldots,10):\ E(R/I_R \,|\, nR = \bar{z}) = Max\left[E(L/I_R \,|\, nR = \bar{z}); E(H/I_R \,|\, nR = \bar{z})\right] \tag{11}$$

so

$$E(R/I_R) = \sum_{z=1}^{z=10} \pi(nR = z) E\left(R/I_H \,|\, nR = \bar{z}\right) \tag{12}$$

and the IV for I_R is

$$IV(I_R) = E(R/I_R) - E(R) \geq 0\,. \tag{13}$$

(d) The expected gains with I_R and I_H – The Information Value of I_R and I_H

It is obvious that the IV of both pieces of information about traffic levels is different from the sum of the IVs ($IV(I_R \text{ and } I_H) \neq IV(I_R) + IV(I_H)$). A player who has information about *R* can infer which states of *nH* and *nR* are not possible. Purchasing I_H will then give him or her

perfect information about the state of nature for *R* and *H*. When buying I_R, the player has to choose between *L* and *H*. This choice is made by considering the possible states for *nH* and the probabilities of these states given the state of *nR*. For any *nH*, the player makes the best decision (*L* or *H*). So, for a given value of *nR* = z

$$\forall nR = \bar{z} \rightarrow E\left(R/I_R \, and \, I_H \,|nR = \bar{z}\right) = \sum_{y=0}^{y=\bar{z}} \pi\left(nH = y/nR = \bar{z}\right) Max\left[U\left(td_i\right); U\left(td_{i'}\right)\right] \quad (14)$$

$$E\left(R/I_R \, and \, I_H\right) = \sum_{z=1}^{z=10} \pi\left(nR = z\right) E\left(R/I_R \, and \, I_H \,|nR = \bar{z}\right). \quad (15)$$

Finally,

$$IV\left(I_R \, and \, I_H\right) = E\left(R/I_R \, and \, I_H\right) - E\left(R\right) \geq 0\,. \quad (16)$$

Because having I_R *and* I_H is equivalent to a perfect Information Set, we should have

$$IV(I_R \, and \, I_H) \geq IV(I_H) \geq IV(I_R) \quad (17)$$

3.3. Theoretical results

On the basis of the payoff function, the expected gains and IVs are shown in Table 1.

Table 1

Information Values for I_R, I_H, « I_R and I_H » (ECUs)

Capacity	*L*=2 ; *H*=4	*L*=1 ; *H*=2	Capacity	*L*=2 ; *H*=4	*L*=1 ; *H*=2
Expected Gain			Information Value		
$E(R)$	+13.75	+16.75			
$E(R/I_R)$	+25.9	+19.7	$IV(I_R)$	+12.1	+2.9
$E(R/I_H)$	+28.5	+20.9	$IV(I_H)$	+14.8	+4.1
$E(R/I_R \, and \, I_H)$	+34.1	+31	$IV(I_R \, and \, I_H)$	+20.4	+14.2

It may be helpful to examine, for example, $E(R/I_R \text{ and } I_H)$ in the case where $\{L=2, H=4\}$. Here, the player receives information about the traffic on mode *R* (if he or she buys it!) and then chooses between routes *L* and *H*. The player then gets further information about the traffic on route *H* (if he or she buys it) before choosing a departure time. In this case, the player is in a "perfect information" state (if there are 5 *R* choices there are 5 *T* choices and if there are 3 *H* choices there are 2 *L* choices) - *i.e.* the player knows at the beginning of the game that he or she will be able to know the state of traffic with certainty, but also that for the time being no information is available to make the first choice between mode *T* and mode *R*. Therefore, to use the terminology of game theory, the player has to use *backward induction* to assess his or her best choice at the beginning of the game. At this moment, each state of traffic on *R* is equally probable and the player has to assess each possibility. For example, let us assume that there is 1 *R* (the probability is 10%). There are then two possible states for the traffic on *L* and *H*: either the traffic on *L* is in state "1", in which case the traffic on *H* is in state "0", or the traffic on *L* is in state "0" and the traffic on *H* is in state "1". More generally, if the traffic level on *R* is *x*, there are (*x*+1) possible states for the distribution of this traffic between *L* and *H*, each state being equally probable. For each possible state, the payoff of an *R* choice is the maximum from among the payoffs for *L* and the payoffs for *H*. For instance, if *nR*=2, there are 3 possible states:

1. *H*=0 and *L*=2 (probability equal to 1/3 given a 10% probability that *nR*=2): this implies that the player on *R* has chosen *L* and will receive 35 ECUs (the payoff on *L* given the best departure time);
2. *H*=1 and *L*=1 (probability equal to 1/3): a player who chooses *H* will get 40 ECUs and a player who chooses *L* will get 35 ECUs. Given the state, the best choice is *H*;
3. *H*=2 and *L*=0: this implies that the player on *R* has chosen *H* and will get 40 ECUs.

