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BEHAVIOURAL RESPONSE TO TRAFFIC VARIABILITY: AN EXPERIMENTAL OUTLOOK ON ROAD PRICING AS WILLINGNESS TO PAY FOR CERTAINTY

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Abstract

This paper explores a methodology widely used in economics but rather seldom used in the field of transport economics: Experimental economics. The impact of traffic stochasticity on commuters' behaviour is investigated using standard decision theory under uncertainty. A simple model of route and departure time choices within a stochastic traffic environment is designed. This model provides a basis for a computer-led experiment that was conducted in a preliminary phase of this work. Though at this stage the model seems too straight forward to fit the data, this methodology seems promising to investigate the behavioural impact of various information and pricing environments.

INTRODUCTION

Travel time being seldom constant and stable users' reaction to some variability in traffic level is a component worth being examined. As decision theory (Laffont, 1991) and experimental economics enabled fruitful insights into agents' behaviour under uncertainty, it is attempted to apply this methodology to travel behaviour within an uncertain travel environment.

Uncertainty is here considered as variability in trip time due to traffic stochasticity. We assume that what accounts for traffic variability is mainly recurrent excess demand compared with capacity or unexpected reduction in road capacity. The number of users is assumed as stable from day-to-day. However, the pattern of departure rates varies according to a temporal probability distribution known to all users (heavy congestion is indeed more likely at given time slots). In the route choice model we propose, traffic is assumed variable on the first (free) route while the second (tolled) route secures certainty in travel time. This modelling context is designed in order to investigate agents willingness to pay for a certain prospect as well as sensitivity to traffic variability - causing late / early arrival and possible queuing under given circumstances. Road pricing is not so much addressed as it is typically in the literature. Our focus is to highlight a given component of the toll, namely willingness to pay to avoid uncertainty in arrival time - and not solely delays.

Beyond its focus on road pricing, the paper stresses the part experimental economics could play as a travel behaviour data collection method. Collecting field travel behaviour data within uncertain environments being costly when possible, it is attempted to design a lab experiment to collect data on decision making under traffic stochasticity. Experimental economics may be especially suited to examine such matters. Indeed, it places individuals within the specific framework of an experimental design set up to collect data about effective decision making under uncertainty and to test a normative model. Respondents are asked to make decisions for which they are rewarded depending on the accuracy of their choice. Their observed choices are then compared to theoretically predicted choices.

Experimental economics as a relevant data collection method in transport is first discussed. Then, the relevant transport literature is briefly reviewed to set up the background of the experimental design and of the route choice model presented subsequently. Finally, some experimental results are examined.

EXPERIMENTAL ECONOMICS AS A TRAVEL BEHAVIOUR DATA COLLECTION METHOD

Compared to other data collection methods such as Stated Preference (SP), Revealed Preference (RP) and simulation, experimental economics (EE) could provide interesting methodological opportunities.

Toward a definition of experimental economics

Any comprehensive overview of the achievements of EE is very much beyond the scope of this paper (see Roth, 1995). However, we will attempt to highlight the specificities and the validity of EE as a behavioural data collection method.

What is experimental economics aimed at?

EE was first used as a method to investigate individual preferences over bundles of goods. Then, it developed as a method aimed at empirically refuting models - especially in decision and game theory. The principle of EE is to collect direct data in an environment designed and controlled by the experimentalist. Unlike other experimental sciences gaming prevails in EE: Players have to conform to instructions referred to as « rules of the game ». Players are paid according to the relevance of their choices that differs significantly from the experiments conducted in psychology. Utility-maximising agents are assumed to be rational and to behave according to a theoretical model, underlying a given choice process. For instance, with respect to risk taking behaviours, various theoretical models are competing to approximate as closely as possible individuals' actual behaviour. The relevance of the equilibrium concept used is directly tested by means of the data collected. Thus, alternative models or theoretical approaches are statistically tested so as to determine which one is the most relevant to the situation at hand.

Validity of experimental economics

Bradley (1988) examines the validity of SP as a data collection method through two dimensions: Internal and external validity. We draw on his work to assess the validity of EE.

