Pre-trip Information and Route-Choice Decisions with Stochastic Travel Conditions: Experiment

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Abstract

This paper studies the effects of pre-trip information on route-choice decisions when travel conditions on two alternative congestible routes vary unpredictably. It presents and discusses an experiment designed to test a model recently proposed in a companion paper by Lindsey et al. (2013). That model predicts that if free-flow costs on the two routes are unequal, travel cost functions are convex, and capacities are positively and perfectly correlated, then in equilibrium, paradoxically, total expected travel costs increase with the provision of pre-trip information about travel conditions on each route. By contrast, when capacities vary independently, total expected travel costs are predicted to decrease with pre-trip information. We re-formulate the model for finite populations, and then test and find support for its predictions in an experiment where under different capacity scenarios, and with and without pre-trip information, subjects are asked to choose routes with payoff contingent on their performance.
1. Introduction

Travel information has traditionally been provided by newspapers, radio, television, and variable message signs. More recently, these sources have been supplemented, or at times replaced, by Advanced Traveler Information Systems (ATIS) that compile information from various sources and convey it via traffic websites (e.g., waze.com), GPS devices, e-mail, mobile phones, and Personal Intelligent Travel Assistants. Armed with pre-trip travel information, drivers can now adjust their trip destinations and choose departure times, routes, and parking locations to minimize their cost of travel. But is this information always collectively beneficial? To answer this question, the effects of information on traffic congestion have been examined in many analytical and simulation studies; see Chorus et al. (2006) and de Palma et al. (2012) for reviews. Most of these papers conclude that information is likely to increase welfare as measured by expected social surplus, although some identify conditions under which adverse responses may occur. Our contribution is to identify some of these conditions, test them in the controlled environment of the laboratory, and discuss their implications.

The effects of pre-trip travel information on individuals’ trip-making, departure time, route, and other decisions have been extensively studied. As discussed in our companion paper (Lindsey et al., 2013), several papers have identified the possibility that information can have adverse welfare effects. These studies employ analytical or simulation methods, but do not establish that information can actually be counterproductive in practice. In lieu of actual field studies, controlled laboratory experiments provide the best opportunity to obtain evidence of adverse information effects with human decision-makers. A number of experiments on the impact of traffic congestion have been undertaken. Mahmassani and Chang (1986), Iida, Akiyama, and Uchida (1992), Mahmassani and Liu (1999), Helbing et al. (2005), Selten et al. (2004, 2007), Anderson et al. (2008), and Gisches and Rapoport (2012) investigate route-choice problems, whereas Ramadurai and Ukkusuri (2007), Ziegelmeyer et al. (2008), and Rapoport et al. (2010) examine various queueing scenarios in which agents choose when to depart on a trip. Most of these papers examine the effects of providing subjects with information about decisions and outcomes on previous rounds, but none considers the effects of providing information about travel conditions before subjects make their decisions.
Important exceptions are recent experimental studies by Ben-Elia and Shiftan (2010), de Moraes et al. (2011), and Ben-Elia et al. (2013) that do consider the effects of ex-ante information on route-choice decisions. However, the networks they consider are not congestible and subjects' payoffs are assumed to be independent. Lu, Gao, and Ben-Elia (2011) shares some features with our study, namely, route choice in a congestible network with stochastic capacity and under different information regimes. However, their experimental methods and models differ from ours: they use a small set of subjects, rewards are not contingent on performance and, most significantly, only one route in their network has stochastic travel conditions. As Lindsey et al. (2013) show, this latter difference is a key determinant of the value of ex-ante information in a network.

Still other laboratory experiments have focused on the emergence of paradoxical behavior on congested road networks. These include studies of the Braess paradox (e.g., Rapoport et al., 2009), the Pigou-Knight-Downs paradox (e.g., Dechenaux et al., 2013; Morgan et al., 2009), and queueing paradoxes in networks with bottlenecks (e.g. Daniel et al., 2009). However, none of these studies considers ex-ante information about travel conditions that vary across rounds of play. Our paper presents experimental evidence for yet another paradox, termed the information paradox, about the circumstances under which pre-trip information has adverse effect on route choice.

The companion paper by Lindsey et al. (2013) drives the present study. Their paper builds on the classical "two-route network" whose origins trace back to Pigou (1920) and Knight (1924). Similarly to previous studies on route choice (e.g., Selten et al., 2007), Lindsey et al. also assume a fixed set of drivers who independently choose each day which of two routes to travel. The major and critical difference from most previous studies is that the conditions of the two routes vary randomly from day to day rather than being fixed over time and commonly known. This change introduces environmental uncertainty, which is determined exogenously, rather than only strategic uncertainty that characterizes previous studies. Lindsey et al. (2013) study two information regimes. In the zero-information regime, drivers only know the unconditional probability distribution of states on the two routes, while in the full-information regime they are fully and accurately informed about the two states before choosing a route. Under certain conditions, information is welfare-reducing in the sense of decreasing expected travel costs so that the information paradox occurs.
These conditions generalize those identified by de Palma and Lindsey (1994) and Emmerink et al. (1998). Roughly speaking, a paradox is most likely to occur when free-flow costs of the two routes differ, travel cost functions are convex, and road capacities are positively and perfectly correlated. These conditions are explained as follows. First, unequal free-flow costs are conducive to a paradox because the wedge between the private and marginal social cost of a trip increases with traffic volume. When free-flow costs differ, too many drivers use the shorter (or quicker) route in equilibrium, and this provides an opportunity for information to be welfare-reducing. Second, the social cost of deviations from the optimal division of traffic is larger the steeper the travel cost functions are, and steepness tends to be accentuated by convexity. To see why correlation between road capacities also matters, note that if conditions are independent they can be good on one route and bad on the other. Bad conditions increase both the private and the marginal social cost of usage so that the equilibrium response of drivers to shift from the bad route to the good route tends to be socially desirable. By contrast, when road conditions are always similar on the two routes there is less to gain from reallocating traffic between them, and equilibrium responses are more likely to be counterproductive. Moreover, the responses can be particularly harmful when conditions on both routes are good because large shifts can occur when route capacities are high.

Lindsey et al. (2013) propose a model in which players are treated as a continuum. Section 2 below reformulates their model for the case of discrete players (an "atomic game"). It describes the model's properties, and presents a numerical example in which the information paradox occurs. Section 3 describes the experimental setup. Section 4 presents the results, and Section 5 proposes a simple adaptive learning model to account for the observed patterns of aggregate behavior. Section 6 concludes with a summary and suggestions for future research.

2. Theory

2.1 Model specification

A fixed number $N > 0$ of individuals travel each day from a common origin to a common destination. Each person drives her own vehicle and contributes an "atomic" (non-negligible) unit measure to traffic volume. By contrast, fluid models of traffic flow treat vehicles as a continuum so that each vehicle has a zero measure and is "non-atomic". Two routes connect the
origin and destination. Travel conditions on each route vary from day to day because of bad weather, accidents, roadwork, or other shocks. The set of possible states, $S$, can be discrete or continuous. The number of users who choose route $i$ in state $s \in S$ is denoted by $N_{is}$. Since each user must choose one of the two routes,

$$N_{1s} + N_{2s} = N, \; \forall s \in S.$$  (1)

The individual private cost of taking route $i$ in state $s$ is a non-decreasing function $C_{is}(N_{is})$ which satisfies the following assumption:

**Assumption 1**: *Monotonic travel cost functions*

For every state $s \in S$, $C_{is}(N_{is})$ is an increasing function, $i=1,2$, and it is strictly increasing on at least one route.

All users are assumed to be risk-neutral with respect to travel costs (see on-line Appendix A for discussion of non-linear utilities).

### 2.2 Existence and uniqueness of user equilibrium

User equilibrium is a profile of strategies such that drivers independently minimize their private travel cost and do not regret their decisions. It entails a division of traffic between the two routes, $(N_{1s}, N_{2s})$, that can be solved using equation (1) and equilibrium conditions that depend on whether drivers adopt pure or mixed strategies for choosing a route as well as on the information regime.\(^1\) Two information regimes are considered: *full information* ($F$) and *zero information* ($Z$). In the full-information regime drivers learn the state $s$ before choosing a route. If they employ pure strategies, then the division of traffic $(N_{1s}^{F}, N_{2s}^{F})$ is deterministic. An interior equilibrium exists if the following pair of inequality conditions holds:

$$C_{1s}(N_{1s}^{F}) \leq C_{2s}(N - N_{1s}^{F} + 1), \quad (2a)$$

$$C_{1s}(N_{1s}^{F} + 1) \geq C_{2s}(N - N_{1s}^{F}). \quad (2b)$$

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\(^1\) A driver who uses a pure strategy chooses a route deterministically on a given day whether or not she knows the state. A mixed strategy entails choosing route 1 with some probability $p \in (0,1)$, and choosing route 2 with the complementary probability $1 - p$. 

4
Condition (2a) stipulates that a driver cannot reduce cost by switching from route 1 to route 2. Condition (2b) is the analogous condition for switching from route 2 to route 1. In general, \( C_{1r}(N_{1s}^F) \neq C_{2s}(N_{2s}^F) \) because the travel cost on each route changes by a discrete amount if a user shifts from one route to the other.

If drivers employ mixed strategies, then the division of traffic varies randomly from day to day. The equilibrium conditions analogous to (2a) and (2b) are:

\[
E \left[ C_{1s} \left( N_{1s}^F \right) \right] \leq E \left[ C_{2s} \left( N - N_{1s}^F + 1 \right) \right],
\]
\[
E \left[ C_{1s} \left( N_{1s}^F + 1 \right) \right] \geq E \left[ C_{2s} \left( N - N_{1s}^F \right) \right],
\]

where \( E [ \ ] \) is the expectations operator, and expectations are taken over the mixed strategies.

In the zero-information regime drivers only know the unconditional probability distribution of states on the two routes. If drivers employ pure strategies, then the division of traffic \( (N_1^Z, N_2^Z) \) is deterministic. An interior equilibrium exists if

\[
E \left[ C_{1s} \left( N_1^Z \right) \right] \leq E \left[ C_{2s} \left( N - N_1^Z + 1 \right) \right],
\]
\[
E \left[ C_{1s} \left( N_1^Z + 1 \right) \right] \geq E \left[ C_{2s} \left( N - N_1^Z \right) \right],
\]

where expectations are now taken over states. If drivers employ mixed strategies, then the division of traffic \( (N_1^Z, N_2^Z) \) varies randomly from day to day. An interior equilibrium in mixed strategies exists if conditions (4a) and (4b) hold when expectations are taken over both states and mixed strategies.

Existence and uniqueness of equilibrium in the two information regimes are described in the following four propositions (see on-line Appendix B for proofs). Propositions 1 and 2 concern pure-strategy equilibria.

**Proposition 1.** (Existence of pure-strategy equilibrium):

*Given Assumption 1, there exists at least one pure-strategy equilibrium in each information regime.*

**Proposition 2.** (Number of pure-strategy equilibria):

*Given Assumption 1, there exist at most two pure-strategy equilibria in each information regime. If there are two equilibria, then both of them are weak.*
Propositions 3 and 4 concern mixed-strategy equilibria.