Then, in the case where *nR*=2, the expected payoff is $(1/3 \times 35) + (1/3 \times 40) + (1/3 \times 40) = +38.3$. This expected payoff has to be multiplied by 0.1 to obtain the expected payoff for the state *R*=2 that is to say +3.83. This kind of calculation has to be performed for each possible state of *R* and at the end the expected payoff of $(R/I_R \text{ and } I_H)$ is the sum of $3.83 + \ldots = +34.1$ ECUs.

A rational player (an expected utility maximizing individual) should perform this process for each possible state in order to assess the expected payoff of the *R* choice with these two levels of information and to assess the *R* choice in a bayesian manner. Given all the possible messages (*i.e.* all the possible levels of traffic) and the payoffs attached to each state for each possible choice, the player has to compare the expected value of *R* without any kind of information (in the example +13.75) with the expected value of *R* in a "perfect information" state (in our example, the expected payoff of *R* in a "perfect information" state is +34.1).

Not surprisingly, the first thing we find is that the expected utility of choice *R* increases as additional information is provided to individuals, *i.e.* that IVs are strictly positive. Secondly, the IV of I_H is higher than the IV of I_R. We cannot say that this result is linked to the fact that the information I_H is "perfect" compared to I_R, which is imperfect. Although I_H amounts to perfect information when the player has chosen *H*, this is not true when the player has chosen *L*. So, I_H is obviously a refinement of I_R, but it is not equivalent to perfect information: both I_R and I_H are "imperfect" information. This explains the small difference between IVs which is confirmed by the large difference between the IV of (I_R *and* I_H) and IV(I_H), IV(I_R), because both messages are equivalent to a complete IP for any choice *R*.

It should also be noted that the IVs for any kind of information are greater when the capacities of roads *L* and *H* are high than when the capacities are low, which could seem paradoxical. However, what occurs is that the uncertainty about payments grows as the capacities of both roads increase (the relative capacities of *H* and *L* are constant in our experiment), as do the

IVs. The level of IV is mainly linked to the dispersion of the results in the different states. Another explanation relates to the characteristics of the payoff function, which favors an early departure time.

The data in Table 2 enable us to build the different scenarios for the experiment, *i.e.* the prices for information I_R and I_H for given infrastructure capacities, which give an information price that is over or under the IV. The aim is to observe different information purchase possibilities for any kind of information in the two differing capacity scenarios.

Table 2

Price levels (ECUs) for I_R and I_H and theoretical predictions

Capacities	Round	P_{I_R}	P_{I_H}	Information which should have been purchased
	1	14	4	I_H *or* (I_R and I_H)
$L = 2$	*2*	6	16	I_R
	5	14	10	I_H
$H = 4$	*8*	2	16	(I_R and I_H) *or* I_R
	9	15	15	none
	3	1	6	(I_R and I_H) *or* I_R
$L = 1$	*4*	1	3	(I_R and I_H) *or* I_R *or* I_H
	6	13	3	I_H
$H = 2$	*7*	1	15	I_R
	10	6	12	none

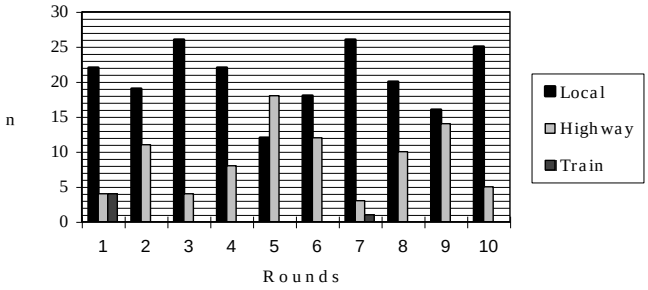
4. EXPERIMENTAL RESULTS

4.1. Descriptive results

Mode *R* was chosen 295 times and mode *T* only 5 times (see Fig. 1), which is explained by the low level of payment for choice *T*. Route *L* was chosen 206 times (69.8%) and route *H* 89

times (30.2%). Choice *L* was dominant within each of the 9 rounds, but the level of this domination varied from one round to another.

