Discussion Paper No. 864

DOES PROVIDING INFORMATION TO DRIVERS REDUCE TRAFFIC CONGESTION?

by

Richard Arnott*

Andre de Palma**

Robin Lindsey***

First version June 1989

Revised November 1989

---

*Boston College, Chestnut Hill, Massachusetts, U.S.A., 02167.

**Northwestern University, Evanston, Illinois, U.S.A., 60208.

***University of Alberta, Edmonton, Alberta, Canada, T6G 2H4, and University of California, Irvine, Irvine, California, U.S.A., 92717.

Abstract

The purpose of this paper is to question the presumption that route guidance and information systems necessarily reduce traffic congestion, and to point out the need to consider the general equilibrium effects of information. A simple model of the morning rush hour is adopted in which commuters choose a departure time and one of two routes to work. While expected travel costs are reduced by perfectly informing all drivers about route capacities, this is not necessarily the case if imperfect information is provided. Furthermore, if the number of drivers is random, both perfect and noisy information can raise expected costs. A heuristic explanation is that, absent tolls, congestion is an uninternalized externality. Information can cause drivers to change their departure times in such a way as to exacerbate congestion.

Introduction

Funds for highway investment have long failed to keep pace with growing traffic volumes and congestion. Traffic engineers and operations researchers have been redirecting attention to other measures for congestion relief. Experiments with route guidance and information systems are under way in several countries. Systems like LISB in Berlin and Autoguide in London are intended to provide on-line up-to-date information to drivers. Such information can influence route and departure time decisions as well as driving speed. A majority of experts believe guidance systems will be in use by the mid-1990s (see the survey of Bieder (1987), and overviews of Boyce (1988) and Ben-Akiva and de Palma (1989)).

In the few pilot studies of route guidance and information systems a small fraction of drivers has been equipped with in-vehicle communications devices. Preliminary results suggesting that the information aids drivers give the impression that information necessarily improves traffic conditions. What this overlooks are the general equilibrium effects of information. When drivers with communication devices receive information and alter their behavior, they affect driving conditions for others, both those with devices and those without. Moreover, if uninformed drivers know that informed drivers are out there they may adjust their behavior too, albeit on a routine rather than daily basis since they lack day-specific information. This may cause informed drivers to make further adjustments, and so on.

In equilibrium, it is conceivable that uninformed drivers could experience an increase in costs that more than offsets the gains to informed drivers.[1] A heuristic explanation for this is that, with unpriced congestion, drivers ignore the effects of their actions on other drivers. In economic parlance, there is an uninternalized externality. There is no reason to believe that in such an environment more information is necessarily better, even if all drivers receive the same information.

The purpose of this paper is to examine analytically the effect of information on drivers' travel costs when congestion is underpriced: that is, no road tolls or parking fees are levied. Tsuji *et al.* (1985) have also investigated this topic at the analytic level. They focus on the benefits from route guidance systems in reduced travel time costs for guided vehicles. Our work goes further in three respects: (1) we allow for schedule delay as well as travel time costs, (2) we model congestion explicitly, and (3) we consider departure time as well as route choice.

Since a general analysis of this extended problem would be very difficult, and since our objective is to exposit some basic ideas, we adopt a simple model of the most severely congested environment: the rush hour. Drivers are assumed to commute each morning from a common origin to a common destination connected by two routes. Drivers receive any information early enough that they can adjust both their departure time and route. Adjustments to information on these two margins are shown to affect congestion quite differently.

The focus of this paper is on one potential source of inefficiency from information systems: drivers who receive common information may tend to make similar route and departure time decisions, thereby increasing congestion. Ben-Akiva and de Palma (1989) call this behavior "concentration". Drivers may also fail to predict how others will react on any given day to information, the possible result again being convergence in actions and greater congestion. This problem, which Ben-Akiva and de Palma (1989) call "overreaction", is not studied here. Also sidestepped are how the response of informed drivers to information affects uninformed drivers, and what fraction of drivers it is optimal to inform, an issue addressed experimentally by Mahmassani and Herman (1988).[2] We do however consider the case where a single driver is informed in order to measure the benefit derived from proprietary information. This may approximate the benefit participating drivers experience in pilot studies of route guidance and information systems, in which only a small fraction of vehicles on the roadway are guided.

In the next section of the paper we outline the model and describe user equilibrium in a nonstochastic environment. Section 2 describes the various sources of uncertainty facing automobile drivers. Section 3 considers user equilibrium with stochastic road capacity and zero information. Section 4 measures the benefits accruing to a single individual from proprietary information, and then examines the case where all drivers are fully informed about capacity. Expected travel costs in equilibrium under zero information are compared with expected costs under full information. Imperfect information is considered in Section 5, correlation in route capacities in Section 6, and demand variability in Section 7. Section 8 summarizes and discusses policy implications.

1. A Nonstochastic Environment

Our model derives from a seminal paper by Vickrey (1969) that has been extended by Hendrickson and Kocur (1981), Fargier (1983), Newell (1988) and Arnott *et al.* (1988, 1989) *inter alios*. Each morning N identical commuters travel from a common origin (home) to a common destination (work downtown) using one of two routes. Individuals are assumed to have a common preferred arrival time (*e.g.* their official work start time), t^*. The cost of arriving early is taken to be β per unit of time early, and the cost of arriving late γ per unit of time late. The unit cost of in-vehicle travel time (including vehicle operating cost and the opportunity cost of time) is α. The trip cost of a commuter departing at time t and using route j, j = 1,2, is thus

$$C_j(t) = \alpha\, T_j(t) + \beta \max\,[0,\ t^* - (t+T_j(t))] + \gamma \max\,[0,\ t+T_j(t)-t^*], \qquad (1)$$

where $T_j(t)$ is travel time on route j for a driver departing at time t.

Travel on route j is assumed to be uncongested except at a bottleneck with flow capacity s_j. If the arrival rate at the bottleneck exceeds capacity, a queue develops behind it. Free-flow travel time between home and the tail of the queue at the bottleneck, and after clearing the bottleneck and reaching work, are taken to be the same on the two routes; without loss of generality they can then be set to zero.[3] Travel time is thus simply

$$T_j(t) = D_j(t)/s_j,$$

where $D_j(t)$ is the number of vehicles in the queue on route j. If $r_j(t)$ is the departure rate from home along route j at time t then

$$D_j(t) = \int_{t_{qj}}^{t} r_j(u)du - s_j(t-t_{qj}),$$

where t_{qj} is the time at which queuing starts on route j.

Drivers are assumed to know the daily departure rate on each route. In equilibrium, no driver can reduce travel cost by changing route or departure time. Equilibrium on route j, with capacity s_j and N_j drivers, is shown in Figure 1. The number of vehicles in the queue is measured by the vertical

Insert Figure 1

distance between the cumulative departures and cumulative arrivals curves. Travel time is measured by the horizontal distance. From the beginning of the rush hour at time t_{qj} the queue builds up to a maximum for the driver departing at time t_{nj} and arriving on time at t^*. The queue decreases thereafter, reaching zero at time $t_{qj} + \frac{N_j}{s_j}$ when the last driver departs.

Total travel time costs are given by α times the area ABCA in the figure, early arrival costs by $\beta \circ$AEFA, and late arrival costs by $\gamma \circ$EGCE.

Equilibrium travel cost per driver is derived as follows. The first driver incurs a cost of early arrival $\beta(t^* - t_{qj})$ and no queuing time cost. The last driver incurs a cost of late arrival of $\gamma(t_{qj} + \frac{N_j}{s_j} - t^*)$ and again no queuing time cost. Equating the two drivers' costs, one obtains $t_{qj} = t^* - \frac{\gamma}{\beta+\gamma} \frac{N_j}{s_j}$ and cost per driver $C_j = \delta \frac{N_j}{s_j}$, where $\delta \equiv \frac{\beta\gamma}{\beta+\gamma}$ is half the harmonic mean of β and γ. With two routes, equilibrium dictates $C_1 = C_2$, or $\delta \frac{N_1}{s_1} = \delta \frac{N_2}{s_2}$. With $N_1 + N_2 = N$, the solution is $N_1 = \frac{s_1}{s_1+s_2} N$ and $C_1 = C_2 \equiv C = \delta \frac{N}{s_1+s_2}$. Total costs are

$$TC^e = \delta \frac{N^2}{s_1+s_2}. \tag{2}$$

In the nonstochastic equilibrium, total travel costs thus depend only on aggregate capacity, not on how it is allocated between routes. Costs are also independent of the unit cost of travel time, α.