First, internal validity refers to the design and its conforming to the issue at hand and to the model to be tested. The choice alternatives are to be carefully identified. Such a choice set is typically represented by a decision tree so as to make sure every possible choice is taken into account. Second, the experiment has to provide an adequate scale of rewards (payoffs) with respect to every possible answer so as to measure the accuracy of players' answers. Third, the instructions handed out to players obviously matter. Realism is not systematically sought so as to avoid perception biases. Players are to conform as much as possible to instructions which are closer to the instructions of a game than to any real-world situation or to a situation they have encountered already. The latest point raises the issue of external validity. Is EE good enough at predicting actual behaviours? Does it assess preferences and their strength? These questions exceed the bounds of the paper. We solely highlight that EE can usefully help test behavioural hypotheses when agents are confronted with strategic interactions - for instance, congestion - with uncertainty.

Traditional travel behaviour data collection methods

In order to assess the external validity of EE, it is to be compared with competing methodologies belonging to the same experimental paradigm.

The experimental paradigm

Polak and Jones (1997) identify an experimental paradigm which developed significantly in transport under theoretical, statistical and financial pressures. The testing of alternative theories, the need to eliminate statistical and observational biases and the need for data - when field data can not be collected - are the incentives that explain its development. It derives either from the need to confront data or from the need to cope with unsatisfactory or non-existent observations. Though it belongs to this experimental paradigm, EE has some specificities. It differs from RP methods in the way data are collected as well as in the use made of data. EE does neither collect observations derived from trips actually made nor from the simulation of an hypothetical though more realistic trip choices. Actually, realism does not necessarily mean deeper involvement of the respondent: Gaming situations may well guarantee the respondent's involvement equally. The behavioural involvement in the game and the accuracy of the responses obtained may well not mean higher realism. EE is based on purely hypothetical scenarios, placing individuals in unexperienced contexts. However, it is not aimed at determining a willingness to accept or new behavioural determinants. It is suited to the empirical validation of existing models. It may also help point out unexplained phenomena. Individuals are not asked directly about their preferences as in SP surveys which may however be suited to reveal values of time and willingness to pay.

Relevance and specificities of experimental economics as a transport data collection method

Obviously, EE provides no direct observation of what people would do in real life. It provides a means of assessing significant variations in individuals' behaviour. What they do in a lab context is not directly transposable to the real world, since much of the complexity of the real world is ruled out - that is precisely what the design is aimed at. It enables to focus on the variables of interest in an attempt at reducing statistical as well as variables correlation. It explains much of the advantages of experimentation but also some of its drawbacks. The well known difficulty encountered by SP data is not met in EE: Whether people would do what they say they will do due to the fact that players are paid. No attempt is made at measuring *all* the variables which are to explain the behaviour and choice of respondents.

Several attempts have been made to design experiments in transport. Denant-Boèmont and Petiot (1998) investigate bayesian behaviour to collect data on willingness to pay to obtain en-route traffic information. Schneider and Weimann (1997) test the relevance of Nash equilibrium as an equilibrium concept to model the bottleneck situation.

ROAD PRICING IN A STOCHASTIC CONGESTION CONTEXT

We examine the part played by congestion day-to-day variability as a relevant variable that may explain behaviours. The more significant this variation, the more sensitive agents may be - due to the psychological cost associated with uncertainty - and then the more willing they may be to pay for certainty in their arrival time and in the level of queuing they will encounter. This outlook on road pricing implicitly reveals the cost associated with traffic uncertainty.

Congestion stochasticity

Congestion recurrence *vs.* congestion variability are two components worth being studied *per se.* Emmerink *et al.* (1996) assume that a major part of urban congestion is due to more or less unpredictable events - such as unexpected *ceteris paribus* reduction in road capacity due to accidents. A more in-depth study of travel behaviour in an uncertain context may be politically as well as theoretically relevant. Indeed, congestion stochasticity may impact transport policies significantly. Moreover, incident induced congestion may result in deviation from standard theoretical equilibrium due to perfect unpredictability (such as User Equilibrium). Their psychological costs are typically not included in such a distinction while they obviously take part into this cost variability. We attempt at assessing the cost of congestion variability *per se.*

Factors accounting for day-to-day variability of traffic congestion

Congestion is typically broken down into a variable or non-recurrent and a recurrent component. The variations in traffic levels can be explained by variations in demand and by perfectly unpredictable events - such as - accidents affecting road capacity. This distinction may though be specified since some incidents may be predictable (planned roadworks) as well as others may be unexpected (accidents). However, it is here assumed that the non recurrent component is occurring with a given probability (denoted by p in the discrete outlook which is ours but could also be a random variable). Congestion severity depends on a recurrent component that may be worsened by a stochastic component. Among the factors accounting for day-to-day variability in congestion, two main factors are stressed. First variability may be caused by some variations in road capacity. It may also be explained by behavioural factors such as switching attitudes - i.e. day-to-day differences in any choice made at the same decision point (Lotan, 1996). This behavioural component of variability may be explained by personal experience.