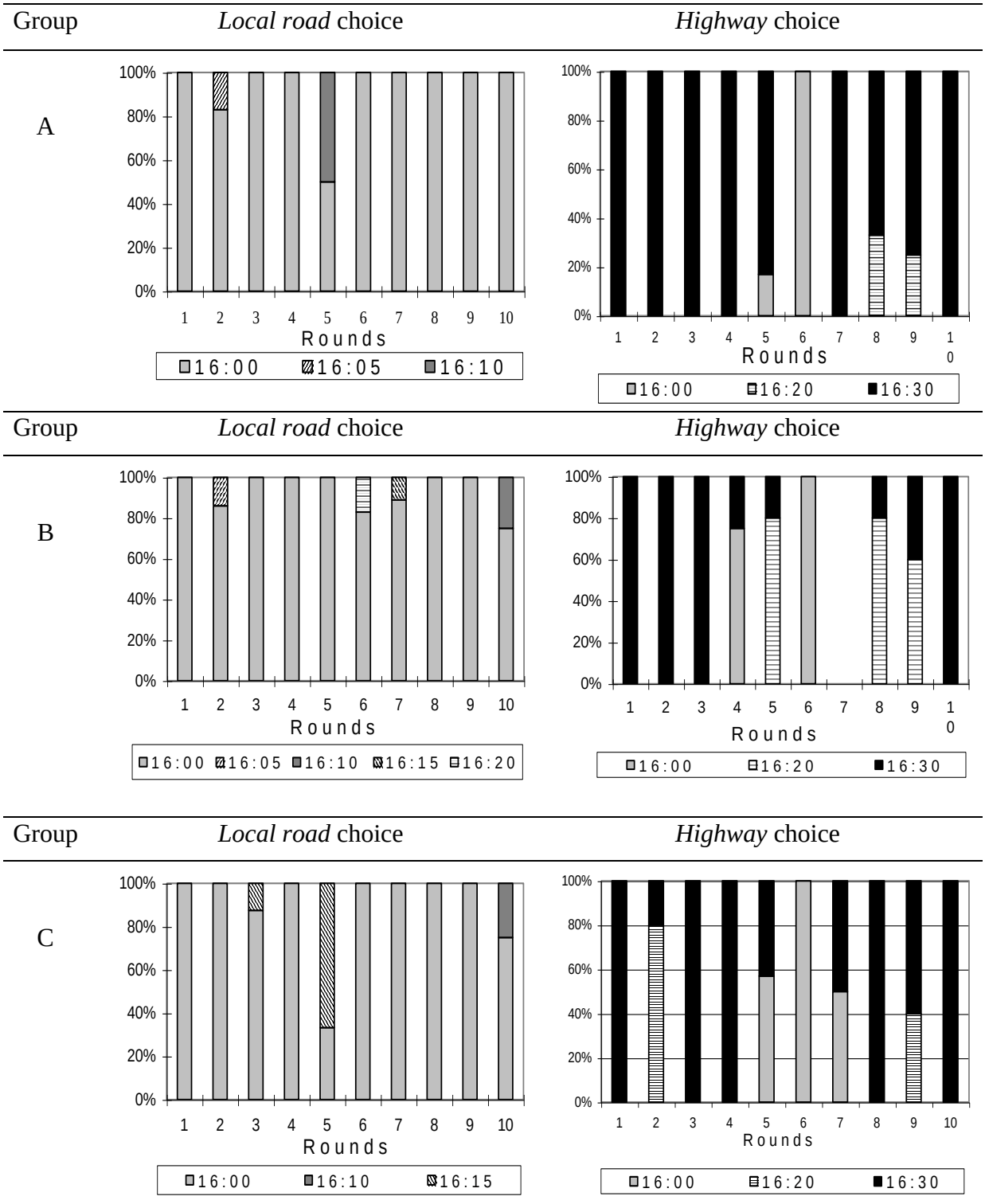
Fig. 1. Aggregated modal and route choices



The choice of departure time should depend on the possible travel time on each route, with reference to the traffic level and capacities. A departure time of before 16:20 for *L* or before 16:30 for *H* is considered to be an early departure. Experimental outcomes are given in Figure 2. It shows the share of the chosen departure times for *L* and *H* for each round. First, choice *L* requires an earlier departure time (16:00 for about 90% of the choices *L*) than choice *H* because the payoff function means that *H* is the riskier choice (the expected gain is lower while the variance is higher). The individuals choosing *H* therefore are adopting a risky strategy (more than 50% of the players choose 16:30 which maximizes the payment if there is no congestion). Some other players are risk averse and play *H* with an early departure time (16:00 or 16:20). In this case, the dispersion around the departure time is higher for the *H* choice. The second explanation is that the information about traffic on route *H* plays a greater part in the choice of *H* than it does in the choice of *L*: when the individual receives I_H, he or she chooses the best answer, which could be quite different from the choices made by individuals without I_H. The behavior of the groups is practically similar and explains 37.7%

of the variance for choice *L* and 23.1% of the variance for choice *H*. Therefore, a "group effect" is not sufficient to explain the variability of the choices between *L* and *H*.