**Proposition 3.** *(Uniqueness of symmetric mixed-strategy equilibrium)*: Given Assumption 1, there exists a unique symmetric mixed-strategy equilibrium in each information regime in which all drivers randomize between routes with the same probability.

In addition to the symmetric mixed-strategy equilibrium, there also may exist asymmetric equilibria in which some drivers use pure strategies and others use mixed strategies. In any such equilibrium, all mixed strategies are identical.

**Proposition 4.** *(Equilibria with pure and mixed strategies)*: Given Assumption 1, in any equilibrium for either information regime all drivers who adopt mixed strategies adopt the same mixed strategy.

### 2.3 Welfare effects of information

Social welfare in any equilibrium is given by expected users' surplus; given fixed $N$, it can be measured by the negative of expected total costs. Let $E[TC_s^r]$ denote expected total costs in information regime $r$, $r = Z, F$, where $E[TC_s^F] = E[C_{1s} (N_{1s}^F)N_{1s}^F + C_{2s} (N_{2s}^F)N_{2s}^F]$ and $E[TC_s^Z] = E[C_{1s} (N_{1s}^Z)N_{1s}^Z + C_{2s} (N_{2s}^Z)N_{2s}^Z]$. The welfare gain in shifting from the zero-information regime to the full-information regime, $G^{ZF}$, is then $G^{ZF} = E[TC_s^Z] - E[TC_s^F]$.

In general, neither the zero-information nor the full-information equilibrium is socially optimal because the marginal social cost of a trip on either route exceeds the private cost when there is congestion. The optimal division of traffic between routes with full information in state $s$ is a pair $(N_{1s}^*, N_{2s}^*)$ that minimizes total costs $TC_s^F$. The social optimum with full information serves as a benchmark for measuring the efficiency of the user equilibrium outcomes.

Using a non-atomic version of the model, Lindsey et al. (2013) investigate the welfare effects of full information when the travel cost function has the form:

$$C_{is} (N_i) = a_i + b_i N_i^d, \quad d \geq 0, \; i = 1, 2, \; \forall s.$$  \hspace{1cm} (5)
The parameter $a_{is}$ measures the free-flow travel cost on route $i$ in state $s$, and the parameter $b_{is}$ is a congestion coefficient that varies with road capacity. Lindsey et al. (2013) show that the welfare ranking of the zero-information and full-information regimes depends on several factors including the value of parameter $d$, and whether the parameters $a_{is}$ and $b_{is}$ are correlated between routes.

### 2.4 Experimental setup

The main goal of the current paper is to test whether the paradoxical predictions of the theory are borne out in the laboratory. To strengthen the test, it is desirable to examine conditions in which full information is predicted to be welfare-reducing (relative to zero information) as well as conditions in which full information is predicted to be welfare-improving. We have chosen a setting that satisfies the following conditions:

- Travel conditions on each route are either good ($s=G$) or bad ($s=B$). Bad conditions correspond to lower road capacity so that $b_{1B} > b_{1G}$, $i=1,2$.
- Free-flow travel costs are deterministic, and higher on route 2 than route 1 so that $a_2 > a_1$.
- The probability of bad conditions, $\pi$, is the same for the two routes.

After considerable experimentation with alternative parameter sets (see the sensitivity analysis in the companion paper by Lindsey et al. 2013), we have chosen the following parameter values: $N=20$, $d=2$, $a_1=0$, $a_2=3$, $b_{1G}=0.01$, $b_{1B}=0.09$, $b_{2G}=0$, $b_{2B}=0.1225$, and $\pi = 0.25$. The resulting travel cost functions are therefore:

$$
C_{1G} = 0.01N_{1G}^2 \quad \quad C_{1B} = 0.09N_{1B}^2 \\
C_{2G} = 3 \quad \quad C_{2B} = 3 + 0.1225N_{2B}^2.
$$

Costs vary quadratically with usage except for Route 2 on good days when travel is congestion-free. The number of drivers ($N=20$) matches the number of subjects who participated in each round of our experiments. Since the absolute magnitude of the welfare effects of information with fixed demand depend only on the relative costs of travel on the two routes, the normalization $a_1 = 0$ is without loss of generality. Route 1 is mildly congested on good days.
\((b_{1G} = 0.01)\) and considerably more heavily congested on bad days \((b_{1B} = 0.09)\). Route 2 is free of congestion on good days \((b_{2G} = 0)\) and congestion-prone on bad days \((b_{2B} = 0.1225)\). The specification \(b_{2G} = 0\) effectively means that route 2 has an infinite capacity on good days. The relevant assumption, however, is that route 2 is uncongested on good days. On expressways, speeds typically remain nearly constant until flows approach capacity (see Small and Verhoef, 2007, Section 3.3.2, and Transportation Research Board, 2010). Therefore, travel will be relatively uncongested on good days as long as flows are not too high.

Travel conditions on the two routes are assumed to be either uncorrelated or perfectly and positively correlated. Uncorrelated conditions are plausible in the case of shocks due to accidents, whereas perfect and positive correlation is plausible in the case of bad weather or special events that affect the two routes in the same way.\(^2\)

Given the abstract nature of the example, it should not be considered descriptive of any particular real setting. Nevertheless, an interpretation may help to fix ideas. Route 1 may be thought of as a high-speed freeway that becomes congested at high traffic volumes — perhaps because ramp metering is not used. Route 2 comprises a set of parallel surface streets that are congestion-free on good days, but slow because of low speed limits and stop signs or signalized intersections.

### 2.5 Numerical results

Propositions 1-4 establish that at least one pure-strategy equilibrium and at least one mixed-strategy equilibrium exist in the zero-information regime as well as for each state in the full-information regime. For the specific parameter values given in (6), all the equilibria are unique. The equilibria with zero information are presented in Table 1 along with the socially-optimal distribution of traffic, given zero information. The equilibria are the same for correlated and uncorrelated route conditions because the probabilities of the states are the same. The first and second rows of Table 1 show the expected number of users choosing each route, and the bottom

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\(^2\) Since free-flow speeds are sometimes reduced in bad weather one might assume that parameters \(a_1\) and \(a_2\) are stochastic and higher in bad conditions than good conditions. However, this specification would be inappropriate for the scenario in which route conditions are uncorrelated. To enhance the power of the experiments to test for the information paradox, it is desirable to use the same specifications of the travel cost functions for the two treatments except for the correlation between routes.
row shows the probability of choosing each route in the mixed-strategy equilibrium. The expected travel cost for each route is indicated in brackets. For the social optimum and pure-strategy equilibria the cost of using route 2 is higher than route 1, whereas in the mixed-strategy equilibrium the costs are equal because the probability of choosing each route is a continuous variable and drivers are indifferent between routes only when their expected costs are equal.

--Insert Table 1 about here--

Table 2 presents the optima and equilibria for each of the four states in the full-information case. Similar to the zero-information case, for the social optimum and pure-strategy equilibria travel costs are higher on route 2 than route 1, whereas in the mixed-strategy equilibrium the costs are equal. All the symmetric mixed-strategy equilibria feature higher expected costs than the corresponding pure-strategy equilibria. This is because players randomize independently, and a disproportionately large fraction of them can end up on one route. By contrast, the pure-strategy equilibria entail perfect coordination.

Except for the case of full information, pure-strategy equilibrium, and bad conditions on both routes (italicized), none of the equilibria are socially optimal. Moreover, while any deviations from equilibrium (e.g., due to out-of-equilibrium play in an experiment) toward the social optimum decrease total costs, any deviations away from the social optimum increase costs. Because total costs are a convex function of the division of traffic between routes, balanced deviations away from equilibrium increase costs.

--Insert Table 2 about here--

Table 3 lists the welfare gain or loss in shifting from zero information to full information in each of the four states when drivers use pure strategies. When conditions on both routes are good, full information reduces welfare by 0.84 because five drivers shift from route 2, which is uncongested, to route 1, which is congested and has a higher marginal social cost. This shift is individually rational as it reduces the shifters' individual costs. However, it imposes on the 12 original users of route 1 additional costs that outweigh the benefits gained by the shifters. By contrast, in the other three states information results in a welfare gain because the full-information equilibrium route split is closer to the social optimum (in the case of bad conditions on both routes the split coincides with the optimum). The welfare gain is particularly large in the [Bad, Good] state because zero information results in grossly excessive use of route 1.
Information induces a majority of drivers (7 of 12) to shift away from route 1, and the resulting route split of (5, 15) is close to the optimal split of (3, 17).

When route conditions are uncorrelated, the four states in Table 3 occur with probabilities of [Good, Good]: 0.5625, [Good, Bad] and [Bad, Good]: 0.1875 each, and [Bad, Bad]: 0.0625. The expected welfare gain from full information is $0.5625 \times (-0.84) + 0.1875 \times (1.93) + 0.1875 \times (6.16) + 0.0625 \times (0.31) = 1.06$. Expected costs are displayed in Table 4 (experimental payoffs are discussed later). Expected costs fall from 4.58 to 3.51, and the welfare gain of 1.06 amounts to 23.36% of expected travel costs in the zero-information equilibrium. By contrast, if route conditions are correlated, only the [Good, Good] and [Bad, Bad] panels of Table 3 are applicable, and their probabilities are 0.75 and 0.25, respectively. The expected welfare gain from full information is now $0.75 \times (-0.84) + 0.25 \times (0.31) = -0.55$. Expected costs rise by 12.13% from 4.58 to 5.13 (Table 4) and the information paradox occurs. The large gain in state [Bad, Good] is absent because this state no longer occurs.

--Insert Tables 3 and 4 about here--

Numerical results for the mixed-strategy equilibria are presented in Tables 5 and 6. The results are very similar to those in Tables 3 and 4. Full information yields slightly higher benefits with uncorrelated conditions (compare -26.67% to -23.36%) and results in slightly smaller losses with correlated conditions (compare 9.16% to 12.13%), but the information paradox is still clearly evident (compare Tables 4 and 6).

--Insert Tables 5 and 6 about here--

The numerical example provides a lesson that generalizes to more complicated probability distributions and route-choice settings (see Propositions 5 and 6 in Lindsey et al., 2013). When travel conditions vary independently across routes, conditions can be bad on some routes and good on others. Bad conditions increase both the private cost and the marginal social cost of trips so that it is both an equilibrium response and socially efficient for traffic to shift from bad routes to good routes. Consequently, it is generally beneficial in this case to inform users about travel conditions. By contrast, when route conditions are always similar there is less to gain from reallocating traffic between them, and any equilibrium shifts that do occur are less likely to improve system performance.
3. Experimental Setup

3.1 Payoffs and equilibria

The experiment was designed to test the equilibrium solutions described in Section 2 with groups of 20 players who independently choose one of the two routes on each round (or "day") of play. The route-choice predictions of the atomic game serve as a benchmark for evaluating the players’ performance. Although there is a unique aggregate pure-strategy equilibrium with either zero information or full information (i.e., a unique distribution of players over the two routes), there are multiple individual pure-strategy equilibria. For example, if both routes have good conditions, 17 players choose route 1 and 3 players choose route 2. There are C(20,3) = 1140 ways in which 20 players can achieve such a split on the two routes. Because these equilibria cannot be Pareto ranked, this presents the players with a difficult coordination problem. (Selten et al., 2007 and Rapoport et al., 2009 study coordination games with considerably more pure-strategy equilibria that are also Pareto unrankable.) To reach the pure-strategy equilibria, they need to coordinate on a single equilibrium allocation with no communication and only the history of aggregate route choices on previous rounds as a guide.