2. A Stochastic Environment

2.1 *Sources of uncertainty*

The nonstochastic setting of Section 1 ignores fluctuations of various sorts that affect traffic. Some are predictable weekly and seasonal fluctuations in commuting patterns. Others are unpredictable (accidents and signal failures), or only imperfectly predictable (bad weather and transit strikes). Since drivers can adapt to predictable fluctuations without the help of information systems, only unpredictable fluctuations are considered in this paper.[4] For simplicity, random factors that affect traffic conditions are assumed to be day-specific, *i.e.* unchanging over the course of the day.[5]

Probably the greatest uncertainty facing drivers is road capacity. Poor visibility, precipitation and other adverse weather conditions reduce safe driving speed and affect flow capacity in a continuous manner. Accidents and road repairs that block traffic lanes impact capacity discretely.

In addition to these disruptions, transit strikes, gasoline rationing and other shocks may induce commuters to change their mode of travel. Variations in the mix of commercial and noncommercial vehicles, and commuting and noncommuting traffic also affect congestion and so on. These shocks can be viewed as unpredictable *demand* fluctuations. As shown in Section 7, the impact of information can be quite different where there are demand, rather than capacity, fluctuations.

2.2 *Information and quality of information*

Two polar information regimes are considered in subsequent sections: zero information and full information.

With *zero information*, users learn nothing about road capacities or demand on a given day. Departure time and route decisions, which must then be based on unconditional probability distributions, are the same each day. Users are assumed to have rational expectations, perhaps acquired with long experience, so that the probabilities they perceive coincide with the true unconditional probabilities.

With *full information*, users learn capacity and demand each day.[6] Information is assumed available sufficiently early that users can adjust their departure time and route.[7] Equilibrium each day is thus given by the deterministic solution (2) of Section 1 with the values of s_1, s_2 and N realized on that day.

Zero and full information are extremes. Frequently, individuals receive imperfect day-specific information. Imperfect information can mean one of two things: either *partial information*, *i.e.* information about traffic conditions on only part of the road network, or *noisy information*, which reduces but does not eliminate uncertainty about part or all of the network.

We characterize *partial information* in the case of two routes with stochastic capacity and nonstochastic demand by assuming a signal concerning capacity is received for one of the two routes. With *complete information*, a signal is received for both routes.[8] We characterize noisy information by a quality index, Q, ranging from 0 (no information) to 1 (full information).

3. Equilibrium with Stochastic Capacity and Zero Information

3.1 The zero information setting for one route

We begin by considering one route with a daily capacity s, where $s = s_H$ with probability $(1-\pi)$ and $s = s_L < s_H$ with probability π.[9] In the zero information setting, drivers are assumed to know the probabilities of high and low capacity, but nothing further about capacity on a given day. We assume drivers are risk neutral, so that each minimizes *expected* cost.[10] In equilibrium, expected costs are thus constant during the departure period.

The analytical solution for the zero information regime, which is rather tedious even for this simple case, is derived in Arnott *et al.* (1988). For clarity of exposition we adopt the numerical values given in Table 1. The cost parameters α, β and γ are taken from Small (1982). (The value of t^* is immaterial.)

Insert Table 1

Expected costs per driver under zero information, C^0, are plotted against the probability of low capacity in Figure 2 (the C^F and C^f curves are discussed

Insert Figure 2

below). Observe that C^0 increases monotonically with π, a property that can be shown to hold for all parameter values. While this is intuitive, it is not logically obvious because the possibility of low capacity has a damping effect on the departure rate, and hence congestion. But this turns out to be insufficient to offset the direct effect of lower capacity in increasing congestion.

Another characteristic of C^0, central to later results, is that it bulges upward for intermediate values of π. While it is difficult to elucidate without going into the derivation, this behavior is central, and hence worth an attempt at explanation. In equilibrium, all drivers incur the same expected cost, so it suffices to consider one, say the last driver to depart. With π=0, capacity is high with certainty: the last driver arrives late but never encounters a queue, as in Figure 1. As π rises, the last driver faces a growing probability of a longer trip and greater lateness. To preserve equilibrium, departure times shift earlier, including that of the last driver, which partially offsets his increase in costs. This continues until the last driver is departing at t^*. Further increases in π do not shift the last departure any earlier. (Proof: If they did, the last driver (or any other driver) could delay departure until t^*, which would decrease his schedule delay cost and/or his travel time cost.) The last driver thus bears the full brunt of the increase in expected late time cost, and C^0 rises more rapidly with π. As π continues to increase, however, and departures begin ever earlier, the increase in cost suffered by the last driver when low capacity occurs becomes smaller, and C^0 flattens out.[11]

3.2 *The zero information setting for two routes*

The zero information equilibrium on two routes can be solved in two simple steps. First, equilibrium on each route is computed analytically with an arbitrary number of drivers. Let $C_j^0(N_j)$ denote expected travel cost on route j when N_j drivers use it. N_1 and N_2 can then be determined by the condition that costs are the same on the routes:

$$C_1^0(N_1) = C_2^0(N_2) \equiv C^0(N) \equiv C^0,$$

where $N_1 + N_2 = N$. Total expected costs are simply $TC^0 = NC^0(N)$. With zero information, N_1 and N_2 of course cannot depend on the actual capacities realized on a given day, and hence on whether or not capacities are statistically independent.

4. Stochastic Capacity: Zero Information versus Full Information

4.1 *The value of private information*

Before considering public information, it is useful to assume a single driver learns about capacity before the rush hour begins, and compute the expected benefit to him. With all other drivers uninformed, the numbers of drivers taking each route are independent of day-specific capacities. In general, the route chosen by the informed driver *does* depend on the capacity. But is is easier to assume the driver sticks to one route. While this provides only a lower bound on his benefits, it suffices to make our point.

It is easy to see that if the driver learns capacity is high, he travels in the middle of the rush hour, since the queue will be relatively small. Conversely, if capacity is low, he departs early. In either case, he incurs a lower cost than the average informed driver; hence his expected travel cost, C^f, is less than C^0, as shown for the numerical example in Figure 2. With π = 0 or π = 1, the informed driver is no better off than other drivers since there is nothing to learn. But for intermediate values of π, the expected savings are quite high. For example, with $\pi = 0.1$ the informed driver's expected travel cost (not including free-flow travel time) is \$3.20 per trip, compared to \$7.09 for other drivers. More striking is the fact that the informed driver is actually *better off* over a wide range of positive values of π than at $\pi = 0$, despite the fact that expected capacity is lower.[12]

Of course, these cost savings accrue to just one driver. Most information sources, such as radio reports on accidents and weather are publicly available. Indeed, collecting and disseminating information is cost-effective only if many drivers use it. As more drivers take advantage of the information by altering their departure time or route, benefits per person are likely to decrease. Moreover, informed drivers could gain at the expense of the uninformed. Whether information confers benefits in the aggregate is considered next.

4.2 Full information

We turn now to a situation in which *all* drivers know road capacities each day before departure; we call this full information. Equilibrium is then as described in Section 2 for whatever values of s_1 and s_2 are realized on the given day. Total *expected* travel costs are simply

$$TC^F = \int_{s_1}\int_{s_2} p(s_1,s_2)TC^e(s_1,s_2)ds_2ds_1, \tag{3}$$

where $p(s_1,s_2)$ is the joint probability distribution of s_1 and s_2, $TC^e(s_1,s_2)$ is given by equation (2), and the superscript F denotes full information.