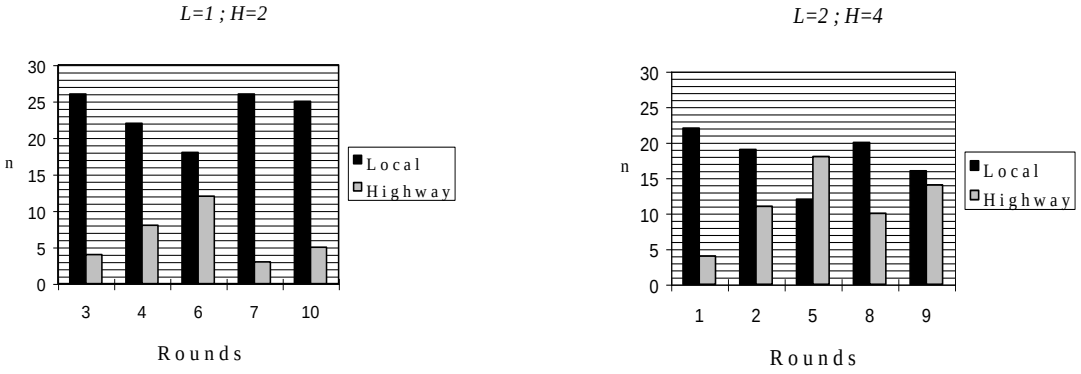
Fig. 2. Departure time frequencies for *L* and *H*



There is no bar chart for the choice *H* for the group B because no player have chosen the route *H*.

Is this variability explained by the difference in route capacities? The global preference for choice *L* is again observed in both capacity situations (see Fig. 3). It is obvious that choice *H* is more frequent when the capacity of the route *H* is the largest, but choice *L* seems to be preferred when all the rounds are considered.

Fig. 3. Aggregated Route choices and Route capacities

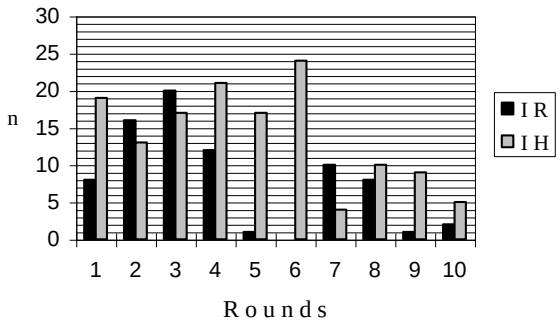


Perhaps the choices made by players can be explained by some of the characteristics of payments. The dispersion of payments as a result of choice *H* deters more players from choosing *H* than the dispersion of payments as a result of choice *L*. Let us assume that players first try the route which allows them to improve their initial monetary endowment. They are then in a position where they can take the risk of choosing route *H* (Rounds 5 and 6) as they have enough money to do so. Some of them lose money as a result of choosing route *H* and return to route *L* (Rounds 7, 8, 9, 10). Risk aversion analysis might shed some light on this situation, but we shall not attempt this here.

So, a certain "capacity effect" would seem necessary to explain some of the variability that affects route choices during the rounds. Nevertheless, this capacity effect seems to be closely linked to the payment structure for both routes. Clearly, choices should be explained from the point of view of information purchase.

The players more often purchased information about the traffic level on *H* than on *R*, 139 times versus 78 times respectively (see Fig. 4). Furthermore, information purchase behavior changed in different rounds. Most players purchased messages in the early rounds (I_R and/or I_H). Towards the end a small number of players bought message. Players who still purchased information preferred to by I_H .