In the model description, the equilibrium predictions are expressed in terms of travel costs. To convert the game into one in which players are likely to earn positive payoffs, on each round they were awarded 8 payoff units for reaching their destination (one may think of this as the ‘value’ of the trip). Travel cost was then subtracted from this reward. Table 4 presents in brackets the (atomic) pure-strategy equilibrium payoffs associated with this payoff scheme. An important effect of this cost-to-profit transformation is that it enhances the proportional effects of information. In the treatment with correlated conditions the loss increases from 12.13% to 16.08%, and in the treatment with uncorrelated conditions the gain increases from 23.36% to 31.29%. Table 6 presents similar information in brackets for the mixed-strategy equilibrium.
3.2 Procedure

Two hundred university students in roughly equal proportions of males and females volunteered to participate in a route-choice experiment for payoff contingent on their performance. The subjects were divided into ten groups (sessions) of 20 members each. Using a between-subject design, five groups participated in the fully correlated treatment and five other groups in the uncorrelated treatment. Each session lasted about 90 minutes. The ten experimental sessions were conducted in a computerized laboratory with multiple terminals located in separate cubicles. The subjects were handed the first set of instructions that they read at their own pace. Instructions for the uncorrelated treatment are presented in on-line Appendix C.

Each session was divided into two parts called Part I and Part II. The instructions for Part I explained the game and the procedure for choosing one of the two routes, and noted that players would not be informed about travel conditions before making their choices. After completing Part I, the subjects were handed a new set of instructions for Part II that were identical to Part I except that subjects were told that they would be fully informed of the route conditions before making their choices. Each set of instructions exhibited the network, explained the cost functions, and illustrated the computation of the travel cost. In each of the two parts, the players completed 80 rounds for a total of 160 rounds in the session.

At the end of each round, the players were informed of the number of players who chose each route, the travel conditions, and the payoffs associated with the choice of each route. As explained above, on each round each player was given a reward (endowment) of 8 payoff units; individual payoff for the round was computed by subtracting the travel cost incurred from the value of the reward. After Part II was completed, the players were paid their earnings in 8 rounds that were randomly drawn from the 80 rounds in Part I, and 8 additional rounds randomly drawn from the 80 rounds in Part II, for a total of 16 payoff rounds. This payoff scheme was implemented in order to minimize wealth effects during the session; that is, payment is deferred until all the decisions have been made. Payoff units were accumulated across these 16 rounds and converted to money at the rate of 3 payoff units=$1. Overall, players in the correlated treatment earned an average pay of $14.06, and those in the uncorrelated treatment an average of $19.58. In addition, each player received a $5 bonus for participation. Although negative payoffs were possible on any given round, no player ended up with an overall negative payoff.
Three features of the design warrant attention. First, communication between the players was not allowed. Second, consistent with the model assumptions, the group size \( N=20 \) was common knowledge. Third, a within-subject (rather than between-subject) design was chosen to present the two information regimes. With zero information, the pure-strategy equilibrium \((12, 8)\) and social optimum \((11, 9)\) route allocations are close to each other, whereas with full information and good conditions on both routes the equilibrium \((17, 3)\) and social optimum \((10, 10)\) allocations are quite different. Players who experience the zero-information regime first may learn to coordinate on the social optimal distribution, and this could impede the predicted effects of information. This feature renders it more difficult to find evidence in support of the information paradox. Nevertheless, if the information paradox emerges when using a within-subject design — as in the present experiment — then the finding should prove more convincing.

4. Results

If group members interact repeatedly over iterations of the stage game, then the appropriate statistical unit of analysis is the group rather than the individual player. Consequently, unless otherwise specified, we conducted non-parametric (and Bootstrapping) tests on group statistics to compare the two information regimes and the two correlation treatments.

Two types of equilibria were derived in Section 2, namely, pure-strategy equilibria and symmetric mixed-strategy equilibria. In order to analyze the observed behavior, it is necessary to choose a single model as a benchmark. Both models yield very similar predictions about the division of players between routes, but the mixed-strategy equilibria result in higher costs because of round-to-round fluctuations in the route split. Following usual practice in the experimental economics literature, we chose the pure-strategy equilibria for the atomic game, and refer to them hereafter as the model prediction.\(^3\) However, we also consider the mixed-strategy equilibria when examining payoffs.

The two main predictions of the model concern system variables: the mean number of players choosing each route and the mean payoffs for the two information regimes. We test these predictions and report the results below. First, we describe the aggregate route-choice behavior, and then the mean payoffs across all the 80 rounds. Finally, we investigate individual behavior.

\(^3\) As described below, only a small fraction of subjects chose between routes in a way consistent with the mixed-strategy equilibrium probabilities.
4.1 Aggregate route-choice behavior

Table 7 presents the mean number of players choosing route 1 in the correlated and uncorrelated conditions. In both treatments, with zero information (rounds 1-80) the mean is about one player above the prediction (e.g., compare 13.13 and 13.09 to 12 in rows 1 and 2, respectively). A Wilcoxon-Mann-Whitney test shows that, as predicted, the observed and predicted means in the two conditions are not statistically different ($U=29$, n.s.). The same non-significant difference (confidence interval containing zero) was obtained when the two conditions were compared using Bootstrapping with 10,000 samples drawn from all the data collected in each condition. With full information (rounds 81-160), when both routes have good conditions the observed mean number of subjects choosing route 1 is slightly below the equilibrium. Here too, a Wilcoxon-Mann-Whitney test yields no significant difference between the two conditions ($U=34$, n.s.). Once again, a 10,000 sample Bootstrapping test did not reveal a significant difference (confidence interval containing zero) between them. When both routes have bad travel conditions, the means are slightly above the prediction of 11 and more so when the conditions are uncorrelated. In this case, while a Wilcoxon-Mann-Whitney test yields a significant difference between the two conditions ($p<.01$), Bootstrapping with 10,000 samples, as in the other cases, does not (confidence interval containing zero). One explanation is that this combination occurred infrequently. There is also a small difference between the observed and the predicted frequencies when conditions are good on one route and bad on the other. Overall, Table 7 shows that aggregate behavior is very similar in the correlated and uncorrelated treatments.

---Insert Table 7 about here---

The dynamics of play are exhibited in Figure 1, which displays the mean number of players choosing route 1 over the entire course of the session. The top panel displays the mean number across the five sessions of the correlated treatment. The left half of the graph shows the results for the first eighty rounds of play with zero information. The solid horizontal line depicts the model prediction with zero information (12 players choosing route 1), and the broken lines exhibit the predictions if full information had been available (17 players choose route 1 under good conditions, and 11 under bad conditions). The right half of Figure 1 depicts the observed mean number of subjects choosing route 1 with full information (rounds 81-160). Circles denote
good conditions, and squares denote bad conditions. The squares are more widely spaced than
the circles because bad conditions occur only about one quarter of the time. For the same reason,
mean usage is more variable from round to round under bad than good conditions.

The lower panel of Figure 1 displays similar results for the uncorrelated treatment. The four
jagged series in rounds 81 to 160 correspond to the four possible states (circles denote [Good,
Good] conditions, squares denote [Bad, Bad] conditions, plus signs [Good, Bad] conditions, and
asterisks [Bad, Good] conditions). Solid lines again show the model equilibria. Figure 1 suggests
two major findings. The first is that the number of players choosing route 1 is quite close to the
equilibrium prediction. The other is that the mean number of players choosing route 1 converges
to the equilibrium prediction during the early rounds of each part of the session and fluctuates
around it thereafter.

--Insert Figure 1 about here--

4.2 Mean payoffs

In the model, the probabilities of good and bad conditions on each route were set at 0.75 and
0.25, respectively. In the experiment, a random number generator was used to draw the two
conditions with these probabilities so that the actual proportions in which the two conditions
were realized deviated slightly from these probabilities. As a result, to properly compare the
payoffs earned by the subjects to the model predictions it is necessary to normalize the earnings.
This was achieved by calculating the mean payoff for each combination of conditions and
adjusting it to the proportion assumed in the model. (For example, in Session #1 of the correlated
treatment [Good, Good] conditions appeared on 61 out of 80 rounds. The weight of the mean
payoff on these rounds was therefore scaled down by a factor of 60/61.) Table 8 presents the
mean normalized payoff across sessions in both treatments (columns) and under both
information regimes (rows). It also presents the model predictions\textsuperscript{4}.

--Insert Table 8 about here--

For both route conditions and in both information regimes, the observed mean payoff was
lower than predicted. This result is mainly due to the high (quadratic) cost of coordination

\textsuperscript{4} We do not report Bootstrapping test results in this section since the prediction should hold on the
aggregate session level. Hence, we opted instead to use non-parametric tests with the entire (normalized)
\textit{session} as the statistical unit.
failure. As predicted by the model, the Wilcoxon-Mann-Whitney test shows no significant difference between the two treatments with zero information. However, in both treatments players earned about 25% less than predicted. When route conditions are uncorrelated, providing the players with information increased their earnings by a staggering 59%, almost twice the predicted effect and highly statistically significant. In contrast, when information was provided to the players in the correlated treatment their mean payoff decreased by more than 12%. While this effect is slightly smaller than the predicted 16%, it is nevertheless statistically significant at the 7% level (using the group as the unit of analysis). This finding is especially intriguing since with zero information, coordination failure resulted in payoffs much lower than predicted. As a result, the opportunity for information provision to prove beneficial was much greater. Indeed, payoffs with full information could have exceeded those with zero information while remaining below the full-information prediction.

Table 9 compares the experimental results with the predicted results for the mixed-strategy equilibria. (Results of the statistical tests, including those of the information paradox, are the same as in Table 8 and are therefore omitted.) Compared to the pure strategies shown in Table 8, the predicted payoffs are much lower and closer to the observed payoffs. For correlated conditions, the predicted change in payoffs from providing information is nearly the same as in Table 8, but for uncorrelated conditions the predicted increase is much higher and closer to the observed increase. This suggests that individual subjects might have been using strategies closer to the equilibrium mixed strategies than to the equilibrium pure strategies. However, as will be explained in Section 4.3, this was not the case.

--Insert Table 9 about here--

4.3 Individual behavior

Pure-strategy equilibrium analysis was used to derive predictions from the model regarding route choice. Equilibrium analysis is heroic in presuming that individual players can coordinate on a single equilibrium allocation. Furthermore, equilibrium analysis is static in that it predicts choices in each trial while disregarding the dynamics of play across rounds. The aggregate results reported here suggest that individual play deviated somewhat from what is predicted.
Hence, it is insightful to examine individual route choices in order to ascertain the extent to which mean results appropriately represent individual behavior.

As noted earlier, the statistical unit of analysis in our experimental design is the group rather than individual players. However, we assume hereafter that participants within a group are mutually independent. This assumption may be justified by the fact that our groups were relatively large so that any one player was unlikely to significantly influence group outcome.