4.3 Relative efficiency of zero and full information

Since the number of drivers is assumed given (*i.e.* nonstochastic and independent of travel costs) the efficiency of the zero and full information regimes can be ranked by comparing their respective total travel costs. It turns out to be possible to do so for any joint probability distribution of s_1 and s_2; for example, those entailing correlation in capacity or mass points. The result is given in:

THEOREM 1

If road capacities are stochastic, but the number of drivers is deterministic, then total costs with full information are lower than with zero information: that is, $TC^F < TC^0$.

Proof: The proof, which is lengthy, is in an appendix available on request.

Theorem 1 is illustrated in Figure 2, where $C^F < C^0$ for $0 < \pi < 1$, and hence $TC^F = NC^F < TC^0 = NC^0$. Theorem 1 suggests that, despite the caveats raised earlier, public information is in fact welfare-improving. As will be seen, however, this is not necessarily true if demand is stochastic, or if only imperfect information is available: the subject of the next section.

5. Stochastic Capacity and Imperfect Information

The full information regime just considered is an abstraction rarely approached in real life. Information about some routes may be available irregularly, if at all. Drivers can miss information bulletins, or simply choose not to listen. Traffic conditions can change during the rush hour, putting earlier information out of date. These remarks apply to route guidance systems in the foreseeable future as well as everyday radio news reports. In this section we examine how imperfect information affects travel costs, and in particular whether it is preferable to no information at all.

5.1 Modeling imperfect information

To avoid unnecessary complexity we resume the assumption of two-point capacity distributions on each route. We characterize imperfect information about s_j by a signal, σ_j. A signal $\sigma_j = \sigma_{jL}$ indicates that s_j is likely to be low, and a signal $\sigma_j = \sigma_{jH}$ that it is likely high. The *ex post* probability of low capacity, conditional on σ_j, is specified in Table 2, where $Q_j \in [0, 1]$ is

Insert Table 2

an index of signal quality. If $Q_j = 0$, the signal conveys no information: the conditional probability distribution of capacity equals the unconditional distribution. At the other extreme, $Q_j = 1$ means the signal is perfectly accurate.

For all values of Q_j the signal is assumed unbiased in the sense that forecasts are made with the same frequency that they occur in reality. Thus, the expected *ex post* probability of low capacity is from Table 2:

$$(1-\pi_j)\pi_j(1-Q_j) + \pi_j[1-(1-\pi_j)(1-Q_j)] = \pi_j.$$

We further assume that the signals on the two routes are independent.

After receiving σ_1 and σ_2, drivers face the same problem as under zero information, but with the conditional probability distributions of capacity instead of the unconditional ones. Expected costs with imperfect information, denoted TC^i, are

$$TC^i = \sum_{\sigma_1} \sum_{\sigma_2} p_1(\sigma_1)p_2(\sigma_2)\ TC^0(\hat{\pi}_1(\sigma_1),\ \hat{\pi}_2(\sigma_2)), \tag{4}$$

where $p_j(\sigma_j)$ is the probability that signal σ_j is received about route j, $\hat{\pi}_j(\sigma_j)$ is the probability of low capacity on j conditional on signal σ_j, and TC^0 is expected cost under zero information for the given probabilities.

Given unbiasedness of the signals, $p_j(\sigma_{jL}) = \pi_j$ and $p_j(\sigma_{jH}) = 1 - \pi_j$.

The efficiency of imperfect information in reducing expected total travel costs relative to full information can be measured with the index

$$\omega \equiv \frac{TC^0 - TC^i}{TC^0 - TC^F} . \tag{5}$$

(Recall from Theorem 1 that $TC^0 - TC^F > 0$.) As TC^i ranges from TC^0 to TC^F, ω ranges from 0 to 1. Yet values of TC^i greater than TC^0, or smaller than TC^F, are also possible as will be seen.

In the next two subsections we compute TC^i, first when signals are received for both routes (complete information), and second when a signal is received only for one route (partial information). For ease of comparison with previous sections, we continue with the numerical example specified in Table 1. To highlight results we assume $\pi_1 = \pi_2 = 0.1805$, where the zero information cost curve C^0 is kinked: see Figure 2. (The importance of the kink is explained below.) If commuters encounter an accident or bad weather on average one day a workweek, which is plausible for some cities, then $\pi = 0.2$, close to the values chosen.

5.2 Complete but noisy information

Under complete information, signals are received for both routes. To begin, assume that the signals are of equal quality. This is shown as Case A in Table 3 (the column labelled 'Capacity Correlation' can be ignored until Section 6) and in Figure 3. Consistent with Theorem 1, $C^F = C^i(Q=1) < C^i(Q=0) = C^0$.

Insert Table 3

Insert Figure 3

is thus negative in this range, attaining a minimum value of about -0.15. This illustrates strikingly that low-quality information can have perverse efficiency effects.

The reason for the perversity is that the probability of low capacity on each route is revised when information is received, upward or downward depending on the signals. Because the unconditional probabilities (0.1805) were chosen at the kink in the cost curve (Figure 2), expected costs are increased when the revisions are not too large, *i.e.* the signals are of low quality. This follows from Jensen's inequality, since expected costs are (locally) a convex function of π, and the signals generate a mean preserving spread in the distribution of π.

It might appear that the informational perversity is an artifact of the assumption that the unconditional probabilities coincide with the kink in the cost function. In fact, the perversity is rather extensive, as shown in Figure 4 by the range of Q and π values (with $\pi_1=\pi_2$) over which it occurs.

Insert Figure 4

In Case B of Table 3, $Q_1 = 1$. Expected costs are plotted against Q_2 in Figure 3. As in Case A, low quality information (small values of Q_2) raises costs. The minimum ω is -0.14, similar to Case A.

5.3 Partial and noisy information

A situation of partial information ($Q_1 = 0$) is considered in Case C. TC^1 behaves similarly to Case B, with the same minimum ω value. The similarity suggests that perversity of low-quality information on one route is insensitive to quality of information elsewhere in the network. Of course, further analysis on a more general network will be necessary to test the robustness of this result.

5.4 Discussion

The results here demonstrate that Theorem 1 is misleading from a practical standpoint: *low-quality information can be counter-productive.* Furthermore, high-quality information may be difficult to achieve, either because weather forecasts or accident reporting are intrinsically imprecise, or because accurate information cannot be conveyed intelligibly and/or with sufficient dispatch to drivers. Given these limitations, the possibility that imperfect information reduces welfare (raises travel costs) should not be taken lightly.

6. Correlation in Capacity

So far it has been assumed that s_1 and s_2 are statistically independent. This may be reasonable for fluctuations caused by accidents and unscheduled road maintenance, but is implausible for bad weather, which is likely to have similar effects on capacities. Correlation in capacities might appear to be an exogenous factor, and hence of no policy interest. However, situations may exist where some control can be exerted. For example, the allocation of snow removal equipment, police surveillance and towing services between routes affect correlation. Also, there may be a choice between constructing two routes that are similarly affected by weather, or making one relatively impervious to the elements (say at equal total cost).

Correlation in road capacities could thus be a tool for improving traffic flow under stochastic conditions. And whether it is or not, it is a significant feature of road networks that deserves attention. In this section the analysis is generalized to investigate the effect of correlation on system performance.

6.1 Modeling correlation

The simple correlation coefficient between s_1 and s_2, ρ, is given by the standard formula

$$\rho = \frac{E(s_1-\bar{s}_1)(s_2-\bar{s}_2)}{[\mathrm{Var}(s_1)\mathrm{Var}(s_2)]^{1/2}} ,$$

where E is the expectations operator, $\bar{s}_j$ is mean capacity of route j and $\mathrm{Var}(s_j)$ is its variance. The joint probability distribution of s_1 and s_2 is then as given in Table 4.

Insert Table 4

Information on route capacities can be considered along with correlation; for simplicity, a signal is assumed available on only one route. The joint probability density of capacities, conditional on the signal, is specified in Table 5, where Q is the quality of one signal.

Insert Table 5

6.2 Robustness of previous results

To test the robustness of the results derived with zero correlation, we begin with the polar case of perfect correlation. Information about capacity on one route is then equally applicable to the other route; in effect $Q_1 = Q_2$ and the two routes are equivalent to a single route with capacity $s_1 + s_2$. This puts us back in Case A except for the correlation, hence the label A^c in Table 3 and Figure 3.