Day-to-day dynamics can be broken down into several components depending on whether it is derived from behavioural adaptations or to external behavioural components (activity patterns). Factors accounting for day-to-day variability in traffic conditions sorted out in ascending degree of simplicity:

- *Endogenous factors*: Drivers may be more or less familiar with the network due to learning - they may stick to their previous choices or not.
- *Exogenous factors*: These factors are not behavioural since they are basically external and non dynamic constraints (i.e. involving no feed back). Two sub-types of factors can be isolated: Those external to drivers - such as incidents - or those - depending on activity patterns and work schedules. Though, learning may occur at this stage also, it is not considered here.

Methodological consequences

The very brief overview presented above highlights uncertainty and attitude towards risky prospect - i.e. an accident that may occur - as a significant choice variable. So as to take this distinction into account, we have designed a traffic environment. Three traffic levels are discriminated following recent attempts at measuring traffic regimes (Leurent, 1996). Easy traffic - free flow - is a level of service where cars drive 80km/h speed. Difficult traffic is a level of service where cars move about 50km/h. Very difficult traffic exhibits a bottleneck situation with queuing time - it refers to a risky prospect due to unexpected reduction in road capacity. The regime of a traffic distribution is indeed not easily identifiable (Couton *et al.* 1996). However, some traffic levels are more likely to occur at given times and places. This likelihood is identified in the design so as to simulate a strongly peaked congestion situation.

Our choice is not to endogenise congestion (having players play together and generate congestion due to convergence in their choices). Here we first consider congestion as being exogenous to players: We think that this suites our aim which is to test the impact of congestion variability in itself - more considered as it is imposed on individuals than modelled as it is collectively generated. Congestion could be endogenised by computing a congestion equilibrium using game theory.

A road pricing experiment

This sub-section elaborates on the perspective in which road pricing is considered in the model put forward in the next section. It highlights what follows from this with respect to the experimental design.

Issues considered with respect to road pricing

Road pricing is typically addressed in the literature in three main perspectives. First, by considering the optimal level to which the toll is to be levied - for instance, the relevance of marginal cost pricing in a welfare perspective. The second most raised issue is that of the way road pricing shall be put into practice. Is road pricing to serve demand-regulation purposes or is to help finance the construction of infrastructures? Finally, when/if applied, will people agree to it?

Our focus is more on the behavioural impact of pricing: Will people shift (and agree to pay while shifting) to avoid uncertainty on their arrival time. Certainty is here regarded as a component of the toll paid by users who choose this tolled route against its free alternative. We assume that individuals are willing to pay for some level of certainty in arrival time. Thus, the fact that they decide to pay the toll somehow reveals the implicit price associated with certainty.

The difficulty in assessing the cost of uncertainty and traffic variability to the individual lies on its correlation with the value of time. For this reason, we think that EE is a method especially fitted. Indeed, all players are assumed to behave according to the same value of time - though their own true values of time may differ significantly. The value of time is taken into account in the individual cost function known to each player, in the payment player will receive. Since player maximises its payoff given the costs its choice may incur. Therefore, the effect of the value of time is experimentally controlled in order to emphasise individual behaviour in an uncertain context.

On what theoretical grounds will then the toll be designed?

We consider mainly dynamic pricing - although the toll does not vary according to *real time* traffic conditions but according to expected traffic conditions on the free route only calculated for each time slot. Obviously, this toll level is correlated with the traffic level but does not preclude the actual traffic level that will prevail. Though some additional level of information is included in the toll.

The model

Let us consider the basic choice: Either take the free route (i=2) where traffic is highly uncertain or choose to commute on a tolled route (i=1) where agents will arrive at a certain time slot since this route will for sure be uncongested.
Commuters choose departure time t_d which minimises their travel costs depending on congestion level or/and toll. They have to join the arrival place B at a fixed time slot t^* from departure point A.