Fig. 4. Aggregated information purchase per round

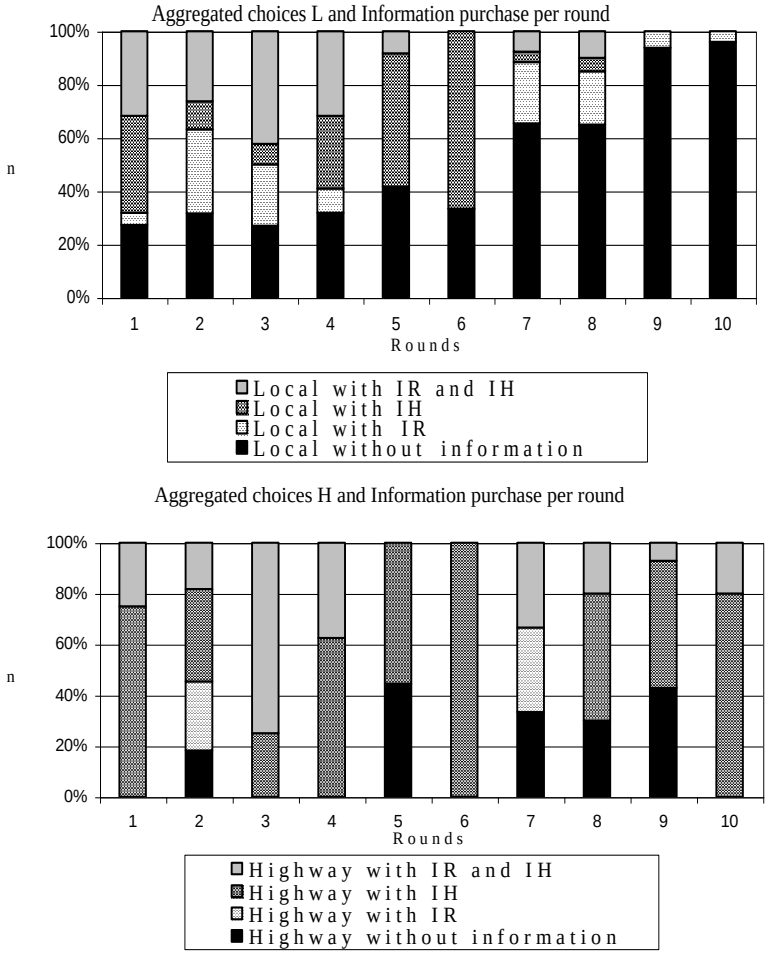


An initial hypothesis we can make is that the price of information influences the amount bought. However, there is no clear cut relationship between price and information demand. The elasticity of I_H purchase with respect to information price is -0.7 whereas the elasticity of I_R purchase is –0.26. If these results are not conclusive enough concerning the price impact on the information purchase, I_H purchase seems yet more sensitive than I_R purchase. The players appraisal leading to buy I_H with respect to its price seems more accurate than it is for I_R. Perhaps this is explained by the fact that I_R is offered at the beginning of the round, whereas I_H is sold at the end of the round and may thus be more beneficial to the subject. It seems possible that information purchase may depend on the chosen route.

Most of the players who choose *L* begin to purchase information in the 6 first rounds, but most of them do not purchase any information in the 2 last rounds (94% for the round 9 and

96% for the round 10). According to the I_R elasticity, the I_R purchase cannot be explained by the I_R price, but it seems clear that I_R becomes less and less interesting as rounds go along. On the contrary, most of those who choose *H* purchase I_H (more than 57% in the experiment) (see Fig. 5). Nevertheless, the variation in the purchasing behavior of those choosing *H* seems to be erratic. According to the I_H elasticity, it seems obvious that this purchasing behavior cannot be explained without exploring the IV; this is considered below.

Fig. 5. Aggregated route choices and Information purchase per round



4.2. A comparison between theoretical results and observations

(a) Information Value in comparison to its price

An individual's behavior can be predicted from route capacities. If the IV is higher than its price, the player should buy it. The aim of the experiment is to test whether individuals buy information when and only when its value exceeds its price. The statistical test has to show whether individual demand for information is greater in the rounds where the IV is higher than its price than in the rounds where the IV is lower than its price. We have thus carried out a "within subject" comparison test for non-independent data. We have chosen a nonparametric test (the Wilcoxon test) for which the null hypothesis is:

H0: the information demand in the set of rounds where the player should not have bought the information is not significantly different from the demand in the set of rounds where the player should have bought it, *versus* H1: the demand for information is higher in the set of rounds where the information should be bought than in the set of rounds where the information should not be bought.

Because of the respective levels of price and IV (see Tables 1 and 2), I_H should not have been bought in rounds 2, 3, 7, 8, 9 and 10, but should have been bought in rounds 1, 4, 5 and 6. The test was made for each group of 10 players (A, B and C).

Table 3

Actual information purchasing behaviors

Rounds	1	2	3	4	5	6	7	8	9	10
Actual number of buying I_R	8	16	20	12	1	0	10	8	1	2
Actual number of buying I_H	19	13	17	21	17	24	4	10	9	5
Actual number of buying I_R and I_H	6	7	14	10	1	0	3	4	1	1

In Table 4, the second column (positive ranks) shows the number of players who bought more information in the rounds where it was profitable to do so than in the rounds where it was not. The third column (negative ranks) shows the number of players who bought more information in the rounds where it was not worth buying than in the rounds where it was worthwhile. The fourth column shows the number of players who were not sensitive to information price and whose demand for information did not differ between the rounds where information purchase was worthwhile and the rounds where purchase it was not. The fifth column shows the level of statistical significance (the asterisk indicates that H0 should not be accepted for $\alpha = 5\%$). Except for the purchase of I_H by group A, it is difficult to accept H0, *i.e.* the individuals have bought more information when it was worth more than its price. The results favor H1 even more strongly.