First, note from Figure 3 that for any $Q > 0$, expected costs are greater than in Case A. As earlier, this follows from Jensen's inequality since total costs are a convex function of s_1+s_2 and correlation creates a mean preserving spread in total capacity.

Second, observe that low-quality information has a more detrimental effect than with no correlation: the minimum ω is -0.39 compared to -0.14.

This reinforces the conclusion that imperfect information can be worse than no information. Moreover, the range of Q over which the informational perversity occurs is considerably greater than with zero correlation: compare Figure 5

Insert Figure 5

with Figure 4. This suggests that information has a beneficial effect on route choice that partially offsets the adverse effect on the departure rate. Both effects are present in Figure 4, whereas in Figure 5 only the departure rate is relevant, since with perfect capacity correlation route split is invariant to the signal.

The effect of partial correlation on travel costs is examined in cases B^c and D^c over the range $\rho \in [0, 1]$. (Negative correlation is a theoretical possibility, but we suspect rare in reality, and hence not considered.) Case B^c is similar to case B in that full information is available about route 1, and partial information about route 2. But in case B^c, information on route 2 is obtained *indirectly* through correlation, whereas in case B it is obtained directly from a separate signal. In Case D^c, which has no counterpart, capacity on both routes is assumed to be known exactly. Case D^c isolates the effect of correlation on expected costs, since there is no informational effect.

As shown in Figure 6, expected costs in Case D^c increase monotonically with ρ, as expected. But in case B^c, costs *increase* with ρ initially. This

Insert Figure 6

behavior is the result of two opposing forces. On the one hand, correlation increases the variance of total capacity, which tends to increase costs. This is the only effect at work in case D^c. On the other hand, the quality of information about s_2 contained in σ_1 increases with ρ. For small values of ρ, the quality of this indirect information is low. From Section 5 we know that low quality information increases costs. The informational effect of correlation thus reinforces the capacity effect. But at higher values of ρ, the informational effect becomes negative, and eventually dominates the capacity effect, so that total costs fall.

6.3 Discussion

Earlier, the possibility was raised that correlation between road capacities can be controlled, perhaps through highway design, or the mixture of bridges and tunnels running in parallel into major cities. For the most part, the results of this section indicate that correlation should be minimized. But in case B^c, both high and low correlation are preferable to intermediate correlation. Thus, if correlation is naturally high to begin with, it may be simpler to reduce costs by increasing correlation further than reducing it a lot.

Overall, the conclusion of this section is that correlation in capacities does not alter qualitatively the findings of Section 5. Partial information can affect efficiency perversely, though full information is preferable to no information. In the next section, we examine whether these findings hold up when the number of drivers is random.

7. Fluctuations in Demand

Until now the analysis has been limited to capacity fluctuations. But, as argued earlier, the number of drivers, even on commuting routes, can be affected by such events as transit strikes and gasoline rationing. For clarity it is now assumed that road capacities are constant and only the number of drivers is subject to fluctuations. Zero information thus means that only the unconditional probability distribution of N is known. Full information means that the actual value of N is learned each day.

With constant capacities, two (or more) routes are equivalent to one with the same total capacity, and a theorem in Arnott *et al.* (1988) is applicable; we restate it here without proof as a counterpart to Theorem 1:

THEOREM 2

If the number of drivers is stochastic, but road capacities are deterministic then, depending on parameter values, total costs with full information may be higher or lower than with zero information: $TC^F \lesseqgtr TC^0$.

Theorem 2 casts further doubt on the conclusion suggested by Theorem 1 that traffic flow is improved by providing drivers with information. Furthermore, by continuity of expected costs in parameters, full information may still be inferior to zero information when capacities are random as well as demand, and whether or not they are statistically independent.

8. Conclusions

Pilot studies of route guidance and information systems indicate that drivers can benefit from information about driving conditions. The purpose of this paper is to question the presumption that such information is necessarily beneficial for traffic as a whole. While a single driver can benefit from proprietary information, when all drivers are informed they may end up worse off. If only road capacity is random, expected travel costs are lower when individuals are fully informed than when uninformed. But this need not be the case if the number of drivers is also random. Moreover, if only imperfect information is available, drivers may be worse off than without information even when only capacity is variable. The adverse impact on welfare would be enhanced if costs of collecting and processing information were taken into account.

Our findings suggest caution against undiscerning use of information systems. Pilot studies in which a few vehicles are equipped with communications devices do no measure the overall welfare effects of information. Rather than conducting small-scale studies, effort might be better directed at a large-scale experiment in which the general equilibrium effects of driver adjustment to information can be assessed.

We hasten to note that the model we have used is very simple and the analysis exploratory. There are several directions in which extensions could be fruitfully pursued. First, the analysis was limited to one route or two routes in parallel. It should be extended to more complex networks, as Tsuji *et al*. (1985) have done.

Second, we have only considered information available to drivers before they depart. Road guidance systems are also intended to supply in-vehicle information and advise drivers on route changes while they are in transit. To analyze this it will be necessary to enrich the time dimension of the model, and allow for changes in the state of the system (*e.g.* removal of a traffic obstruction) during the travel period. In addition, it would be useful to consider the effects of lags in getting information to drivers, and the implications of under- or over-reaction of drivers in the aggregate to new information.[13]

Third, traffic information rarely reaches everyone. An interesting question is whether traffic flow conditions are optimized when all drivers are informed, or whether information should be provided to only some. Mahmassani and Herman (1988) and Mahmassani and Jayakrishnan have considered this by using special-purpose simulation programs.

Finally, the analysis has been static in the sense that drivers are assumed to utilize information available to them. However, rather than adjusting instantaneously to temporary or permanent changes in their driving environment, drivers often react with lags. Models incorporating the day-to-day adjustment of drivers may capture more accurately the ways individuals react to changes.

One of the challenges for designers of road guidance systems is to determine what type of information to provide, when to provide it, to whom and in how much detail. We hope that this paper has shed some light on these problems, or at least raised questions that deserve further investigation.

FOOTNOTES

* Financial support from the Natural Science and Engineering Research Council of Canada and from NATO is gratefully acknowledged.

---

1 Hirshleifer (1971) has shown that the private benefits from proprietary information can be more than offset by the losses of other agents in the economy.

2 Haltiwanger and Waldman (1985) have considered the implications of informational heterogeneity for abstract environments in which individuals impose either negative externalities on each other (*e.g.* congestion) or positive externalities.

3 Computations in later sections were also done with different free-flow travel times, but the results of interest were little affected. To economize on space they are not reported.

4 A study of Greater London found unpredictable incidents occur about twice as frequently as predictable ones (Jeffrey and Russam (1984)). CALTRANS has reported that nonrecurring congestion accounts for 57% of delays on Los Angeles freeways (Ju *et al.* (1987)). And incident delay contributes over 60% of urban freeway delay in the U.S. (Lindley (1987)).

5 Admittedly, this is not true of most traffic incidents; see Giuliano (1989). It is not obvious what effect relaxing this assumption would have on the results.

6 Information reports are usually couched in terms of travel times or delay, rather than capacity and demand. At least in our model, however, the duration of a trip for any given departure time and route can be computed from capacity and demand; we assume drivers have learned to do this through experience. From the perspective of decision-making, the two types of information are equivalent, and since capacity and demand are assumed to be the source of uncertainty, it is convenient to speak in terms of them directly.

[7] All drivers need not adjust, just enough for the departure rate on each route to change from day to day consistent with the equilibria derived below. Ben-Akiva *et al.* (1986) have described for a nonstochastic environment a day-to-day adjustment process for drivers by which their decisions converge from starting conditions in the neighborhood of equilibrium.

Since commuting trips are made regularly, it is reasonable to assume that, except perhaps for rare circumstances, equilibrium in the sense of equal expected travel costs obtains each day. If drivers adopt pure decision strategies, each will stick to a given departure time and route when presented with the same information. If drivers adopt mixed strategies, stochastic queuing will occur, but if individual randomizations are statistically independent these perturbations are likely to be insignificant.