The following notations are set down:
A: Departure point
B: Arrival point
t^*: Fixed arrival time at B
t_d : Departure time from A
$t_{ai}(t_d)_{(i=1,2)}$: Effective arrival time at B
$CT(t_d)$: Total travel cost
$q(t_d)$: Time spent queuing
$\psi\left(t_d,\phi_j\right)_{j=1,2,3}$: Toll level
α: Monetary penalty per minute of travel time excluding queuing time
β: Monetary penalty per minute of advance
γ: Monetary penalty per minute of delay
δ: Monetary penalty per minute of queuing time

The commuter's problem can be expressed as follows further to Vickrey (1969) and Arnott, (1990), choose $t_d\left(t_d\in\left[t_1,\ldots,t_{10}\right]\right)$ and route $i_{(i=1,2)}$ so as to minimise:

$$CT(t_d)=\alpha\left[t_{ai}(t_d)-t_d-q(t_d)\right]+\beta\left\{Max\left[0;t^*-t_{ai}(t_d)\right]\right\}+\gamma\left\{Max\left[0;t_{ai}(t_d)-t^*\right]\right\} \\ +\delta\, q(t_d)+\psi(t_d,\phi_j) \tag{1}$$

where the first term is the cost of travel time without taking account of any waiting time. The second term is the cost for early arrival at point *B*. The third term is the cost for arriving behind schedule. The fourth term refers to the cost for waiting in the queue. The last term is the toll which is obviously equal to zero on the free route.

Agents are said to undergo no queuing if they choose the tolled road. If they decide to take the risky route, then they are to face any of the $\phi_{j(j=1,2,3)}$ randomly assigned traffic levels. They may be severely delayed in case ϕ_3 occurs. Then, they suffer for each time slot t_d a waiting time $q(t_d)$ between point *A* and point *B*. We assume that commuters spend two time slots queuing. If commuters decide to take the tolled road, they have to pay a toll $\psi\left(t_d,\phi_j\right)_{j=1,2,3}$ which depends on the excess travel cost due to congestion on the free route in case of ϕ_2 and ϕ_3. So, commuters may encounter for each departure slot a random congestion level on the free route. The travel time and the travel cost on the free route depend on this uncertain level. On the contrary, the tolled route is characterised by a given travel time. So, for each departure time, the toll level amounts to the difference between the expected travel cost on the free route and the expected travel cost on the tolled road, namely the excess travel cost on the free route. An expected toll level is computed which corresponds to the expected excess cost on the free route given congestion states ϕ_1, ϕ_2 and ϕ_3.

So, there is for each $t_{d\left(t_d\in[t_1,\ldots,t_{10}]\right)}$ a distribution of probabilities of congestion where $\sum_{j=1}^{j}\Phi_j=1$:

$$\psi(t_d,\Phi_j)=\begin{cases}\sum_{j=1}^{3}\Phi_j\left[\alpha\left(t_{a2}(t_d)-t_{a1}(t_d)\right)+\beta\left(t_{a1}(t_d)-t_{a2}(t_d)\right)+\delta q(t_d)\right], & t_{a1}\le t_{a2}\le t^* \quad (2)\\ \sum_{j=1}^{3}\Phi_j\left[\alpha\left(t_{a2}(t_d)-t_{a1}(t_d)\right)-\beta\left(t^*-t_{a2}(t_d)\right)+\gamma\left(t_{a1}(t_d)-t^*\right)+\delta q(t_d)\right], & t_{a1}\le t^*\le t_{a2} \quad (2')\\ \sum_{j=1}^{3}\Phi_j\left[\alpha\left(t_{a2}(t_d)-t_{a1}(t_d)\right)+\gamma\left(t_{a2}(t_d)-t_{a1}(t_d)\right)+\delta q(t_d)\right], & t^*\le t_{a1}\le t_{a2} \quad (2'')\end{cases}$$

eqn. (2) represents the case where commuters arrive earlier via the tolled route than they would have arrived via the free route for the same departure time. The toll amounts to the travel cost saved due to shorter travel time on the free route, plus the excess cost of arriving early due to their choice of the tolled route, plus the cost of waiting time saved on the tolled route;

eqn. (2') represents the case where commuters arrive earlier via the tolled route while they would have arrived behind schedule via the free route for the same departure time. The toll amounts to the travel cost saved due to shorter travel time on the free route, minus the excess cost of early arrival time *via* the tolled route, plus the excess cost saved from the time behind schedule due to the free route, plus the cost of waiting time saved on the tolled route;

eqn. (2'') represents the case where commuters arrive behind schedule whatever route they choose. However, they arrive less behind schedule via the tolled route than they would have arrived via the free route for the same departure time. Thus, the toll amounts to the travel cost saved due to shorter travel time on the free route, minus the excess cost of the later arrival time due to the tolled route, plus the cost of waiting time saved on the tolled route;

