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Socio-economic Attributes and Impacts of Travel Reliability: A Stated Preference Approach

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ABSTRACT

This research examines the behavioral reactions to the impact of changes in the probability of a non-recurrent incident and how this effects the expected costs of a commute trip. The basic approach combines the estimation of a travel demand model (estimated with data collected from a stated preference survey) with a supply side model of a congested highway. We also examine the impact of various socio-economic variables, including a detailed classification of occupational groupings. Our demand model is based on a theoretical model developed to explain how unreliability in travel times affects expected travel costs. We find that expected schedule delay (early and late), lateness probability, and expected travel time influence the expected costs of travel. Our parameter estimates confirm the anticipated values of these parameters: lateness probability has a high disutility, while expected schedule delay early is preferable to expected schedule delay late, and the disutility of expected travel time is between these two. We do not find a high level of significance for planning costs, as expressed by the variance in travel times. Our simulation model shows that schedule costs and lateness probability represent a large fraction of the total cost to the commuter; these are generally not affected by capacity increases but can be reduced by decreasing the probability of a non-recurrent incident.

KEYWORDS: Computer Simulation, Dynamic Departure Time Choice, Policy, Travel Behavior

EXECUTIVE SUMMARY

This research investigates the question: How do travelers react to'changes in the reliability of the highway system? There is much evidence that people place considerable importance on the certainty with which they can anticipate travel conditions at any particular time of day. But very little empirical measurement has been done of just how this affects their travel. What little has been done is limited to measuring the overall deterrent effect of unreliability on choice of mode or route.

Yet theoretical analyses of reliability emphasize that its main effect is to make the traveler's arrival time at the destination unpredictable. This suggests that one primary form of adjustment that can be expected is shifts in schedule, for example leaving home earlier in order to provide a greater buffer against late arrivals at work.

These adjustments may be incomplete, leaving a residual probability of arriving late; this imposes a cost on the traveler. Also, the adjustments have their own costs: for example time spent at the destination prior to the desired arrival time may be unproductive or unpleasant compared to the alternative of starting the trip later. In order to fully evaluate measures that change the reliability of the highway system, these behavioral adjustments must be anticipated and their costs measured. This research addresses these tasks through a theoretical model of scheduling choice in the face of uncertain travel times, and through a survey of commuters in the Los Angeles region.

The theoretical model (section 3) takes as its starting point two previous types of models found in the literature: (i) choice of travel schedule in situations of dynamic congestion but no uncertainty; (ii) choice of travel schedule in situations of uncertainty but no recurrent congestion.

By merging these strains of literature, we obtain a richer model that explicitly addresses how people react to both recurrent and non-recurrent congestion by altering their travel schedules, and that provides a measure of the costs to them of each aspect of the scheduling choice. The theory suggests that travelers will make substantial but not necessarily complete adjustments to offset increases in the unreliability of the system, and that these adjustments impose considerable costs.

In our survey work (section 4), respondents are asked a series of questions about their actual commuting situation, their flexibility regarding arrival time at work, related work traits such as ability to stay late or take work home, and the nature of their occupation. They are then asked a set of “stated preference” questions in which they report their preferences among different hypothetical commuting situations, which are designed to resemble to some degree their actual commuting situation. Each hypothetical situation specifies a set of five possible travel times for the commute, each to be realized with equal probability; and a departure time from home (stated relative to the previously ascertained desired work arrival time). Respondents therefore have the opportunity to consider how they trade off mean travel time, variation in travel times, and schedule.

The analysis of actual commutes (section 5) shows that there are wide variations in employers’ degree of flexibility toward travel schedules and in workers’ ability to adjust their work arrival times. These variations are somewhat related to occupational categories, with roughly the more structured occupations showing less flexibility. The specific consequences of late arrivals also differ across occupations, with those in more professionally or business oriented occupations reporting loss of reputation as the main cost while others are more likely to report lost earnings. These results offer the possibility that local data on occupational distributions could be used to ascertain how likely workers in that area might be to shift travel schedules in response to changes in travel conditions.

The analysis of the stated preference questions (section 6) leads to a behavioral model of schedule choice in the face of uncertainty. Implicit in this model are estimates of the costs of various characteristics of the travel schedule: mean travel time, average "schedule delay early" (defined as time spent at work prior to the preferred work start time), average "schedule delay late" (defined as number of minutes that an arrival is later than that preferred work start time), probability of being late, and standard deviation of travel time. The results show that, consistent with prior research, people are moderately averse to arriving early at work and more averse to arriving late, with a substantial discrete penalty to being late at all in addition to a per-minute cost of lateness. Further investigation shows that these effects differ between wage earners and salaried workers, and to a lesser degree among various occupational categories. Carpooling did not seem to affect the results. Finally, the results show that once these scheduling costs are taken into account, there is little additional residual cost to uncertainty per se.

In order to assess the practical importance of these findings, we performed simulations in which both recurrent and non-recurrent congestion was generated by a set of hypothetical commuters making their scheduling choices according to the model estimated as just described. In these simulations, congestion results from insufficient capacity and uncertainty results from random "incidents" which reduce capacity in a specified manner. These simulations show that slightly less than half of the increase in travel costs caused by incidents is due to increased travel time; the rest is due to scheduling costs, primarily increased probability of arriving late. The latter occurs despite a small tendency for people to adjust to increasing uncertainty by leaving for work earlier, which does occur and imposes an additional cost.