[8] We use the term complete information in a different sense from that of game theory.

[9] Except if indicated otherwise, two-point capacity distributions are used throughout the paper. The analysis can be extended to more complicated distributions, but we believe this would not alter the qualitative results.

[10] Since the combined monetary, schedule delay and travel time cost of one commute is a tiny fraction of wealth, this is unobjectionable. Extreme aversion to, say, arriving late could be captured with a nonlinear schedule delay cost function.

[11] It may appear from this explanation that the convexity in C^0 arises from the kink in the schedule delay cost function at t^*. It can be shown, however, that convexity also occurs with a quadratic schedule delay cost function - which is everywhere differentiable.

[12] This result would be strengthened if the informed driver were allowed to choose his route.

[13] For example, in the recent strike by bus, railway and underground workers in London England, road traffic was abnormally light. Anticipating massive traffic jams, many commuters apparently departed for work earlier than usual, walked, or stayed home (Globe and Mail (1989, p. A4)).

List of Tables

Table 1: Parameter Values for Numerical Example

Table 2: Conditional Probability Distribution of Capacity

Table 3: Effect of Information on Expected Travel Costs

Table 4: Joint Probability Distribution $p(s_1,s_2)$ with Capacity Correlation

Table 5: Joint Probability Distribution of Capacity with Correlation and Partial Information

List of Figures

Figure 1: Equilibrium Departure Rate and Arrival Distribution on Either Route in Equilibrium.

Figure 2: Expected Travel Cost per Driver: One Route

Figure 3: Effect of Information on Expected Travel Cost per Driver

Figure 4: Parameter Values for which Partial Information Increases Expected Travel Costs

Figure 5: Parameter Values for which Partial Information Increases Expected Travel Costs

Figure 6: Effect of Capacity Correlation on Expected Travel Cost

Table 1

Parameter Values for Numerical Example

Unit cost of travel time	α	\$6.40/hr.
Unit cost of early arrival	β	\$3.90/hr.
Unit cost of late arrival	γ	\$15.21/hr.
Number of commuters	N	8,000
<u>One route</u>		
High capacity	s_H	4,000
Low capacity	s_L	2,000
<u>Two routes</u>		
High capacity on either route	s_H	2,000
Low capacity on either route	s_L	1,000

Values of α, β and γ from Small (1982, Table 2, model (1)).

Table 2

Conditional Probability Distribution of Capacity

Signal	Probability of low capacity on route i
None	π_i
Indicates high capacity	$\pi_i(1-Q_i)$
Indicates low capacity	$1 - (1-\pi_i)(1-Q_i)$

Table 3

Effect of Information on Expected Travel Costs

Case	Quality of Signal Q_1	Q_2	Capacity Correlation ρ	Minimum Efficiency of Information ω
A	$Q_1=Q_2$	$\in[0,1]$	0	-0.15
B	1	$\in[0,1]$	0	-0.14
C	0	$\in[0,1]$	0	-0.14
A^c	$Q_1=Q_2$	$\in[0,1]$	1	-0.39
B^c	1	0	$\in[0,1]$	N/A
D^c	1	1	$\in[0,1]$	N/A

$\pi_1 = \pi_2 = 0.1805$. Other parameter values given in Table 1.

Table 4

Joint Probability Distribution $p(s_1, s_2)$

with Capacity Correlation

		s_2: High	s_2: Low
s_1	High	p	$1-\pi_1-p$
	Low	$1-\pi_2-p$	$\pi_1+\pi_2+p-1$

$$p \equiv (1-\pi_1)(1-\pi_2) + \rho\sqrt{\pi_1(1-\pi_1)\pi_2(1-\pi_2)}.$$

Table 5

Joint Probability Distribution of Capacity

with Correlation and Partial Information

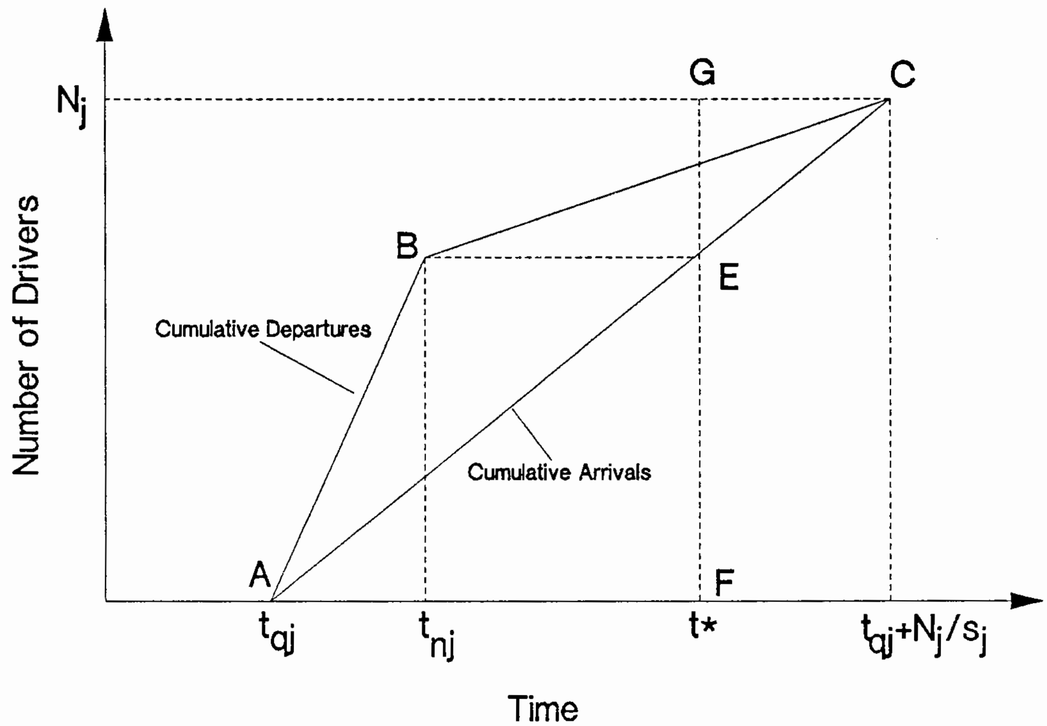
(a): If signal indicates high capacity

s_1 \ s_2	High	Low
High	$\frac{p}{1-\pi_1}\,[1-\pi_1(1-Q)]$	$\frac{1-\pi_1-p}{1-\pi_1}\,[1-\pi_1(1-Q)]$
Low	$(1-\pi_2-p)(1-Q)$	$(\pi_1+\pi_2+p-1)(1-Q)$