Depending on the accuracy of their choice in terms of departure time t_d and route i, individuals receive the following payoff, a function of their schedule delay. Their payoff is the difference between their gains and their costs. $D(t_a - t^*)$ is the monetary gain a function of the schedule delay - i.e. the difference between the actual and fixed arrival time. The payoff writes as follows where $CT(t_d)$ refers to eqn. (1):

$$\pi(t_d) = D(t_{ai}(t_d) - t^*) - CT(t_d) \tag{3}$$

According to the Von Neumann-Morgenstern expected utility assumption, risk neutral agents choose departure time and route by maximising their expected payoffs. The commuters' choice writes as the choice of the maximum expected payoff (the utility function is thus assumed linear):

$$\text{Max } E(\pi(t_d, i)) \text{ for } t_d \in [t_1, \ldots, t_{10}],\ i=1,2 \tag{4}$$

THE EXPERIMENT

The setting of the instructions is as much as possible "decontextualized" so as to involve people in a gaming situation. Though the context is implicitly that of daily commute, it is not to be mentioned in the instructions handed out to players. To avoid biases, they are not to be told they take their car to travel to their working place on a daily basis.

11 players (students) played this computer-led game. First step, the instructions were read outloud to the players. Step 2, the players could test their understanding of the instructions by playing a trial-game. Step 3, the game could start. Five series of games were played.

Each player is asked to make a departure time and a route choice. Each round corresponds to a daily trip. Free-flow prevails on the tolled route. As specified in the model, on the free route, players are likely to encounter traffic congestion, which basically depends on their departure time choice. Players know the probability distribution of traffic. However, they ignore what traffic level will in the end prevail. The actual traffic level is determined randomly. This assumption typifies the following idea: "real life" commuters capitalise on their daily experience. They repeatedly make judgements comparing day-to-day observed variability when they make their route choice using en-route experience. By providing players with a probability distribution over traffic levels, it is attempted to simulate such an experience and expectations formation in a laboratory context.

Subjects are given the cost function based on commuters' values of time (Papon, 1991) namely α=1.2, β=1.8, γ=2, δ=2.4. Before making their decision, they know the toll level, the congestion random distribution on the free route and the monetary gain for each departure time slot. At the end of each series, subjects are advised on their payoff by the experimentalist. Players capitalise their payoffs from session to session.

We have built up three scenarios based on contrasted traffic environments (figures 1, 2, 3):

Scenario 1

In this scenario congestion is not severely peaked: it rises steadily. The peak appears at slot 5 and 6. The first scenario is made up of 2 series. In the first series the toll is calculated as mentioned in eqns. (2), (2') and (2"). In the second series the toll is flat so as to compare the impact of toll variability on users' behaviour.

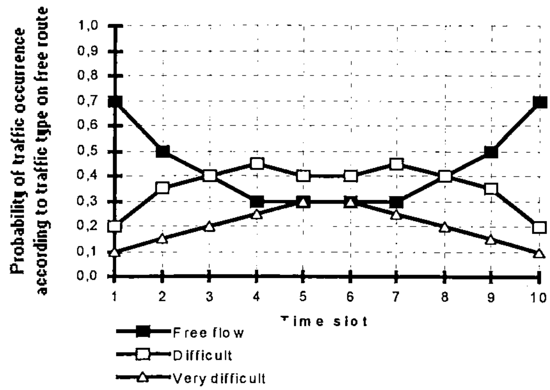

Figure 1 - Traffic probabilities on free route (scenario 1)

Scenario 2

Congestion is more severely peaked at slot 6 where traffic is more likely to be difficult and even heavy.

The second scenario is also made up of 2 series, which follow the same toll varying and then flat toll patterns.

Congestion is here more severe than in the previous scenario especially at time slots 4, 5, 6 and 7.

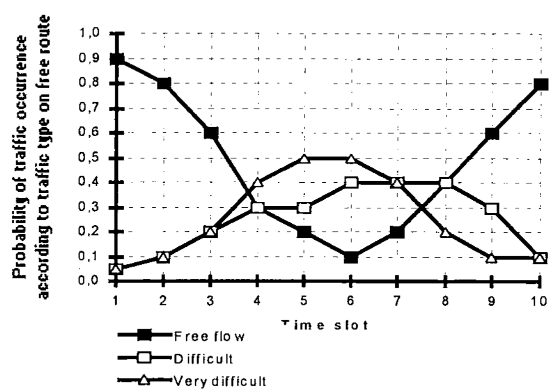

Figure 2 - Traffic probabilities on free route (scenario 2)

Scenario 3

This scenario differs significantly from the previous ones. The earlier you leave *A*, the more likely you are to face difficult traffic conditions.