Figure 2 displays the route choices of the 20 players in Session #4 of the uncorrelated treatment. (Session #4 is representative of all other sessions.) Rounds 1-80 were played with zero information and rounds 81-160 with full information. Several patterns of behavior are apparent. Some players never changed route (player #6), some changed route infrequently (player #8), some changed route more frequently in the second part than the first part (players #13, #19), and others changed route on almost every round (players #1, #4, #15, #17). Deciphering what behavioral rules (heuristics), if any, the players were following in their choice of route is difficult. Nevertheless, and most importantly, this heterogeneous — if not erratic — behavior at the individual level results in aggregate behavior that is broadly consistent with equilibrium play. To achieve equilibrium, subjects had to switch their routes across iterations of the stage game.

We now consider the frequencies and patterns of individual route switching.

Switching routes. Denote player $i$’s route choice on round $t$ by $R_i$. Player $i$ is said to switch routes from round $t$ to round $t+1$ if $R_{i,t+1} \neq R_i$. Switching routes was reported by Selten et al. (2007) in an experiment involving the two-route network with linear congestion costs. It was also examined by Rapoport et al. (2009) in a study of the Braess Paradox, by Morgan et al. (2009) who studied both the Braess Paradox and the Pigou-Knight-Downs Paradox, by Dechenaux et al. (2013), and by Helbing et al. (2005). It is important for testing any explanatory model of individual route choice that explicitly considers dependencies in route choices in successive rounds.

Why do players switch routes? Are individual differences in rate of switching similar in the zero-information and full-information regimes? Is switching individually beneficial? We address these questions in the remainder of this section. We first ascertain whether the rate of route switching is constant over time, or more frequent in some stages of the game than in others.
Figure 3 displays the mean number of switches for the correlated (upper panel) and uncorrelated (lower panel) treatments. (The maximum number of switches is 20.) To attenuate the fluctuations caused by changes in route conditions from round to round, a running mean of five rounds is shown. Each panel displays two graphs, one for each of the 74 possible (running-mean) switching rounds. Three patterns are apparent. First, information has different effects in the two treatments. In the correlated treatment, players switched more frequently with zero information than with full information (Wilcoxon sign-rank test \(z = -3.89, p<0.001\)), whereas in the uncorrelated treatment the effect was reversed (\(z = -6.69, p<0.001\)). There are four states in the uncorrelated treatment but only two states in the correlated treatment. Therefore, when subjects know the state, more frequent switching is expected in the uncorrelated treatment.

Second, in both panels the mean frequency of switches with zero information decreased with experience. In the correlated treatment, the mean frequency of switching decreased from 6 on round 2 to 3.5 on round 74 (Spearman \(\rho = -0.91, p<0.001\)). Corresponding values for the uncorrelated treatment are 6.8 and 4.8 (Spearman \(\rho = -0.83, p<0.001\)). A similar decline occurs with full information in the correlated treatment (5.5 to 3.9, Spearman \(\rho = -0.57, p<0.001\)) but not in the uncorrelated treatment where the mean fluctuates around 7 (6.4 to 8, Spearman \(\rho = -0.02, \text{ns.}\)). The third pattern is a small but consistently higher switching frequency in the uncorrelated than the correlated treatment under both information regimes (Wilcoxon rank-sum test, \(z = -3.79, p<0.001\) and \(z = -9.34, p<0.001\)).

Figure 2 exhibits the presence of considerable individual differences in frequency of route switching. Most players switched routes, but generally not as often as the mixed-strategy equilibrium play would suggest, and they did not mix their choices with the probabilities specified by the equilibrium solution.\(^5\) These findings raise two additional questions. The first is

---Insert Figure 3 about here---

\(^5\) In the zero-information regime, players choose Route 1 with probability 0.63 in the mixed-strategy equilibrium. Over 80 rounds of play, they would choose Route 1 49.8 times on average with a 95-percent confidence interval of (42, 59). Only 36 of 100 players in the correlated treatment actually chose Route 1 with a frequency in this interval. For the uncorrelated treatment the number was 39. To test for sequential dependencies we performed a runs-test for these players. Absence of sequential dependencies could not be rejected for 17 of the 36 players in the correlated treatment, and for 20 of the 39 players in the uncorrelated treatment. Thus, only about a fifth of the players in each treatment behaved consistently with the mixed-strategy equilibrium. For the full-information regime the tests were less powerful because of few observations in each of the four states.
whether switching pays off. The second is whether the tendency to switch is a relatively stable individual propensity manifested in both information regimes.

To answer the first question, we computed the Spearman correlation between the individual number of switches (range: 0-79) and the player’s payoff for the session. The correlations were computed separately for each route condition and each information regime. The correlations for the correlated treatment are -0.164 (p=0.1 ns) with zero information, and -0.286 (p<0.005) with full information. The corresponding values for the uncorrelated treatment are -0.148 (ns) and -0.183 (p=0.07). All four correlations are negative. (Selten et al., 2004 obtain similar results for games played with a similar number of players (18) over slightly longer time horizons of 200 rounds. Helbing et al., 2005 also obtain similar results for games played with smaller numbers of players over much longer time horizons of 3300 rounds). We conclude that, in general, switching did not pay off in either treatment: individual payoff declined with frequency of route switching.

We also examined the payoffs of players who never switched routes. The results are reported in Table 10. With zero information and uncorrelated route conditions, six out of the 100 players never switched. If players are ranked in order of decreasing payoffs, the rankings of these players are 1, 19, 20, 45, 46, and 47. Thus, all six players scored in the top half of the distribution. With full information only two players never switched and both of them were among the six who never switched with zero information. Both of these players also ranked in the top half of the distribution. With correlated conditions seven players never switched with zero information. Remarkably, three of the seven earned the top-three payoffs of all 100 subjects. With full information three players never switched of whom two were among those who never switched with zero information. These players, too, earned payoffs in the top half of the distribution. In summary, only a few players never switched routes in the experiment, but in all 18 cases they earned above-median payoffs and in seven out of the 18 cases their earnings ranked in the top six out of 100.

--Insert Table 10 about here--

To answer the second question, we computed for each treatment the Spearman correlation between the individual numbers of switches in the two information regimes. The correlations (n=100 in each case) are 0.435 and 0.396 for the correlated and uncorrelated conditions, respectively (p<0.001 in each case). Regardless of which treatment they were assigned, players
who switched routes more frequently with zero information also switched more frequently with full information. The rate of switching seems to be an individual propensity.

We also investigated whether players tended to switch routes less frequently after receiving a positive than negative payoff. We did this by calculating the frequency with which each player switched routes following either a positive or negative payoff. Table 11 reports the results for both treatments and both information regimes. In three of the four cases, subjects switched more frequently following a negative than positive payoff. (The exception is zero information and uncorrelated conditions.) Such a pattern is intuitively plausible at least during the learning phase of the experiments.

--Insert Table 11 about here--

5. Adaptive Learning

Recall that each subject completed 80 rounds (1-80) in the zero-information condition and 80 additional rounds (81-160) in the full-information condition. Analysis of the dynamics of play (see both panels of Figure 1) yielded two major patterns of aggregate behavior. First, under the zero-information regime mean route choices converged to equilibrium with no systematic changes in behavior over the 80 rounds of play. This pattern of "no learning" under zero information appeared in both the correlated and uncorrelated treatments. Second, after rapid learning in the early rounds of Part II of the experiment, mean route choices approached the pure-strategy equilibrium predictions, two in the correlated treatment and four in the uncorrelated treatment, and fluctuated around the point predictions thereafter. Figure 2 strongly suggests that no simple adaptive learning model may successfully account for the individual profiles, which vary widely from one subject to another. In light of the results exhibited in these two figures, we have proceeded with the modest goal of identifying a simple learning model that accounts for the major findings listed above, namely, the aggregate mean route choices in both correlation treatments and in both information regimes. In adopting this approach, we implicitly assume that the same learning model (possibly with different parameter values) accounts for the complex patterns of aggregate results exhibited in both panels of Figure 1.

For this purpose, without getting involved in model comparison (which is beyond the scope of the paper), we chose the Experience-Weighted Attractions (EWA) model of Camerer and Ho
(1999) due to its generality, simplicity, and most importantly its relative success in accounting for learning in multiple settings. In the EWA model, each strategy in a finite set of strategies is assigned a measure of attractiveness (termed attraction). The attraction of each strategy is updated on every round of play by the payoff gained from choosing it. These attractions are then translated into probabilities of choosing each strategy.

For player $i$, let $\pi_i^j(s_i(t), s_{-i}(t))$ denote the payoff earned by player $i$ on trial $t$ for choosing strategy $j$, where $s_i(t)$ is the strategy chosen by player $i$ and $s_{-i}(t)$ are the strategies chosen by all other $N-1$ players. The reinforcement that player $i$ attaches to strategy $j$ is denoted by

$$R_i^j(t) = [\delta + (1 - \delta) \cdot I(s_i^j, s_i(t))]\pi_i^j(s_i(t), s_{-i}(t)),$$

where $\delta$ is a weight given to the strategies not chosen,$^6$ $I(x, y)$ is an indicator (or bias) function which equals 1 if $x=y$ (i.e., strategy actually chosen by the player) and 0, otherwise. This reinforcement is then used to update strategy $j$’s attraction by

$$A_i^j(t) = A_i^j(t-1) + R_i^j(t).$$

On round $t+1$, player $i$ stochastically determines her route choice using a logistic response function $p_i^j(t+1) = e^{\lambda A_i^j(t)}/\sum_k e^{\lambda A_i^k(t)}$, where $p_i^j$ is the probability that player $i$ chooses strategy $j$, and $\lambda$ is an attraction sensitivity estimator.

--Insert Figure 4 about here--

Using a grid search, we searched for a parameter combination that best describes the observed mean route choice in the two treatments and under both information regimes.$^7$ Figure 4 exhibits the mean aggregate route choice for both treatments and under both information regimes using 100 simulated games. The simulated mean route choice displayed in Figure 4 closely resembles the observed mean route-choice pattern in Figure 1. In both figures, the mean number of players choosing route 1 under the zero-information treatment is only slightly above the prediction of 12. Under the full-information condition, both figures display major oscillations in the mean route choice around the equilibrium, especially in the less frequent condition.

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$^6$ In our experiment players were fully informed of the outcomes on both routes. Therefore, to maintain parsimony, we set $\delta=0$, i.e., all routes are assigned equal weight.

$^7$ We set the initial attractions at $A_i^1(t=1)=2\cdot A_i^2(t=1)=2\cdot 8$, where 8 is the size of the reward (endowment). This ratio mimics the initial attraction ratios observed in the experiment. We also set $\lambda=0.1$ for all the players in each session.
combinations (e.g., bad conditions on both routes under full information), where the players are presented with fewer opportunities to learn. And in neither of the two panels of Figure 4 is there evidence for learning in the zero-information condition. Comparison of Figures 1 and 4 suggests that a simple and parsimonious reinforcement-based learning model can account for our major findings regarding mean route choice (see, e.g., Chmura and Güth, 2011). To summarize, these include:

- In the zero-information condition, convergence to equilibrium mean route-choice behavior is reached within very few trials.
- In the full-information condition, convergence to equilibrium is slower, with more fluctuations around the equilibrium (mainly due to fewer observations in each round).  