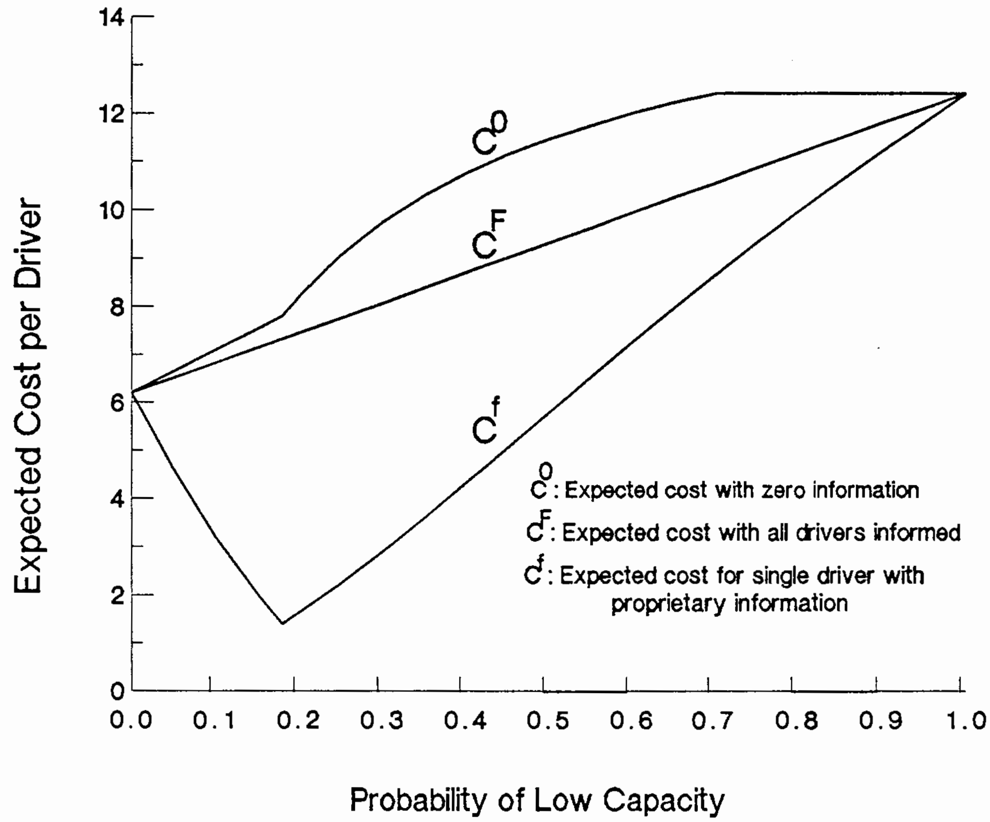
(b): If signal indicates low capacity

s_1 \ s_2	High	Low
High	$p(1-Q)$	$(1-\pi_1-p)(1-Q)$
Low	$\frac{(1-\pi_2-p)}{\pi_1}\,[1-(1-\pi_1)(1-Q)]$	$\frac{(\pi_1+\pi_2+p-1)}{\pi_1}\,[1-(1-\pi_1)(1-Q)]$

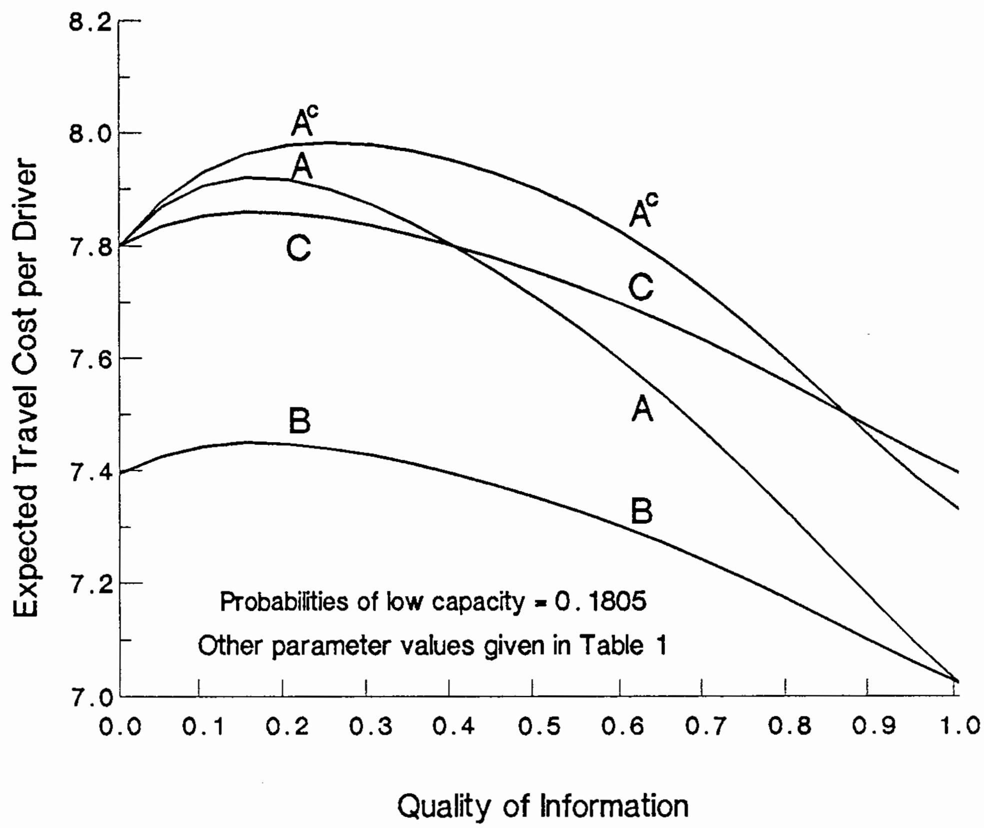
$$p \equiv (1-\pi_1)(1-\pi_2) + \rho\sqrt{\pi_1(1-\pi_1)\pi_2(1-\pi_2)}.$$



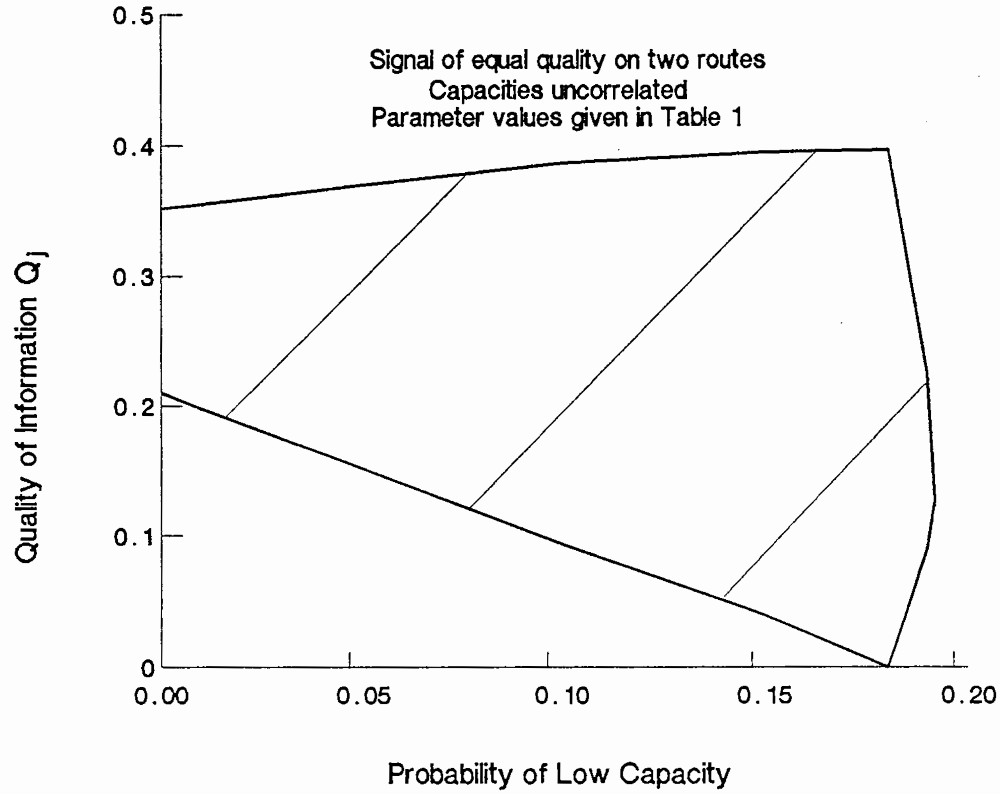
G
C
N_j
B
E
Cumulative Departures
Number of Drivers
Cumulative Arrivals
A
F
t_qj
t_nj
t*
t_qj+N_j/s_j
Time