The latest scenario is constituted of a unique series of games.

Congestion is here even more severe than in the previous scenarios.

This congestion pattern -and its time distribution-is meant to be disruptive since it occurs at unexpected slots. Congestion is indeed the most severe at slots 1, 2, 3, 4, 5.

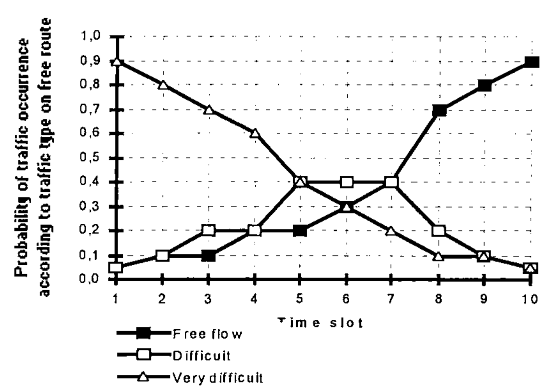

Figure 3 - Traffic probabilities on free route (scenario 3)

FIRST RESULTS

Scenario 1

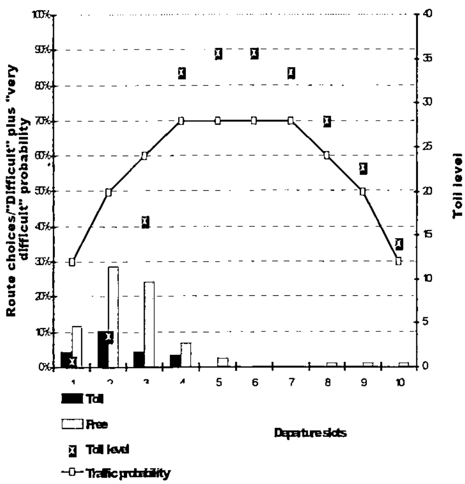

Figure 4 - Observed choices, toll level and traffic probability (scenario 1 - series 1)

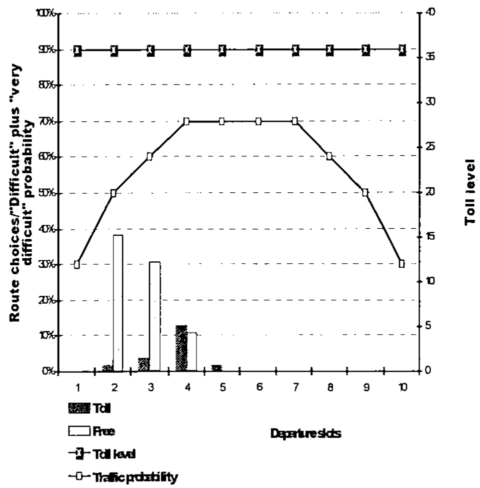

Figure 5 - Observed choices, toll level and traffic probability (scenario 1 - series 2)

Series 1 compared to series 2 exhibits a larger variety of choices. It may be due to the high toll level chosen. It widely favors the free route and higher time security margins. The hypothesis according to which individuals conform to the theoretical choice has to be rejected (Khi-square test / 5% c. p.).

Scenario 2

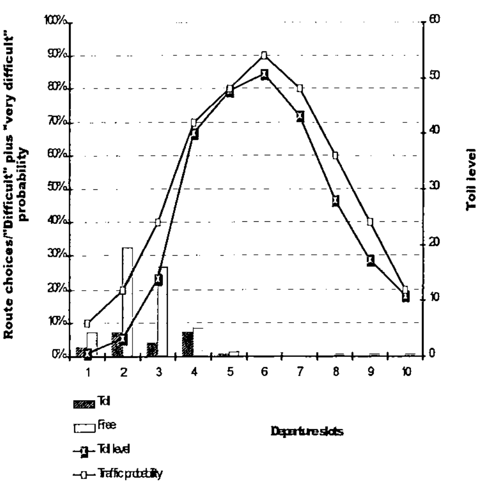

Figure 6 - Observed choices, toll level and traffic probability (scenario 2 - series 3)