The learning model does not account well for the observed mean number of switches; it prescribes higher frequencies than the ones displayed in Figure 3. The learning model also yields lower mean payoffs in the correlated treatment with a decrease from 1.7 to 1.1, and an increase in mean payoffs in the uncorrelated treatment from 1.1 to 3.7. One possibility to fine-tune the model would be to divide the population of subjects into different types with different parameter values for each type. We have opted not to proceed in this way because of the difficulty in identifying distinct subsets of players and adding more parameters. The contribution of this model is in providing a parsimonious explanation to some of the main findings, namely, convergence to equilibrium route-choice distribution and the information paradox.

6. Concluding Remarks

We have studied experimentally the effects of pre-trip information on route-choice decisions when travel conditions are congested and vary unpredictably. We adopt a variant of the classical two-route network but, rather than postulating fixed capacities, assume that the capacities on each route fluctuate randomly due to weather, accidents, and other disturbances. Each day, users

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8 The faster convergence to equilibrium in Figure 1 suggests some level of ‘other regarding’ thinking on the part of the subjects. The Cognitive Hierarchy model of Camerer et al. (2004) embeds a degree of strategic behavior into the choices of the subjects. When fitting this model to our data, we obtain almost immediate convergence as in Figure 1. However, we have chosen to present the EWA model only because of its parsimony and success in accounting for the subject behavior in the first few rounds. Additionally, the Cognitive Hierarchy model indicates that there is little value to be gained by trying to ‘out-think’ other subjects. Most subjects appear to quickly realize this implication and consequently base their decisions exclusively on their own outcomes.
independently choose which route to take. As shown in the companion paper (Lindsey et al., 2013), the welfare effects of pre-trip information about travel conditions depend on the free-flow costs of the routes, the shape of the trip cost functions, and the correlation in conditions between routes. In the numerical instance of the equilibrium model that we have chosen for the experiment, information has adverse effects when travel conditions on the routes are positively and perfectly correlated, and positive effects when conditions are independent.

We test the model predictions in the laboratory using a within-group design with financially motivated subjects whose payoffs are contingent on their performance. The experiment is novel for studying a setting in which travel times are endogenous and information is provided to subjects before they choose a route. The results of the experiments are broadly consistent with the theory. Information proves to be beneficial when route conditions are uncorrelated, but detrimental when conditions are perfectly correlated. This finding adds to the growing body of research on traffic congestion paradoxes.

The experiments revealed a rather complex and rich pattern of collective and individual behavior. Mean payoffs in both information regimes and both correlation treatments are lower than predicted by pure-strategy equilibrium, but similar to predictions of mixed-strategy equilibrium. Lower payoffs are attributable to a failure of subjects to coordinate on route choices. The proportions of subjects who choose each route are close to the equilibrium predictions for both information regimes and for both route correlation treatments. The mean number of players choosing either route converges to the equilibrium prediction during the early rounds in each information regime and treatment, and fluctuates around it thereafter. Dynamics of play are reasonably well accounted for by a simple version of the Experience-Weighted Attractons model based on adaptive learning.

Individual subject behavior is quite diverse. Most players switched routes during the experiment, but not in a way consistent with the mixed-strategy equilibrium probabilities. As expected, when information about route conditions was provided, subjects switched more frequently in the uncorrelated treatment with four possible states than in the correlated treatment with only two states. In both treatments, individual payoffs were negatively correlated with switching frequency and the (few) players who never switched routes all earned above-median payoffs.
In summary, the aggregate behavior exhibited in the experiments is reasonably similar to equilibrium predictions, but individual behavior is very diverse and cannot be explained by a single existing theory. This pattern is typical of experiments on interactive group decision-making. Fortunately, for many issues of system design the predictability of aggregate behavior is most important. Nevertheless, better models of individual behavior remain a future research goal.

We turn next to the assumptions underlying the design of the current study, and assess their impacts on the results.

6.1 Modeling assumptions

Like other useful models, our model requires parsimony if it is to shed light on significant issues and render them amenable to laboratory experimentation. Below is a brief discussion of four significant simplifying assumptions that we make toward this end.

First, attention is limited to two polar information regimes: zero information and full information. Participants in the laboratory are faced with a difficult decision-making task, and might encounter problems in comprehending the game with a more complex information regime.

Second, in the full-information regime users are informed of the state. Traffic information studies often assume that users are informed about travel times rather than underlying demand or supply conditions. (See, for example, Ben-Elia and Shiftan, 2010; De Moraes Ramos et al., 2011; and Ben-Elia et al., 2013.) We assume that information is about the state (i.e., road conditions) because the model is static and all users have to choose a route before beginning their trips. Any information about travel times is necessarily predictive; it is a function of route choices that drivers have yet to make. Popular community-based traffic information providers present members with similar information. Practically, conveying travel time forecasts to subjects could "steer" them toward Nash equilibrium and would undermine the main purpose of the experiment, namely, to test whether an information paradox emerges solely as a function of driver use of objective information.

Third, users are risk-neutral with respect to travel costs. This assumption seems to fly in the face of a growing body of evidence that drivers are risk-averse with respect to travel time, perhaps because they face a large penalty for arriving late. However, there is no inconsistency because travel cost can be a nonlinear function of travel time. With fixed demand, utility can be expressed as the negative of travel costs, and risk aversion with respect to travel time is captured
by convexity of the travel cost function. Moreover, attitudes towards risk are predominantly measured in individual decision making tasks (e.g., choice between gambles); the generalization of their findings to interactive decision making, which ignores strategic interaction, is highly problematic. Equilibrium solutions that assume risk-neutrality often account quite well for route choice (e.g., Rapoport et al., 2009; Gisches and Rapoport, 2012) and departure-time choice (e.g., Daniel et al., 2009) when groups are relatively large. The model does assume that agents maximize expected utility. Therefore, it rules out reference-dependent preferences or other types of behavior inconsistent with expected utility theory. In on-line Appendix A, we discuss some of the difficulties in applying other theories to our setting.

Fourth, all users have the same travel cost function. Homogeneous preferences and risk-neutrality are plausible in the case of the students recruited for our laboratory experiments who played for moderate monetary stakes. Moreover, single-user class models are widely used in transportation demand analysis, and may be a serviceable approximation in settings such as peak-hour travel when a large fraction of travelers are commuters facing similar work time scheduling constraints (Lam et al., 2008). Nevertheless, work habits are changing as technology advances, and there is a trend towards more flexible schedules in which people can differ widely from one another in their preferred travel times (Alexander et al., 2010).

### 6.2 Extensions

Our analysis could be extended in several directions. One is to determine what drives individuals’ behavior. Some possible candidates for explaining the adverse effects of information that are manifested in the laboratory are concentration and overreaction (Schelling, 1978; Ben-Akiva et al., 1991) as well as oversaturation. Distinguishing between these alternatives is not straightforward — especially in the early rounds when subjects are either learning about the game or in the process of coordinating their actions to reach equilibrium. The task is further complicated by the fact that experimental subjects differ widely in their behavior. Some appear to use pure strategies while others may adopt mixed strategies although with probabilities that typically differ from aggregate equilibrium mixed-strategy probabilities. As in Chmura and Güth

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9 Unlike in some experiments, such as those in De Moraes Ramos et al. (2011), our subjects were not told either the purpose of their trips or the length of time the trips should take (see the instructions in on-line Appendix C). A priori, there is no reason to believe that subjects are risk-averse.
(2011), it would be interesting to test alternative equilibrium concepts and compare their explanatory powers.

Our model featured two polar information regimes: a zero-information regime in which subjects know only the unconditional probability distribution of states, and a full-information regime that conveys perfectly accurate information about travel conditions. Perfect information, as we have argued, is an important first step in the analysis of information effects but it is an idealization that is practically unattainable for several reasons (Bonsall, 2008). Information on travel conditions may be collected with a delay, or not at all. Information about conditions downstream may be obsolete by the time a user gets there. Users may ignore or misinterpret information updates. Information systems can malfunction. And there is a problem of consistency: a message about conditions that induces changes in user behavior can lead to changes in the conditions themselves that invalidate the message. These complications can be accommodated by considering imperfect information that is conveyed in the form of messages that may be imprecise or wrong. A few theoretical studies have pursued this approach (e.g., Kobayashi, 1994; Arnott et al., 1996, 1999; Lam et al., 2008). It is not straightforward as to how this can be adopted in a laboratory setting in a way that is both intelligible to the subjects and yet does not impact the hypotheses being tested. Ben-Elia et al. (2013) have recently conducted route-choice experiments in which subjects are provided with information that varies in its accuracy. Surprisingly, they find that many subjects comply with advice even when accuracy is low. Their experimental setting differs from ours in several respects. In particular, travel times on each route are independent of usage and uncorrelated between routes.

The potentially counterproductive effects of providing information are evident in Tables 3 and 5 since informing drivers about the [Good, Good] state is welfare-reducing relative to zero information. This might suggest that a policy of selective information provision could be superior to providing full information in all cases. Selective or imperfect information dissemination may, in fact, be advantageous in some circumstances as is demonstrated by Allon et al. (2011) in the case of customer decisions whether to join a queue, and Lee and Shin (2011) in the case of drivers' route-choice decisions. However, if messages were conveyed in all but the [Good, Good] state, then drivers could infer that when the information service is silent, conditions must be [Good, Good]. At least in simple settings such as the one considered here,
withholding information selectively is unlikely to be effective even if ethical concerns do not arise. A general discussion of strategic information provision is outside the scope of this paper.

A third extension is to combine information provision with congestion tolls as a way to internalize congestion externalities and avoid the information paradox. Several theoretical studies have examined the joint implementation of Advanced Traveler Information Systems and congestion pricing (e.g., de Palma and Lindsey, 1994, 1998; Verhoef et al., 1996; Yang, 1999; Fernández et al., 2009); it would appear possible to implement them experimentally.

7. Acknowledgments

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9. List of Tables and Figures

Table 1. Social optimum, pure-strategy equilibrium, and symmetric mixed-strategy equilibrium in the zero-information condition (expected costs appear in brackets)

Table 2. Social optimum, pure-strategy equilibria, and symmetric mixed-strategy equilibria in the full-information condition (expected costs appear in brackets)

Table 3. Gains and losses from full information for pure-strategy equilibria

Table 4. Expected costs for pure-strategy equilibria [experimental payoffs appear in brackets]

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Table 7. Predicted and observed mean number of players choosing route 1 by information regime and route conditions

Table 8. Predicted (pure-strategy) and observed mean normalized payoffs across sessions by information regime and route conditions
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Table 10. Payoff rankings for players who never switched routes

Table 11. Frequency of route switching

Figure 1. Observed mean number of players choosing route 1 in the correlated (top panel) and uncorrelated (bottom panel) treatments (rounds 1-80: zero-information condition, rounds 81-160: full-information condition)

Figure 2. Individual route choice in Session 4 of the uncorrelated condition.

Figure 3. Observed mean number of route switches by information regime and correlation between route conditions.

Figure 4. Simulated route choice using the EWA learning model.