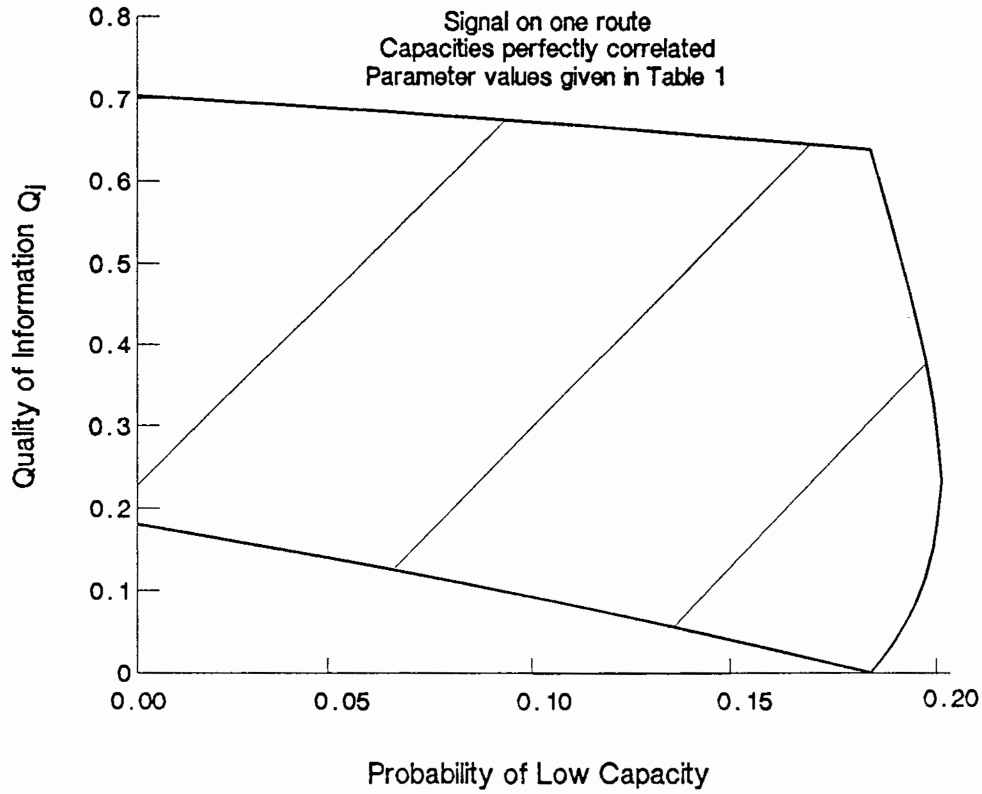


Expected Cost per Driver
14
12
10
8
6
4
2
0
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
Probability of Low Capacity
C^0
C^F
C^f
C^0: Expected cost with zero information
C^F: Expected cost with all drivers informed
C^f: Expected cost for single driver with proprietary information

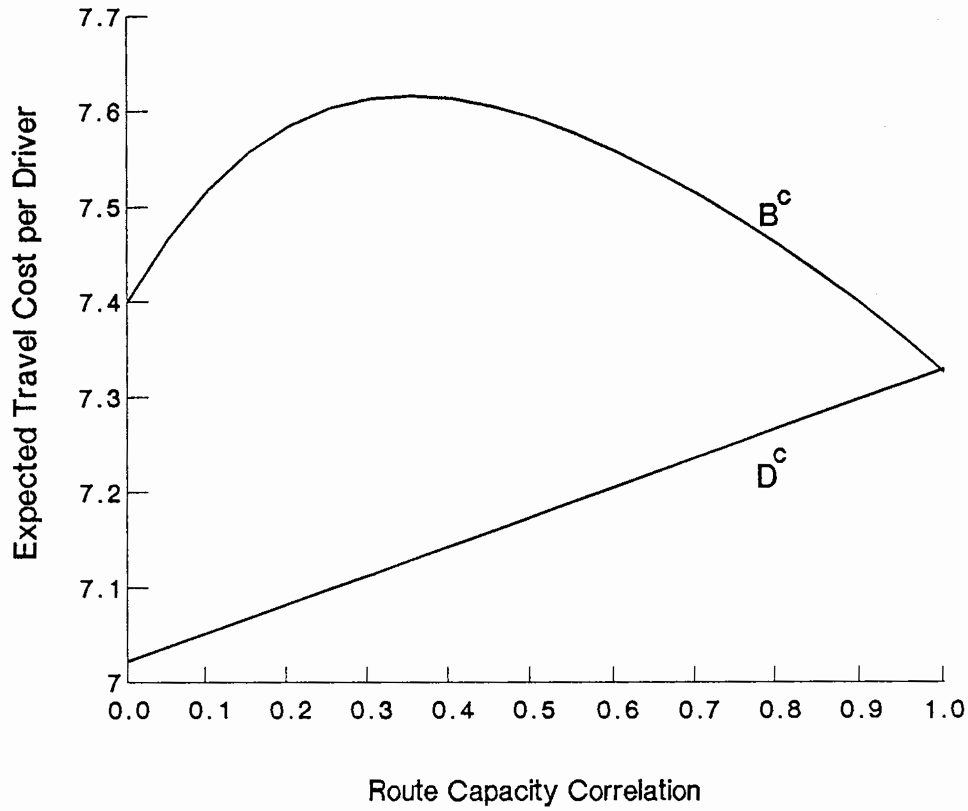


Expected Travel Cost per Driver
8.2
8.0
7.8
7.6
7.4
7.2
7.0
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
A^c
A
C
B
A^c
C
A
B
Probabilities of low capacity = 0.1805
Other parameter values given in Table 1
Quality of Information


Signal of equal quality on two routes
Capacities uncorrelated
Parameter values given in Table 1
Quality of Information Q_j
Probability of Low Capacity
0.5
0.4
0.3
0.2
0.1
0
0.00
0.05
0.10
0.15
0.20



Signal on one route
Capacities perfectly correlated
Parameter values given in Table 1
Quality of Information Q_j
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0.00
0.05
0.10
0.15
0.20
Probability of Low Capacity



Expected Travel Cost per Driver
7.7
7.6
7.5
7.4
7.3
7.2
7.1
7
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
Route Capacity Correlation
B^c
D^c

ACKNOWLEDGMENTS

We are grateful to Fred Hall for motivation, and to an anonymous referee and seminar participants at MIT, Northwestern, and the University of Kyoto for helpful suggestions.

REFERENCES

Arnott, R., de Palma, A. and Lindsey, R. (1988). Information and time-of-use decisions in stochastically congestible facilities. Northwestern Centre for Mathematical Studies in Economics and Management Science working paper No. 788, June 1988.

Arnott, R., de Palma, A. and Lindsey, R. (1989). Economics of a bottleneck. Journal of Urban Economics. Forthcoming.

Ben-Akiva, M. and de Palma, A. (1989). Dynamic Network Models and Driver Information Systems. Paper presented at the U.S.-Italy joint seminar on Urban Traffic Networks, Naples, Italy, June.

Ben-Akiva, M., de Palma, A. and Kanaroglou, P. (1986). Dynamic model of peak traffic congestion with elastic arrival rates. Transpn. Sci. 20, 164-181.

Bieder, A. (1987). Le project ARISE. Recherche Transport Securité. 15, 46-52.

Boyce, D.E. (1988). Route guidance systems for improving urban travel and location choices. Transportation Research A. 22, 275-281.

Fargier, P.H. (1983). Effects of the choice of departure time on road traffic congestion: theoretical approach. In Proceedings of the Eighth International Symposium on Transportation and Traffic Theory. University of Toronto Press, 223-263.

Giuliano, G. (1989). Incident characteristics, frequency, and duration on a high volume urban freeway. Transportation Research A. 23A(5), 387-396.

Globe and Mail. (1989). London sidewalks take the brunt of 24-hour rail, transit shutdown. June 22.

Haltiwanger, J. and Waldman, M. (1985). Rational expectations and the limits of rationality: an analysis of heterogeneity. American Economic Review. 75, 326-340.

Hendrickson, C. and Kocur, G. (1981). Schedule delay and departure time decisions in a deterministic model. Transportation Science. 15(1), 62-77.

Hirshleifer, J. (1971). The private and social value of information and the reward to inventive activity. American Economic Review 61. 561-574.

Jeffrey, D.J. and Rusam, K. (1984). Information systems for drivers. Transportation Planning and Technology. 185-198.

Ju, R-S, Cook, A.R. and Maze, T.H. (1987). Techniques for managing freeway traffic congestion. Transportation Quarterly. 41(4), 519-537.

Lindley, J.A. (1987). Urban freeway congestion: quantification of the problem and effectiveness of potential solutions. ITE Journal. 57(1), 27-32.