Table 4

Wilcoxon Test

Test for I_H				
Group	(+) ranks	(-) ranks	number of discarded results	Critical
A	7	1	2	0.098
B	9	1	0	0.002*
C	9	1	0	0.003*
Test for I_R				
Group	(+) ranks	(-) ranks	number of discarded results	Critical
A	8	0	2	0.004*
B	10	0	0	0.001*
C	8	0	2	0.004*
Test for I_R and I_H				
Group	(+) ranks	(-) ranks	number of discarded results	Critical
A	5	1	4	0.031*
B	8	2	0	0.008*
C	6	1	3	0.019*

(b) Demand for I_H compared to Demand for I_R

Another idea is to test the hierarchy between I_R and I_H, because information about *nH* would seem, judging from its IV, to be the most interesting. We have therefore performed a "within subject" Wilcoxon test where the nul hypothesis is:

H0: the individual demand for I_R is not significantly higher than for I_H,

H1: the individual demand for I_H is significantly higher than for I_R

The results show that it is difficult to accept H0: the individuals considered that I_H was more useful that I_R and bought it significantly more frequently.

Table 5

Wilcoxon Test about individual demand on I_R compared to I_H

Group	(+) ranks	(-) ranks	number of discarded results	Critical
A	6	2	3	0.039*
B	8	1	1	0.008*
C	8	1	1	0.006*

5. CONCLUDING REMARKS

Our most important findings are as follows:

(a) In a context of increasing information where information is not free of charge, players compare the utility of information to its cost and this calculation is an important part of the comparison between risk with regard to travel time and monetary travel cost,

(b) The dynamic choice model seems to provide a reasonable approximation of individual valuation. In particular, the willingness to pay (WTP) for more detailed information is higher than for less detailed information. This still applies even when the less detailed information is available before the more detailed information.

(c) Players choose to buy information when the variance in payoffs for the route choice is sufficiently high. This confirms the theoretical result obtained by Emmerink *et al.* (1998).

(d) The types of choices individuals make change over time. At the beginning of the experiment many players explore the environment by making risky choices and by buying information. Gradually, their strategy changes and most individuals choose a less risky mode without information purchase. This illustrates the way in which individual learning substitutes for exogenous information provided by the experimenter.

Our findings show that, in a transport context, players presented with real-time information tend to be rational in their modal and route choice behavior. Moreover, information matters for players, in the sense that behavioral responses could be significant in an evolving environment. Finally, the experiment also shows that it is important to recognize the diversity of users when faced with information provision, and to discriminate between experienced and inexperienced users. It confirms the findings of Dudek and Huchingson (1982) that inexperienced drivers are more likely to change their route in response to a message than experienced drivers. It should therefore be possible to avoid the decrease in the effectiveness of information that may occur when too many users are informed about traffic levels.

One of the first questions we can ask about this kind of transport-related experimental game is whether the results can be transferred to real-life departure time tradeoffs. The problem is that we are dealing with players and not real users; real life can never be exactly produced in the laboratory and subjects are always liable to behave differently. In real world, we are aware that users do not behave rationally as we assume here. Therefore, further developments should consider bounded rationality theory. This applies yet to any work in the field of experimental economics, because the primary aim of a researcher is to perform a normative study by designing an experiment to investigate a single effect. However, our exploratory experiment

can be considered to be quite adequate in order to explain the potential impact of traffic information for driving with a limited number of modes and a limited number of routes.

Finally, we consider that this paper makes a contribution to the application of experimental economics as a rigorous data production method to test theoretical models in the field of transport behavior analysis.

References

Anderhub, V., Güth, W., Härdle, W., Müller, W. and Strobel, M. (1996) *On saving, updating and dynamic programming - An experimental analysis*. Humboldt-University, Faculty of Economics, Berlin.

Arnott, R., de Palma, A. and Lindsey, R. (1990) Departure time and route choice for the morning commute. *Transportation Research* **24B**, **3**, 209-228.

Arnott, R., de Palma, A. and Lindsey, R. (1991) Does providing information to drivers reduce traffic congestion? *Transportation Research* **25A**, **5**, 309-318.

Arnott, R., de Palma, A. and Lindsey, R. (1996) Information and usage of free-access congestible facilites with stochastic capacity and demand. *International Economic Review* **37**, **1**, 181-203.