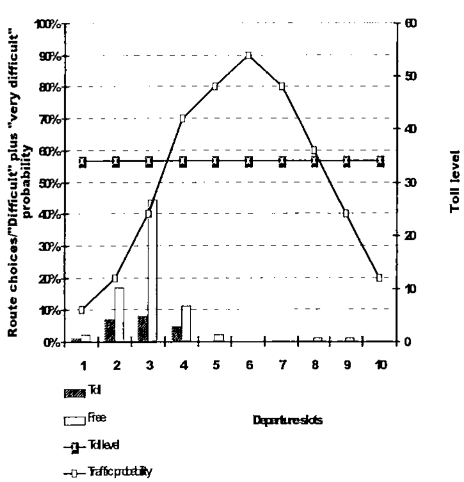

Figure 7 - Observed choices, toll level and traffic probability (scenario 2 - series 4)

The first three slots are characterized by a relatively little likelihood of severe congestion, which favors the choice of the free route. It is significant when compared with the previous scenario. In case of flat tolling, choices are more accurate (slot 3 is chosen more frequently). The free route is more frequently chosen due probably to the high toll level. The hypothesis according to which individuals conform to the theoretical solution has to be rejected (Khi-square test / 5% c. p.).

Scenario 3

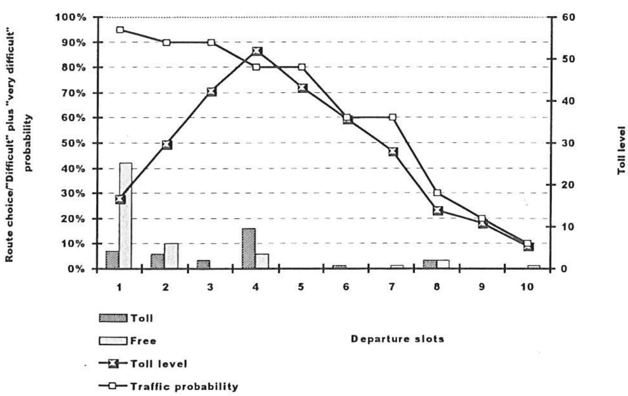

Figure 8 - Observed choices, toll level and traffic probability (scenario 3 - series 5)

The last scenario supports the idea that players' first strategy is to choose the free route and then choose the departure slot so as to maximize time security margins and thus minimize risks to arrive on late: It seems obvious for slot 1 on the free route. The hypothesis according to which individuals conform to the theoretical solution has to be rejected (Khi-square test / 5% c. p.).

In general, the statistical results show that it is not possible to conclude that subjects chose their route and departure time in conformity with the maximization of expected payoff criteria. Other criteria have to be tested to fit observed data.

We notice that players are on the whole more inclined to choose slots at which the environment is more likely to be uncongested. 38% of subjects chose the tolled route when the cumulated probability of difficult and very difficult was over 70%. 15% did the same choice when the probability of free-flow was over 30% (see Figure 9 for disaggregated results).

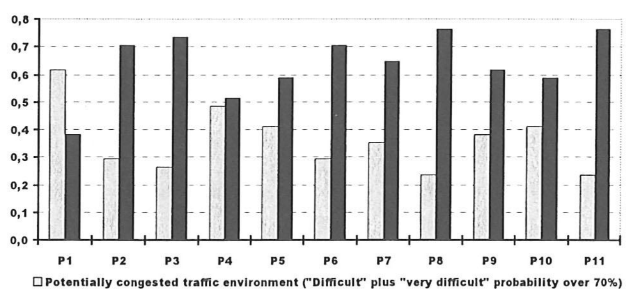

Figure 9 - Players'preference for traffic environments

However, when they select potentially congested environments they are more likely to use the tolled route as opposed to the free one (Figure 10).

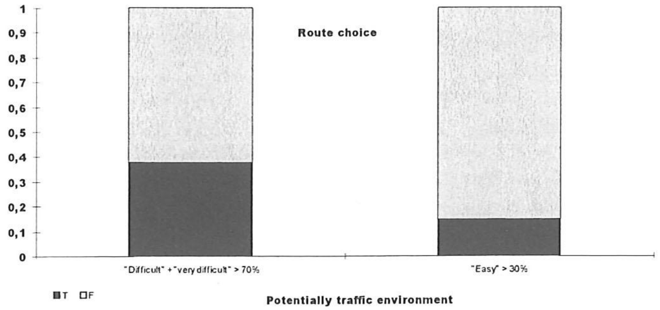

Figure 10 - Route choice frequency given prevailing traffic conditions for each player

6 CONCLUDING REMARKS

Within the framework of the design, players do not seem to be willing to pay for a certain prospect. It seems that they are more inclined to use time security margins than to pay so as to avoid congestion. Some willingness to pay to avoid uncertainty seems only exhibited in situations where the congestion structure forced players onto the tolled route. Otherwise, when players have effective free alternatives, they are more likely to adjust their travel times than their route choices.