10. Notational Glossary

\( a_{is} \) free-flow travel cost on route \( i \) in state \( s \)

\( A_j^i(t) \) attraction of strategy \( j \) for player \( i \) on round \( t \) in EWA model

\( b_{is} \) congestion coefficient on route \( i \) in state \( s \)

\( B \) bad state

\( C_{is}(N_{is}) \) private travel cost on route \( i \) in state \( s \)

\( d \) power coefficient

\( \delta \) weight given to strategies not chosen in EWA model

\( E[\cdot] \) expectations operator

\( F \) full-information regime

\( G \) good state

\( G^{ZF} \) expected welfare gain from shifting from zero information to full information

\( i \) index of route

\( I(x, y) \) indicator function in EWA model

\( \lambda \) attraction sensitivity estimator in EWA model

\( MSC \) marginal social cost of trip
$N$ total number of users  
$N_i$ number of users on route $i$  
$N_{is}$ number of users on route $i$ in state $s$  
$N'_{is}$ system-optimal number of users on route $i$ in state $s$  
$\pi$ probability of bad conditions on either route  
$\pi_i'$ payoff earned by player $i$ for choosing strategy $j$ in EWA model  
$r$ index of information regime  
$R_{it}$ route choice on round $t$ by a player  
$R_i^j(t)$ reinforcement that player $i$ attaches to strategy $j$ on round $t$ in EWA model  
$s$ state  
$S$ set of states  
$s_i(t)$ strategy chosen by player $i$ on round $t$ in EWA model  
$Z$ zero-information regime
11. References


Allon, G., Bassamboo, A., Gurvich, I. 2011. 'We will be right with you': Managing customers with vague promises. Operations Research 59 (6), 1382-1394.


de Palma, A., Lindsey, R., Picard, N. 2012. Risk aversion, the value of information and traffic equilibrium. Transportation Science 46 (1), 1-26.


Rapoport, A. et al., 2010. Endogenous arrivals in batch queues with constant or variable capacity. Transportation Research Part B 44 (10), 1166-1185.


On-line Appendices

Appendix A: Non-expected utility approaches

There is a growing body of evidence that, in a wide range of settings, decisions made under uncertainty are inconsistent with expected utility theory. Some non-expected utility theories have been applied in traffic studies including Prospect theory (Avineri and Prashker, 2003), Regret theory (Chorus et al., 2008), and Reinforcement Learning theory (Ben-Elia and Shiftan, 2010). Prospect theory is seen as especially promising for studying travelers' attitudes towards uncertain travel times. The main challenge in applying prospect theory is to identify the reference point against which travelers perceive gains and losses. The choice may be clear in settings where the probability distributions of travel time on alternative routes are very simple as in the stated preference experiments of de Palma and Picard (2005). But in reality the probability distribution is typically continuous. The number of possible outcomes in our experiments is finite, but with 20 subjects and travel cost functions that depend on the state the number is quite large. Subjects were not told the probability distribution function of travel time, and because play never completely settled down it is unlikely that they perceived the distribution clearly even by the end of the experiments.

Laboratory studies of travel behavior have produced mixed evidence on risk attitudes (see Gao et al. (2010) and Ben-Elia and Shiftan (2010) for reviews). Some results are consistent with prospect theory whereas others are not. The inconsistencies may be due in part to the elusive nature of reference points. As Gao et al. (2010, p.739) remark "Reference points are likely to be context-dependent in addition to being individual specific. For example, on a rainy day the reference point might be larger, since the travelers already expect higher travel times."

A further problem in applying Prospect theory to our setting is that it is unclear whether reference-dependent preferences should be included in the welfare function used to determine whether information is welfare-reducing. This is an unresolved issue in behavioral economics. Yet another complication is that loss aversion tends to erode as subjects gain experience (List, 2003). Since our route choice game was iterated for 80 rounds, subjects had ample opportunity to gain experience. The influence of reference-dependence may, therefore, have weakened during the course of the experiments.
Appendix B: Proofs

Proof of Proposition 1

Proof: Let $E[\ ]$ denote expectations for the information regime in question (where full-information expectations are degenerate). The proof proceeds by elimination. If $E[C_1(1)] \geq E[C_2(N)]$ then $(N_1, N_2) = (0, N)$ is an equilibrium. For $n = 1, \ldots, N-1$, if $E[C_1(n)] < E[C_2(N-n)]$ and $E[C_1(n+1)] \geq E[C_2(N-n-1)]$ then $(N_1, N_2) = (n, N-n)$ is an equilibrium. If $E[C_1(N)] < E[C_2(1)]$ then $(N_1, N_2) = (N, 0)$ is an equilibrium. □

Proof of Proposition 2

By Proposition 4, there exists at least one pure-strategy equilibrium. Suppose $(N_1, N_2)$ is an equilibrium where $N_1 + N_2 = N$. To economize on notation the expectations operator on travel costs will be omitted.

For users of route 1 to be in equilibrium:

$$C_1(N_1) \leq C_2(N_2 + 1), \quad (A1)$$

and for users of route 2 to be in equilibrium:

$$C_2(N_2) \leq C_1(N_1 + 1). \quad (A2)$$

Suppose $(N_1 + n, N_2 - n)$ is another equilibrium with $n \geq 1$. The equilibrium conditions are

$$C_1(N_1 + n) \leq C_2(N_2 - n + 1). \quad (A3)$$

and

$$C_2(N_2 - n) \leq C_1(N_1 + n + 1). \quad (A4)$$

Combining inequalities (A2) and (A3) one has

$$C_2(N_2) \leq C_1(N_1 + 1) \leq C_1(N_1 + n) \leq C_2(N_2 - n + 1). \quad (A5)$$

By Assumption 1, the travel cost function is strictly increasing on at least one route. If $C_2$ is strictly increasing, then inequality $C_2(N_2) \leq C_2(N_2 - n + 1)$ in (A5) cannot hold for $n > 1$. If $C_1$ is strictly
increasing, then the middle inequality in (A5) is strict for \( n>1 \) and (A5) implies \( C_2(N_2) < C_2(N_2-n+1) \) which is impossible for \( n>1 \).

This proves that \( (N_1+n, N_2-n) \) can be an equilibrium only for \( n=1 \). With \( n=1 \), (A5) then implies \( C_1(N_1+1) = C_2(N_2) \). Inequalities (A2) and (A3) then both hold as equalities and \( (N_1, N_2) \) and \( (N_1+1, N_2-1) \) are both weak equilibria. Analogous reasoning establishes that if \( (N_1+1, N_2-1) \) is an equilibrium, then \( (N_1-n, N_2+n) \) cannot be an equilibrium for \( n>0 \). Hence at most two pure-strategy equilibria exist.

Proof of Proposition 3

Let \( p \) be the probability that each player selects route 1. The equilibrium value of \( p \) is such that expected travel costs are the same on the two routes. The expected cost of using a route depends on the probability distribution of the number of other players selecting that route. The probability that \( N_1 \) of the other \( N-1 \) players choose route 1 is

\[
\binom{N-1}{N_1} p^{N_1} (1-p)^{N-1-N_1}.
\]

The expected cost of taking route 1 is therefore

\[
E[C_1] = \sum_{N_1=0}^{N-1} \binom{N-1}{N_1} p^{N_1} (1-p)^{N-1-N_1} C_1(N_1+1), \tag{A6}
\]

where expectations over states are again omitted to ease notation. Similarly, the expected cost of taking route 2 is

\[
E[C_2] = \sum_{N_2=0}^{N-1} \binom{N-1}{N_2} p^{N_2} (1-p)^{N-1-N_2} C_2(N_2+1)
= \sum_{N_1=0}^{N-1} \binom{N-1}{N_1} p^{N_1} (1-p)^{N-1-N_1} C_2(N-N_1), \tag{A7}
\]

Equating equations (A6) and (A7) one obtains an implicit equation for \( p \):

\[
\sum_{N_1=0}^{N-1} \binom{N-1}{N_1} p^{N_1} (1-p)^{N-1-N_1} \left(C_1(N_1+1) - C_2(N-N_1)\right) = 0. \tag{A8}
\]
By Assumption 1, term \( C_1(N_1 + 1) - C_2(N - N_1) \) is a strictly increasing function of \( N_1 \). Equation (A8) therefore has a unique solution in \( p \) because an increase in \( p \) shifts the probability distribution of \( N_1 \) to the right.

**Proof of Proposition 4**

The proof entails showing that any two players who randomize between routes 1 and 2 must use the same probabilities. Suppose player \( j \) randomizes with probability \( p_j \), and player \( k \) randomizes with probability \( p_k \), where \( p_j \neq p_k \). Let \( \tilde{p} \) be the list of probabilities used by the other \( N-2 \) players. Player \( j \) then faces a set of \( N-1 \) other players using probabilities \( p_k, \tilde{p} \), while Player \( k \) faces \( N-1 \) players using probabilities \( p_j, \tilde{p} \). (Note that the order in which the probabilities are listed is immaterial.) Both players are willing to randomize only if their expected travel costs on the two routes are equal. We prove that this is impossible by showing that the difference between routes in expected travel costs is a strictly monotonic function of the probability used by each of the other \( N-1 \) players.\(^{10}\)

Without loss of generality the "designated" player is taken to be player \( N \), and the "other" players are indexed \( 1, \ldots, N-1 \). The following additional notation is employed:

\[
\tilde{p} : (p_1, p_2, \ldots, p_{N-1})
\]

\[
\tilde{p}_{-j} : (p_1, p_2, \ldots, p_{j-1}, p_{j+1}, \ldots, p_{N-1})
\]

\[
F(N_1, \tilde{p}) : \text{the cumulative distribution function of } N_1 \text{ given } \tilde{p}
\]

\[
f(N_1, \tilde{p}) : \text{the probability density function of } N_1 \text{ given } \tilde{p}
\]

\( S \) : the set of other players \( \{1, \ldots, N-1\} \)

\( S_n \) : the set of all subsets of \( S \) that have \( n \) members, \( n = 1, \ldots, N-1 \)

\(^{10}\) The proof is complicated by the fact that all players do not select route 1 with the same probability so that the probability distribution of \( N_1 \) is not binomial.
\(S_{nj}\): sets in \(S_n\) that include player \(j\)

\(S_{n\setminus j}\): sets in \(S_n\) that exclude player \(j\). (Note that \(S_n = S_{nj} + S_{n\setminus j}\)).

The formulas for \(f(n, \tilde{p})\) and \(F(N_1, \tilde{p})\) are

\[
f(n, \tilde{p}) = \sum_{\sigma \in S_n} \prod_{i \in S_\sigma} p_i \prod_{j \in S_\sigma} (1 - p_j).
\]

(A9)

\[
F(N_1, \tilde{p}) = \sum_{n=0}^{N_1} f(n, \tilde{p}).
\]

(A10)

If the designated player is willing to randomize between route 1 and route 2, the expected travel costs must be equal with \(N+1\) players on route 1 and \((N-1)-N_1+1 = N-N_1\) players on route 2:

\[
\Delta C = E[C_1] - E[C_2] = \sum_{n=0}^{N_1} f(n, \tilde{p})(C_1(n_1 + 1) - C_2(N - N_1)) = 0.
\]

Given Assumption 1, \(C_1(n_1 + 1) - C_2(N - N_1)\) is a strictly increasing function of \(N_1\). To prove Proposition 4 it therefore suffices to prove the following lemma:

**Lemma:** Assume \(p'_j > p_j\) for some \(j \in S\). Then \(F(n, p'_j, \tilde{p}_{\setminus j})\) first-order stochastically dominates \(F(n, p_j, \tilde{p}_{\setminus j})\), \(n = 0, \ldots, N-1\).