Mahmassani, J. and Herman, R. (1988). Interactive experiments for the study of tripmaking behavior dynamics in congested commuting systems. In Jones, P. (ed.). New Developments in Dynamic and Activity-Based Approaches. Gower. (In press.)

Newell, G.F. (1988). Traffic flow for the morning commute. Transportation Science. 22(1), 47-58.

Small, K. (1982). The scheduling of consumer activities: work trips. American Economic Review. 72(3), 467-479.

Tsuji, H., Takahashi, R., Kawashima, H. and Yamamoto, Y. (1985). A stochastic approach for estimating the effectiveness of a route guidance system and its related parameters. Transportation Science. 19(4), 333-351.

Vickrey, W.S. (1969). Congestion theory and transport investment. American Economic Review (Papers and Proceedings). 59, 251-261.

APPENDIX: Proof of Theorem 1

THEOREM 1

If road capacities are stochastic, but the number of drivers is deterministic, then total costs with full information are lower than with zero information: that is, $TC^F < TC^0$.

PROOF

Full information

Substitution of equation (2) in the text into equation (3) gives

$$TC^F = \int_{s_1}\int_{s_2} p(s_1, s_2)\ \delta \frac{N^2}{s_1 + s_2}\ ds_2 ds_1.$$

With the number of drivers, N, nonstochastic, and $\sigma_j \equiv 1/s_j$ this can be written:

$$TC^F = \delta N^2\ E\left\{\frac{\sigma_1\sigma_2}{\sigma_1+\sigma_2}\right\}, \tag{A1}$$

where E is the expectations operator.

Zero information

Whatever the actual values of s_1 and s_2 on a given day, the travel cost incurred by the first driver on route j is nonstochastic, and equal to

$$C_j^0 = \beta(t^* - t_{qj}). \tag{A2}$$

We need to express $t^* - t_{qj}$ in a convenient form. Let $H_j(\sigma_j)$ be the CDF of σ_j. Define

$$\tilde{\sigma}_j \equiv H_j^{-1}\left(\frac{\alpha}{\alpha+\gamma}\right),$$

and the mean of σ_j for values greater than this fractile:

$$\hat{\sigma}_j \equiv \frac{\alpha+\gamma}{\gamma} \int_{\tilde{\sigma}_j}^{\infty} \sigma_j \, dH_j(\sigma_j).$$

Arnott *et al.* (1988, Lemma 1) show that if

$$\tilde{\sigma}_j > \frac{\gamma}{\beta+\gamma} \hat{\sigma}_j \tag{A3}$$

then the last driver on route j departs *after* t^*, and

$$t^* - t_{qj} = \frac{\gamma}{\beta+\gamma} N_j \hat{\sigma}_j. \tag{A4}$$

If (A3) does not hold then (Arnott *et al.* (1988, Lemma 2)) the last driver departs *at* t^*, and

$$t^* - t_{qj} = N_j \check{\sigma}_j, \tag{A5}$$

where $\check{\sigma}_j$ is defined implicitly by

$$\check{\sigma}_j H_j(\check{\sigma}_j) + \int_{\check{\sigma}_j}^{\infty} \sigma_j \, dH_j(\sigma_j) - \frac{\alpha+\beta+\gamma}{\alpha+\gamma} \check{\sigma}_j = 0. \tag{A6}$$

Denote the combined solution of (A4) and (A5)

$$t^* - t_{qj} = \frac{\gamma}{\beta+\gamma} N_j \sigma_j^*, \tag{A7}$$

where $\sigma_j^* = \hat{\sigma}_j$ or $\frac{\beta+\gamma}{\gamma} \check{\sigma}_j$, depending on whether or not condition (A3) holds.

In equilibrium $C_1^0 = C_2^0 = C^0$, or given (A2) and (A7)

$$C^0 = \delta N_1 \sigma_1^* = \delta N_2 \sigma_2^*. \tag{A8}$$

Let f_j be the fraction of drivers taking route j. (A8) can be rewritten

$$C^0 = \delta f_1 N \sigma_1^* = \delta f_2 N \sigma_2^*,$$

which can be solved for the route splits

$$f_1 = \frac{\sigma_2^*}{\sigma_1^* + \sigma_2^*}, \quad f_2 = \frac{\sigma_1^*}{\sigma_1^* + \sigma_2^*},$$

and total expected costs

$$TC^0 = \delta N^2 \frac{\sigma_1^* \sigma_2^*}{\sigma_1^* + \sigma_2^*}. \tag{A9}$$

Given (A1) and (A9):

$$TC^0 - TC^F = \delta N^2 \left[\frac{\sigma_1^* \sigma_2^*}{\sigma_1^* + \sigma_2^*} - E\left\{ \frac{\sigma_1 \sigma_2}{\sigma_1 + \sigma_2} \right\} \right].$$

We show this is positive by establishing the dual inequality

$$\frac{\sigma_1^* \sigma_2^*}{\sigma_1^* + \sigma_2^*} > \frac{\bar{\sigma}_1 \bar{\sigma}_2}{\bar{\sigma}_1 + \bar{\sigma}_2} \geq E\left\{ \frac{\sigma_1 \sigma_2}{\sigma_1 + \sigma_2} \right\}, \tag{A10}$$

where $\bar{\sigma}_j$ is the mean of σ_j. The second inequality in (A10) follows from Jensen's inequality since $\frac{\sigma_1 \sigma_2}{\sigma_1 + \sigma_2}$ is a concave function of σ_1 and σ_2.

To establish the first inequality we shall show

$$\sigma_j^* > \bar{\sigma}_j. \tag{A11}$$

If (A3) is satisfied, then $\sigma_j^* = \hat{\sigma}_j$. Since $\hat{\sigma}_j$ is a mean of σ_j with the left-hand tail truncated, (A11) follows immediately. If (A3) is not satisfied, then $\sigma_j^* = \frac{\beta+\gamma}{\gamma} \check{\sigma}_j$, with $\check{\sigma}_j$ defined by (A6). To establish (A11) we need to show

$$\check{\sigma}_j > \frac{\gamma}{\beta+\gamma} \bar{\sigma}_j. \tag{A12}$$

Denote $\check{\sigma}_j$ by σ for short, and call the LHS of (A6) $Y(\sigma)$. We have

$$dY(\sigma)/d\sigma = H(\sigma) - \frac{\alpha+\beta+\gamma}{\alpha+\gamma} < 0.$$

(A12) then follows if $Y(\frac{\gamma}{\beta+\gamma} \bar{\sigma}) > 0$. But

$$Y\left(\frac{\gamma}{\beta+\gamma} \bar{\sigma}\right) = \frac{\gamma}{\beta+\gamma} \bar{\sigma} H\left(\frac{\gamma}{\beta+\gamma} \bar{\sigma}\right) + \int_{\frac{\gamma}{\beta+\gamma} \bar{\sigma}}^{\infty} \sigma dH(\sigma) - \left(1 + \frac{\beta}{\alpha+\gamma}\right) \frac{\gamma}{\beta+\gamma} \bar{\sigma}. \tag{A13}$$

$$\text{Now} \int_{\frac{\gamma}{\beta+\gamma}\bar{\sigma}}^{\infty} \sigma dH(\sigma) = \bar{\sigma} - \int_{0}^{\frac{\gamma}{\beta+\gamma}\bar{\sigma}} \sigma dH(\sigma) > \bar{\sigma} - \frac{\gamma}{\beta+\gamma}\bar{\sigma}\, H\left(\frac{\gamma}{\beta+\gamma}\bar{\sigma}\right). \tag{A14}$$

Substitute (A14) into (A13) to get

$$Y\left(\frac{\gamma}{\beta+\gamma}\bar{\sigma}\right) > \left[1 - \frac{(\alpha+\beta+\gamma)\gamma}{(\alpha+\gamma)(\beta+\gamma)}\right]\bar{\sigma} > 0. \quad \text{QED.}$$

This establishes that (A11) holds whether (A3) is satisfied or not, and hence that it holds for both routes. This in turn establishes (A10) and that $TC^{0} > TC^{F}$. QED.