Arnott, R., de Palma, A. and Lindsey, R. (1999) Information and time-of-usage decisions in the bottleneck model with stochastic capacity and demand. *European Economic Review* **43**, **3**, 525-548.

Ben-Akiva, M. and Lerman, S. (1985) *Discrete Choice Analysis: Theory and Application to Predict Travel Demand*. MIT Press, Cambridge (Mass.)

Ben-Akiva, M., de Palma, A and Kaysi, I. (1991) Dynamic network models and driver information systems. *Transportation Research* **25A**, **5**, 251-266.

Brewer, P.J. and Plott, C.R. (1994) A Binary Conflict Ascending Price (BICAP) Mechanism for the Decentralized Allocation of the Right to Use Railroad Tracks. Caltech Social Science Working Paper: 887.

Broome, J. (1990) Bolker-Jeffrey Expected Utility Theory and Axiomatic Utilitarianism. *Review of Economic Studies* **57**, 477-502.

Davis, D. and Holt, C. (1993). *Experimental Economics*. Princeton University Press.

Delvert, K. and Petiot, R. (1999) Behavioural response to traffic variability: an experimental outlook on road pricing as willingness to pay for certainty. *World Transport Research, Selected Proceedings from the 8th WCTR, Vol. 3: Transport Modelling/Assessment*. eds H. Meersman, W. Van de Voorde, and W. Winkelmans, pp. 232-336. Pergamon, Elsevier.

Delvert, K., Denant-Boèmont, L. and Petiot, R. (2000) Is flexibility in choice option valuable? *9th International Association for Travel Behaviour Research Conference*. Sheraton Mirage Gold Coast, Queensland, Australia.

Denant-Boèmont, L., Delvert, K. and Petiot, R. (1999) Eléments d'évaluation des politiques de transport : une approche par l'économie expérimentale. *Rapport PREDIT 1996-2000 n° N°98 MT92*. LET, Lyon.

Dudek, C., and Huchingson, R. (1982) *Human factors design of dynamic displays*, vol 1. Summary Report for FHWA US DOT. Washington, DC.

Emmerink, R.H.M. (1998). *Information and Pricing in Road Transportation*. Springer

Emmerink, R.H.M., Axhausen, K.W., Nijkamp, P. and Rietveld, P. (1995) Effects of information in road transport networks with recurrent congestion. *Transportation* **22**, 21-53.

Emmerink, R.H.M, Verhoef, E.T., Nijkamp, P. and Rietveld, P. (1998) Information policy in road transport with elastic demand: Some welfare economic considerations. *European Economic Review* **42**, 71-95.

Fischer, A.J., Burns, J.P.A., Meyler, M.J., Tiernan, P. and Hatch, J.H. (1992) The market for taxi-cab licences: An experimental analysis. *International Journal of Transport Economics*, **XIX**, **3**, 329-353.

Friedman, D. and Sunder, S. (1994) *Experimental Methods: A Primer for Economists*. Cambridge University Press, Cambridge.

Grether, D.M., Isaac, R.M. and Plott, C.R. (1989) The allocation of scarce resources: Experimental economics and the problem of allocating airport slots. *Underground Classics in Economics series*. Westview Press, Boulder, Colo. and London

Jones, R. A. and Ostroy J. M. (1984) Flexibility and Uncertainty. *Review of Economic Studies* **LI**, 13-32.

Laffont, J.-J. (1991) *Fondements de l'économie publique. Tome 2. Economie de l'incertain et de l'information*. Economica, Paris.

Mahmassani, H.S. and Chang, G.-L. (1985) Dynamic aspects of departure-time choice in a commuting system: Theoretical framework and experimental analysis. *Transportation Research Record* **1037**, 89-99.

Mahmassani, H.S. and Jayakrishnan, R. (1991) System performance and user response under real-time information in a congested traffic corridor. *Transportation Research* **25A**, **5**, 293-308.

Mahmassani, H.S. and Tong, C.-C. (1986) Availability of information and dynamics of departure time choice: Experimental investigation. *Transportation Research Record* **1085**, 33-49.

Marschak, J. and Radner, R. (1972) *Economic Theory of teams*. Yeale university press, New Haven.

Nilsson, J.-E. (1997) Allocation of track capacity. Experimental Evidence on the Use of Priority Auctioning in the Railway Industry. Center for Research in Transportation and Society, Dalarna University College, working paper n°1997-01-13. 1997, Borlänge.

Rasmusen, E. (1989) *Games and information: An Introduction to Game Theory* Blackwell, Scd Edition, Cambridge.

Rauchs, A. and Willinger, M. (1996) Experimental Evidence on the Irreversibility Effect, *Theory and Decision* **40**, 1, 51-78.