**Proof of Lemma**

We use induction over \(n\) to prove:

\[
\frac{\partial F(n, p_j, \tilde{p}_{\setminus j})}{\partial p_j} = - \sum_{\sigma \in S_n} \prod_{i \in S_\sigma} p_i \prod_{j \in S_\sigma} (1 - p_j) < 0.
\]

(A11)

To economize on notation, \(F(n, p_j, \tilde{p}_{\setminus j})\) is henceforth written \(F(n)\). Setting \(n = 0\) and applying (A9) and (A10), \(F(0) = \prod_{i \in S}(1 - p_i)\), and

\[
\frac{\partial F(0)}{\partial p_j} = - \prod_{i \in S_{\setminus j}} (1 - p_i) < 0.
\]

(A12)

Eq. (A11) reduces to (A12) with \(n = 0\).
Setting $n=1$ and applying (A9), $f(1) = \sum_{k \in S'_{\sigma \lambda}} \prod_{l \in S'_{\sigma \lambda}} (1-p_l)$ and

$$\frac{\partial f(1)}{\partial p_j} = \prod_{l \in S'_{\sigma \lambda}} (1-p_l) - \sum_{k \in S'_{\sigma \lambda}} p_k \prod_{l \in S'_{\sigma \lambda}} (1-p_l).$$  

(A13)

Given equations (A12) and (A13):

$$\frac{\partial F(1)}{\partial p_j} = \frac{\partial F(0)}{\partial p_j} + \frac{\partial f(1)}{\partial p_j} = -\sum_{k \in S'_{\sigma \lambda}} p_k \prod_{l \in S'_{\sigma \lambda}} (1-p_l).$$  

(A14)

Equation (A11) reduces to (A14) with $n=1$.

We now assume that (A11) is true for $n$ and prove it is true for $n+1$. Given Eq. (A9)

$$f(n+1) = \sum_{\sigma \in \mathcal{S}_{n+1,\lambda}} \prod_{k \in \sigma} p_k \prod_{l \in \sigma} (1-p_l) = \sum_{\sigma \in \mathcal{S}_{n+1,\lambda}} \prod_{k \in \sigma} p_k \prod_{l \in \sigma} (1-p_l) + \sum_{\sigma \in \mathcal{S}_{n+1,\lambda}} \prod_{k \in \sigma} p_k \prod_{l \in \sigma} (1-p_l),$$  

$$= p_j \sum_{\sigma \in \mathcal{S}_{n+1,\lambda}} \prod_{k \in \sigma} p_k \prod_{l \in \sigma} (1-p_l) + \sum_{\sigma \in \mathcal{S}_{n+1,\lambda}} \prod_{k \in \sigma} p_k \prod_{l \in \sigma} (1-p_l).$$

$$\frac{\partial f(n+1)}{\partial p_j} = \sum_{\sigma \in \mathcal{S}_{n+1,\lambda}} \prod_{k \in \sigma} p_k \prod_{l \in \sigma} (1-p_l) - \sum_{\sigma \in \mathcal{S}_{n+1,\lambda}} \prod_{k \in \sigma} p_k \prod_{l \in \sigma} (1-p_l).$$  

(A15)

Hence, by Eq. (A11) and Eq. (A15):

$$\frac{\partial F(n+1)}{\partial p_j} = \frac{\partial F(n)}{\partial p_j} + \frac{\partial f(n+1)}{\partial p_j} = -\sum_{\sigma \in \mathcal{S}_{n+1,\lambda}} \prod_{k \in \sigma} p_k \prod_{l \in \sigma} (1-p_l)<0.$$
Appendix C: Instructions to Subjects

Route Choice Experiment

Introduction
Welcome to an experiment on route selection in traffic networks. During this experiment you will be asked to make a large number of decisions and so will the other participants. Your decisions, as well as the decisions of the other participants, will determine your monetary payoff according to the rules that will be explained shortly.

Please read carefully the instructions below. If you have any questions, raise your hand and one of the experimenters will come to assist you.

Note that hereafter communication between the participants is prohibited. If the participants communicate with one another in any way, the experiment will be terminated.

The Route Selection Task
The experiment is fully computerized. You will make your decisions by clicking on the appropriate buttons or areas of the computer screen. A total of 20 persons participate in this experiment (i.e., 19 participants in addition to you). During the experiment, you will be assigned the role of a driver who chooses a route through a traffic network that is described on the next page. The experiment will consist of two parts. You will first receive the instructions for part 1. After completing part 1, you will receive new instructions for part 2. You will participate in 80 identical rounds in each part. In each of these rounds all 20 participants will simultaneously make route choice decisions that, together, will determine the payoffs for all participants.

Description of Part I of the Experiment
Consider the very simple traffic network exhibited in a diagram form below. Each driver is required to choose one of two routes in order to travel from the starting point, denoted by S, to the final destination, denoted by T. These two routes are designated in the diagram as route 1 and route 2.

\begin{align*}
\text{Cost} &= 0 + 0.01 \times n_1^2 \quad \text{if conditions good} \\
\text{Cost} &= 0 + 0.09 \times n_1^2 \quad \text{if conditions poor} \\
\text{Cost} &= 3 + 0.1225 \times n_2^2 \quad \text{if conditions poor}
\end{align*}
Travel is always costly in terms of the time needed to complete a trip from S to T but those costs vary depending on:

- the route selected (road width, traffic lights etc.)
- the number of other travelers taking that same route (how busy it is)
- current travel conditions (weather, construction, accidents etc.).

The travel costs (measured in ‘points’) are indicated on the diagram near the corresponding route. For example, if you choose route 1 and if conditions are good, you will be charged a total travel cost of 
\(0.01 \times n_1^2\) points where ‘\(n_1\)’ indicates the number of participants (including yourself) who choose route 1. Note that costs go up at an increasing rate as a route becomes more congested. If \(n_1\) is 5 then the cost is 0.25 points (=0.01\(\times 5^2\)). However if traffic on route 1 doubles so that \(n_1\) is now 10 then the cost quadruples to 1 point (=0.01\(\times 10^2\)). Similarly, if you choose route 2 and the conditions are poor, you will be charged a total travel cost of \((3 + 0.1225 \times n_2^2)\). For example, if you are the only one taking route 2, then your cost would be \((3 + 0.1225 \times 1^2) = 3.1225\) points. If nine other persons also choose route 2 then your cost would be \((3 + 0.1225 \times 10^2) = 15.25\) points. In all trials of the experiment, all 20 drivers make their route choices independently of one another, leave point S together, and travel at the same time.

In each round, you will receive a reward of 8 points for reaching your destination. Your net payoff for each round will be determined by subtracting your travel cost for the round from your reward. Hence in the first example above, your net payoff for selecting route 1 (along with 9 others) under good conditions would have been 8 \(-\) 1 = 7 points.

Notice that it is possible for drivers to end up with a negative payoff for any particular round as would be the case above in which 10 drivers chose route 2 and the conditions were poor. The travel cost would be 15.25 points, producing a loss of 7.25 (i.e. 8 \(-\) 15.25 = -7.25) points for those 10 drivers on that round.

Travel conditions will vary from round to round and will be generated randomly with no predictable pattern. They will be either good or poor. The probability of good conditions will be 75% and the probability of poor conditions will be 25% on each route. On any round, conditions may be different on the two routes and will be unknown to all participants until after they make route selections.

At the end of each round you will be informed of the number of drivers who chose each route, the travel conditions and your payoff for that round. All 80 rounds have exactly the same structure.

Procedure

At the beginning of each round the computer will display a diagram with the two routes and the cost functions. You will then be asked to choose which of the routes you wish to travel. To choose a route, simply click on that route. The color of the route that you click on will change to indicate your choice. If
you decide to change your route, click on the other route. Once you have chosen your route, press the "Confirm" button. You will be asked to verify your choice.

After all 20 participants confirm their choices, you will receive the following information:
- The route you have chosen and the subsequent route condition.
- The number of drivers (including you) that chose that route and your payoff.
- The number of drivers that chose the other route, their payoff and route conditions.

Payments
At the end of the experiment, you will be paid for 8 rounds that will be randomly selected from the 80 rounds in part I. The payment rounds will be selected publicly by the toss of a die. You will be paid in cash for your earnings in those eight rounds with an exchange rate of $1 = 3 points (i.e. payoff in dollars = total points in the 8 selected rounds divided by 3).

In addition, you will receive a show up fee of $5 (for attending the experiment). This amount will be paid independently of the payments for the randomly selected rounds.

Once you are certain that you understand the task please place the instructions on the table in front of you to indicate that you have completed reading them. If you have any questions, please raise your hand and one of the supervisors will come to assist you.

Part I of the experiment will begin shortly. Thank you for your participation.

Description of Part II of the Experiment
Part II is identical to part I except for the information that participants have regarding travel conditions. As in part I, travel conditions will be generated randomly and vary from round to round. The probabilities also remain unchanged with the probability of good conditions being 75% and the probability of poor conditions equal to 25%. However in part II, participants will be told the travel conditions for each trial prior to making their route selections. All travel costs and payments remain unchanged.

Procedure
At the beginning of each round the computer will display the diagram with the two routes. Also displayed on the screen will be the travel conditions for this round – either ‘good’ or ‘poor’ on each route and the corresponding cost function will be shown. You will then be asked to choose which of the routes you wish to travel. After all 20 participants confirm their choices, you will receive the same information as in part I.

Payoffs will be determined exactly as in part I, that is, 8 payment rounds will be randomly drawn out of the 80 rounds played, and you will be paid for your earnings in those eight rounds with an exchange rate of $1 = 3 points (i.e. payoff = total points on the 8 selected rounds divided by 3). Therefore, across parts I and II together, you will be paid according to your total earnings in 16 randomly chosen rounds.
Once you are certain you understand the task please place the instructions on the table in front of you to indicate that you have completed reading them. If you have any questions, please raise your hand and one of the supervisors will come to assist you.

Part II will begin shortly.