With respect to the validity of the experimental method, we would like to stress the fact that these results are not robust due to the size of the sample of subjects. Moreover, it seems that the model we put forward provides a poor description of players' choices. This conclusion holds when route and time departure choices are made simultaneously. However, this model may be more relevant when these two choices are considered separately as sequential choices.

However, experimental economics seems a promising method in order to observe and account for learning and behavioural adjustments (be it in terms of time security margins or in terms of route choice). The paper provides an example of what experimental economics could achieve. It seems possible to analyse a transport decision by means of a experiment designed for experimental purposes. Quite a number of tolling and information environments could thus be investigated in the future.

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APPENDIX

Instructions

You are taking part into an experiment in which you can earn money. What you earn depends on your own decision as well as on hazard.

You are to join point B departing from point A. Joining B from A requires a certain number of time slots. A slot is a given and fix time interval. At point A, for each game, you have to choose:

A departure time slot among 10 possible time slots (numbered from 1 to 10), and *a route* among two possible routes : A tolled route and a free route.

Your arrival time slot at B depends on your departure time slot from A and on the route you choose. Your aim for each game is to arrive at point B *at time slot Nb.10, which is your target time slot.*

Table 1 : Scale of departure slots and arrival slots

At A: departure slots	1	2	3	4	5	6	7	8	9	10										
At B: arrival slots							7	8	9	10	11	12	13	14	15	16	17	18	19	20

On the tolled route, it takes 6 slots to join B from A, *whatever the departure time slot chosen.* The toll you will have to pay in order to use this route varies as a function of the time departure slot chosen. (...) (see table 4). *On the free route,* it randomly takes 6, 8 or 10 slots to join B from A. When it takes 10 slots to join B, it means that you necessarily undergo a waiting time equal to 2 time slots (included in the 10 time slots you need to join B) before arriving at B. The probability to take 6, 8 or 10 slots to join B (...) (see table 4). The number of slots you need to join B from A on the free route is determined randomly for each game.

How will you be paid ?

You are playing with Experimental Currency Units; the exchange rate is: 1 ECU = 0,15 FF.
Your payment for each game is ***the difference between your gains and your costs:***

Your gains for each possible arrival time slot:

Table 2 : Gains for each possible arrival time slot

Possible arrival time slots	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Gains	85	90	95	100	95	90	85	80	75	70	65	60	55	50

When you arrive at B on arrival time slot 10, you earn 100 ECU (the maximum possible gain).

Your costs:

Table 3 : Table of costs

If you arrive...	on the tolled route	on the free route: 6 or 8 time slots	on the free route: 10 time slots
Before the target time slot	6 ECU × 6 slots to join B + 9 ECU × nb. of slots btw. arrival and target time + toll	6 ECU × (6 or 8) slots to join B + 9 ECU × nb. of slots btw. Arrival and target time	6 ECU × 8 slots to join B + 9 ECU × nb of slots btw. arrival and target time + 12 ECU × 2 waiting time slots
At the target time slot	6 ECU × 6 slots to join B + toll	6 ECU × (6 or 8) slots to join B	6 ECU × 8 slots to join B + 12 ECU × 2 waiting time slots
After the target time slot	6 ECU × 6 slots to join B + 10 ECU × nb of slots btw. arrival and target time + toll	6 ECU × (6 or 8) slots to join B + 10 ECU × nb of slots btw. Arrival and target time	6 ECU × 8 slots to join B + 10 ECU × nb of slots btw. arrival and target time + 12 ECU × 2 waiting time slots

Your payment at the end of each game is the difference between your gains and your costs. At the end of each game, the result of your choice is forwarded to you ; then you can play again. The experiment is made up of 5 series of games. What you earn at the end of the game is the sum of your payoffs over the series.

Table 4 : A synthesis of the additional information provided to players in game series 1

Departure time slots	Probability 6 slots	Free route Probability 8 slots (%)	Probability 10 slots	Money paid on tolled route
Slot 1	70 %	20 %	10 %	1
Slot 2	50 %	35 %	15 %	4
Slot 3	40 %	40 %	20 %	17
Slot 4	30 %	45 %	25 %	33
Slot 5	30 %	40 %	30 %	36
Slot 6	30 %	40 %	30 %	36
Slot 7	30 %	45 %	25 %	33
Slot 8	40 %	40 %	20 %	28
Slot 9	50 %	35 %	15 %	23
Slot 10	70 %	20 %	10 %	14