Schneider, K. and Weimann, J. (1997) Against all odds: Nash Equilibria in a Road Pricing Experiment. Preprint n°30. Fakultät für Wirtschaftswissenschaft, Universität Magdeburg.

Strotz, R. (1955-1996) Myopia and inconsistency in dynamic utility maximisation. Review of Economic Studies, **23**, 165-180.

Vickrey, W. (1969) Congestion Theory and Transport Investment. *American Economic Review*, **59**, 251-260.

Willinger, M. (1989) Flexibilité et valeur de l'information. *Flexibilité, Information et Décision* eds. P. Cohendet and P. Llerena, pp. 103-120. Economica, Paris.

Appendix A

Tables of payoffs

Table 6

Tables of payoffs L=1

L=1		Payoffs according to time departure (ECUs)				
Traffic (actual number of persons who have chosen L)	**Travel time (minutes)**	**16:00**	**16:05**	**16:10**	**16:15**	**16:20**
1	40	-5	0	5	10	35
2	45	-2,5	2,5	7,5	32,5	5
3	50	0	5	30	2,5	-5
4	60	25	-2,5	-10	-17,5	-25
5	60	25	-2,5	-10	-17,5	-25
6	60	25	-2,5	-10	-17,5	-25
7	60	25	-2,5	-10	-17,5	-25
8	60	25	-2,5	-10	-17,5	-25
9	60	25	-2,5	-10	-17,5	-25
10	60	25	-2,5	-10	-17,5	-25

Table 7

Tables of payoffs L=2

L=2		Payoffs according to time departure (ECUs)				
Traffic (actual number of persons who have chosen L)	**Travel time (minutes)**	**16:00**	**16:05**	**16:10**	**16:15**	**16:20**
1	40	-5	0	5	10	35
2	40	-5	0	5	10	35
3	45	-2,5	2,5	7,5	32,5	5
4	50	0	5	30	2,5	-5
5	60	25	-2,5	-10	-17,5	-25
6	60	25	-2,5	-10	-17,5	-25
7	60	25	-2,5	-10	-17,5	-25
8	60	25	-2,5	-10	-17,5	-25
9	60	25	-2,5	-10	-17,5	-25
10	60	25	-2,5	-10	-17,5	-25

Table 8

Tables of payoffs H=2

H=2		**Payoffs according to time departure (ECUs)**								
Traffic (actual number of persons who have chosen H)	**Travel time (minutes)**	**15:50**	**15:55**	**16:00**	**16:05**	**16:10**	**16:15**	**16:20**	**16:25**	**16:30**
1	30	-60	-55	-10	-5	0	5	10	15	40
2	30	-60	-55	-10	-5	0	5	10	15	40
3	40	-55	-50	-5	0	5	10	35	7,5	0
4	60	-45	-40	25	-2,5	-10	-17,5	-25	-32,5	-40
5	65	-42,5	-17,5	-5	-12,5	-20	-27,5	-35	-42,5	-50
6	70	-20	-47,5	-15	-22,5	-30	-37,5	-45	-52,5	-60
7	70	-20	-47,5	-15	-22,5	-30	-37,5	-45	-52,5	-60
8	70	-20	-47,5	-15	-22,5	-30	-37,5	-45	-52,5	-60
9	70	-20	-47,5	-15	-22,5	-30	-37,5	-45	-52,5	-60
10	70	-20	-47,5	-15	-22,5	-30	-37,5	-45	-52,5	-60

Table 9

Tables of payoffs H=4

H=4		**Payoffs according to time departure (ECUs)**								
Traffic (actual number of persons who have chosen H)	**Travel time (minutes)**	**15:50**	**15:55**	**16:00**	**16:05**	**16:10**	**16:15**	**16:20**	**16:25**	**16:30**
1	30	-60	-55	-10	-5	0	5	10	15	40
2	30	-60	-55	-10	-5	0	5	10	15	40
3	30	-60	-55	-10	-5	0	5	10	15	40
4	30	-60	-55	-10	-5	0	5	10	15	40
5	40	-55	-50	-5	0	5	10	35	7,5	0
6	60	-45	-40	25	-2,5	10	-17,5	-25	-32,5	-40
7	65	-42,5	-17,5	-5	-12,5	-17,5	-27,5	-35	-42,5	-50
8	70	-20	-47,5	-15	-22,5	-27,5	-37,5	-45	-52,5	-60
9	70	-20	-47,5	-15	-22,5	-27,5	-37,5	-45	-52,5	-60
10	70	-20	-47,5	-15	-22,5	-27,5	-37,5	-45	-52,5	-60