Thank you for your participation.
Table 1. Social optimum, pure-strategy equilibrium, and symmetric mixed-strategy equilibrium in the zero-information condition (expected costs in brackets)

<table>
<thead>
<tr>
<th>Conditions</th>
<th>Rte 1, Rte 2, Both routes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social optimum</td>
<td>11, 9, 20</td>
</tr>
<tr>
<td></td>
<td>[3.63, 5.48, 4.46]</td>
</tr>
<tr>
<td>Pure-strategy equilibrium</td>
<td>12, 8, 20</td>
</tr>
<tr>
<td></td>
<td>[4.32, 4.96, 4.58]</td>
</tr>
<tr>
<td>Mixed-strategy equilibrium</td>
<td>0.63, 0.37, 1.00</td>
</tr>
<tr>
<td></td>
<td>[5.14, 5.14, 5.14]</td>
</tr>
</tbody>
</table>
Table 2. Social optimum, pure-strategy equilibria, and symmetric mixed-strategy equilibria in the full-information condition (expected costs in brackets)

<table>
<thead>
<tr>
<th>Conditions: Route 1 \ Route 2</th>
<th>Good</th>
<th>Bad</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Rte 1, Rte 2, Both</td>
<td>Rte 1, Rte 2, Both</td>
</tr>
<tr>
<td>Good</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Social optimum</td>
<td>10, 10, 20</td>
<td>16, 4, 20</td>
</tr>
<tr>
<td></td>
<td>[1, 3, 2]</td>
<td>[2.56, 4.96, 3.04]</td>
</tr>
<tr>
<td>Pure-strategy equilibrium</td>
<td>17, 3, 20</td>
<td>18, 2, 20</td>
</tr>
<tr>
<td></td>
<td>[2.89, 3, 2.91]</td>
<td>[3.24, 3.49, 3.27]</td>
</tr>
<tr>
<td>Mixed-strategy equilibrium</td>
<td>0.855, 0.145, 1.00</td>
<td>0.947, 0.053, 1.00</td>
</tr>
<tr>
<td></td>
<td>[3.00, 3.00, 3.00]</td>
<td>[3.61, 3.61, 3.61]</td>
</tr>
<tr>
<td>Bad</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Social optimum</td>
<td>3, 17, 20</td>
<td>11, 9, 20</td>
</tr>
<tr>
<td></td>
<td>[0.81, 3, 2.67]</td>
<td>[10.89, 12.92, 11.80]</td>
</tr>
<tr>
<td>Pure-strategy equilibrium</td>
<td>5, 15, 20</td>
<td>11, 9, 20</td>
</tr>
<tr>
<td></td>
<td>[2.25, 3, 2.81]</td>
<td>[10.89, 12.92, 11.80]</td>
</tr>
<tr>
<td>Mixed-strategy equilibrium</td>
<td>0.235, 0.765, 1.00</td>
<td>0.580, 0.420, 1.00</td>
</tr>
<tr>
<td></td>
<td>[3.00, 3.00, 3.00]</td>
<td>[13.43, 13.43, 13.43]</td>
</tr>
</tbody>
</table>

45
Table 3. Gains and losses from full information for pure-strategy equilibria

<table>
<thead>
<tr>
<th>Conditions: Route 1 \ Route 2</th>
<th>Good</th>
<th>Bad</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Rte 1, Rte 2, E-C</td>
<td>Rte 1, Rte 2, E-C</td>
</tr>
<tr>
<td>Social optimum</td>
<td>10, 10, 2.00</td>
<td>16, 4, 3.04</td>
</tr>
<tr>
<td>Zero information</td>
<td>12, 8, 2.06</td>
<td>12, 8, 5.20</td>
</tr>
<tr>
<td>Full information</td>
<td>17, 3, 2.91</td>
<td>18, 2, 3.27</td>
</tr>
<tr>
<td><strong>Gain from info</strong></td>
<td><strong>-0.84</strong></td>
<td><strong>1.93</strong></td>
</tr>
<tr>
<td>Social optimum</td>
<td>3, 17, 2.67</td>
<td>11, 9, 11.80</td>
</tr>
<tr>
<td>Zero information</td>
<td>12, 8, 8.98</td>
<td>12, 8, 12.11</td>
</tr>
<tr>
<td>Full information</td>
<td>5, 15, 2.81</td>
<td>11, 9, 11.80</td>
</tr>
<tr>
<td><strong>Gain from info</strong></td>
<td><strong>6.16</strong></td>
<td><strong>0.31</strong></td>
</tr>
</tbody>
</table>
Table 4. Expected costs for pure-strategy equilibria [experimental payoffs appear in brackets]

<table>
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<tr>
<th></th>
<th>Uncorrelated conditions</th>
<th>Correlated Conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zero information</td>
<td>4.58</td>
<td>4.58</td>
</tr>
<tr>
<td></td>
<td>[3.42]</td>
<td>[3.42]</td>
</tr>
<tr>
<td>Full information</td>
<td>3.51</td>
<td>5.13</td>
</tr>
<tr>
<td></td>
<td>[4.49]</td>
<td>[2.87]</td>
</tr>
<tr>
<td>Change</td>
<td>-1.06</td>
<td>+0.55</td>
</tr>
<tr>
<td></td>
<td>(-23.36%)</td>
<td>(12.13%)</td>
</tr>
<tr>
<td></td>
<td>[1.07 (+31.29%)]</td>
<td>[-0.55 (-16.08%)]</td>
</tr>
</tbody>
</table>
Table 5. Gain and losses from full information for mixed-strategy equilibria

<table>
<thead>
<tr>
<th>Conditions: Route 1 \ Route 2</th>
<th>Good</th>
<th>Bad</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Rte 1, Rte 2, E-C</td>
<td>Rte 1, Rte 2, E-C</td>
</tr>
<tr>
<td>Good</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Social optimum</td>
<td>2.00</td>
<td>3.04</td>
</tr>
<tr>
<td>Zero information</td>
<td>0.63, 0.37, 2.19</td>
<td>0.63, 0.37, 5.38</td>
</tr>
<tr>
<td>Full information</td>
<td>0.855, 0.145, 3.00</td>
<td>0.947, 0.053, 3.61</td>
</tr>
<tr>
<td><strong>Gain from info</strong></td>
<td><strong>-0.81</strong></td>
<td><strong>1.77</strong></td>
</tr>
<tr>
<td>Bad</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Social optimum</td>
<td>2.67</td>
<td>11.80</td>
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<tr>
<td>Zero information</td>
<td>0.63, 0.37, 10.78</td>
<td>0.63, 0.37, 13.97</td>
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<tr>
<td>Full information</td>
<td>0.235, 0.765, 3.00</td>
<td>0.58, 0.42, 13.43</td>
</tr>
<tr>
<td><strong>Gain from info</strong></td>
<td><strong>7.78</strong></td>
<td><strong>0.54</strong></td>
</tr>
</tbody>
</table>
Table 6. Expected costs for mixed-strategy equilibria [experimental payoffs appear in brackets]

<table>
<thead>
<tr>
<th></th>
<th>Uncorrelated conditions</th>
<th>Correlated conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zero information</td>
<td>5.14</td>
<td>5.14</td>
</tr>
<tr>
<td></td>
<td>[2.86]</td>
<td>[2.86]</td>
</tr>
<tr>
<td>Full information</td>
<td>3.77</td>
<td>5.61</td>
</tr>
<tr>
<td></td>
<td>[4.23]</td>
<td>[2.39]</td>
</tr>
<tr>
<td>Change</td>
<td>-1.37</td>
<td>+0.47</td>
</tr>
<tr>
<td></td>
<td>(-26.67%*  )</td>
<td>(9.16%)</td>
</tr>
<tr>
<td></td>
<td>[1.37 (+47.9%)]</td>
<td>[-0.47 (-16.44%)]</td>
</tr>
</tbody>
</table>
Table 7. Predicted and observed mean number of players choosing route 1 by information regime and route conditions

<table>
<thead>
<tr>
<th>Route conditions</th>
<th>Rounds 1-80</th>
<th>Rounds 81-160</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Unknown</td>
<td>[Good, Good]</td>
</tr>
<tr>
<td>Mean no. occurrences in 80 rounds</td>
<td>80</td>
<td>80</td>
</tr>
<tr>
<td>Correlated [frequency]</td>
<td>13.13</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>[0.7825]</td>
<td>[0.75]</td>
</tr>
<tr>
<td>Uncorrelated [frequency]</td>
<td>13.09</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>[0.5525]</td>
<td>[0.5625]</td>
</tr>
<tr>
<td>$U$</td>
<td>29</td>
<td>-</td>
</tr>
<tr>
<td>$p$ value</td>
<td>ns</td>
<td>-</td>
</tr>
</tbody>
</table>

* Two-sided Wilcoxon-Mann-Whitney test
Table 8. Predicted (pure-strategy) and observed mean normalized payoffs across sessions by information regime and route conditions

<table>
<thead>
<tr>
<th>Information Regime</th>
<th>Correlated conditions</th>
<th>Uncorrelated conditions</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Zero</td>
<td>2.55</td>
<td>3.42</td>
<td>2.71</td>
</tr>
<tr>
<td>Full</td>
<td>2.24</td>
<td>2.87</td>
<td>4.32</td>
</tr>
<tr>
<td>Change</td>
<td>(-12.16%)</td>
<td>(-16.08%)</td>
<td>(+59.41%)</td>
</tr>
<tr>
<td>$U$</td>
<td>35</td>
<td>-</td>
<td>15</td>
</tr>
<tr>
<td>$p$ value</td>
<td>0.075*</td>
<td>-</td>
<td>0.004*</td>
</tr>
</tbody>
</table>

* One-sided Wilcoxon-Mann-Whitney test
** Two-sided Wilcoxon-Mann-Whitney test
Table 9. Predicted (mixed-strategy) and observed mean normalized payoffs across sessions by information regime and route conditions

<table>
<thead>
<tr>
<th>Information Regime</th>
<th>Correlated conditions</th>
<th>Uncorrelated conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zero</td>
<td>2.55</td>
<td>2.86</td>
</tr>
<tr>
<td>Full</td>
<td>2.24</td>
<td>2.39</td>
</tr>
<tr>
<td>Change</td>
<td>(-12.16%)</td>
<td>(-16.44%)</td>
</tr>
</tbody>
</table>
Table 10. Payoff rankings for players who never switched routes

<table>
<thead>
<tr>
<th></th>
<th>Correlated conditions</th>
<th>Uncorrelated conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zero information</td>
<td>1, 2, 3, 24, 27, 42, 43</td>
<td>1, 19, 20, 45, 46, 47</td>
</tr>
<tr>
<td>Full information</td>
<td>5, 6, 41</td>
<td>3, 44</td>
</tr>
</tbody>
</table>
Table 11. Frequency of route switching

<table>
<thead>
<tr>
<th></th>
<th>Payoff</th>
<th>Correlated conditions</th>
<th>Uncorrelated conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Zero information</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Positive</td>
<td>24.34%</td>
<td>29.08%</td>
<td></td>
</tr>
<tr>
<td>Negative</td>
<td>30.36%</td>
<td></td>
<td>23.12% (p&lt;0.001)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Full information</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Positive</td>
<td>19.06%</td>
<td>33.95%</td>
<td></td>
</tr>
<tr>
<td>Negative</td>
<td>43.5%</td>
<td>40.24%</td>
<td>(p&lt;0.01)</td>
</tr>
</tbody>
</table>

Paired t-tests in brackets
Figure 1. Observed mean number of players choosing route 1 in the correlated (top panel) and uncorrelated (bottom panel) treatments (rounds 1-80: zero-information condition, rounds 81-160: full-information condition).
Figure 2. Individual route choice in Session 4 of the uncorrelated condition.
Figure 3. Observed mean number of route switches by information regime and correlation between route conditions.
Figure 4. Simulated route choice using the EWA learning model.