These models offer practitioners the basis for making quantitative predictions about the response to changes in the reliability of the highway system, and for measuring the costs of unreliability after people's adjustments are taken into account. Policies for which this type of evaluation is applicable include capacity expansions, improvements in incident response, and provision of information to travelers about travel speeds. Real-time information systems offer a variety of possibilities for affecting people's actual distribution of travel times and their knowledge of those distributions; simulations like those reported here offer ways to predict the results taking account of the complex and interacting shifts in travel decisions that people are likely to make.

1. INTRODUCTION

One of the great rediscoveries of transportation analysis is the importance of reliability in travel times. Based on instinct and direct statements of travelers (Prashker 1979), travel demand analysts have long suspected that reliability should be one of the important components of travel demand models and that unreliability is one of the primary costs of road congestion. Yet only very recently have such models succeeded in finding measurable effects (Small, 1992, pp. 35-36).

Stated-preference techniques have opened the way to some solid empirical estimates of travel time reliability. Most of them measure how much people are deterred by a higher standard deviation of travel times, relative to a higher mean travel time (Bates, 1990; Black and Towriss, 1993; Abdel-Aty et al., 1994b). These effects have real economic costs since individuals are foregoing the selection of a preferred schedule which would perhaps increase their workplace productivity.

Congestion also plays a role in traveller choices. Commuters may reschedule their trips to avoid peak travel periods, again potentially preventing them from arriving at work at some preferred time. Congested traffic may also increase the unreliability of travel times. That is, the variance of travel times may be greater during peak travel periods than when traffic is relatively uncongested Travel time variance is related to the occurrence of incidents which block highway capacity and thereby cause bottlenecks in the system.

One of the objectives of this research is to identify and measure the costs associated with unreliable travel times. This is done by collecting stated preference survey data to measure the trade-offs between scheduling costs, travel time costs, and costs associated with both travel time variance and the probability of arriving at work late. The focus here is on morning commute trips, although similar models could be applied to any trip that has some preferred arrival time.

Our demand models allow estimation of the trade-offs between various cost attributes. This will then be applied to a simulation of a single route highway facility. The simulation will allow real congestion effects, due to both recurrent and non-recurrent congestion, to be taken into account. Commuters may reschedule their trips to avoid congestion and/or travel time variation resulting in endogenous changes in both congestion and reliability. The simulation methodology allows a stable pattern of congestion over the morning commute to be achieved, thus allowing for a better interpretation of the effects of policy changes.

Another important element of our study is the examination of socio-economic differences in the responses to travel time unreliability. The survey respondents are classified into six occupational groupings and various tests are conducted to determine significant impacts on each group. Applying this type of demand model in a simulation experiment allows us to determine any impacts from future demographic changes. In addition, the significance of various socio-economic parameters in the demand model could be important for planning the marketing of Intelligent Transportation System (ITS) information technologies.

This report is organized as follows. First, we present a review of the relevant literature including previous economic models of traffic congestion and empirical research on travel reliability. We briefly describe the literature on psychological factors in employment choice and how this ties into our socio-economic categories. The next section contains a theoretical derivation of how individuals perceive the costs of travel time uncertainty, providing a theoretical justification for the demand models. Section 4 describes the data collection process including a discussion of stated preference techniques. Section 5 presents summary statistics and an analysis of the occupational categories as we define them. Section 6 provides a detailed discussion of the demand model results. Section 7 discusses the simulation methodology and results. Finally, in section 8 we consider implications for policies to reduce both recurrent and non-recurrent delay, examine the role of traveller information technologies, and make suggestions for future research.

2. LITERATURE REVIEW

2.1 Economic Models of Congestion, Scheduling, and Reliability

The behavioral mechanisms underlying the choice of departure times has been extensively studied. This research can be broken into three basic categories. The first focusses on scheduling choices; how does increased travel time due to congestion affect the choice of late versus early arrival? The second is a group of models that rely on endogenous scheduling choices under equilibrium conditions. Finally, we review recent literature that incorporates travel time reliability into the choice process.

2.1. I Congestion and Scheduling Choice

Some landmarks in the modern economic literature on traffic congestion include Walters (1961), Downs (1962), and Vickrey (1963, 1969). Walters (1961) and Vickrey (1963) analyzed the benefits to be gained from congestion pricing of roads, focussing exclusively on the travel delay due to congestion and the social costs that congestion imposed on all road users, They showed how using congestion pricing would allow those who most value the travel to pay a premium to travel at those periods when demand is greatest. The overall effect is a reduction in congestion at peak hours.

Scheduling of trips is a major cause of congestion. Downs (1962, 1992) explains how "triple convergence" tends to maintain high levels of congestion even when capacity levels are increased. Shifts from alternative routes, other modes, and different schedules are the three converging effects. Commuters tend to have some preferred arrival time and when congestion delay is reduced, they are more likely to reschedule their trip to arrive at a more preferred time, perhaps even at the cost of increased travel time.

As emphasized by Vickrey (1969), arriving earlier or later than the preferred time (usually the official work start time) entails some costs. Cosslett (1977) and Small (1982) provided the first empirical estimates of these effects. Small (1982) estimates how commuters who have an official work start time choose their usual travel schedules from among twelve possible five-minute intervals. The discrete choice specification assumes a fixed penalty (disutility) for arriving later than 2.5 minutes prior to the work start time. It also assumes additional per-minute penalties for arriving at work either early (schedule delay early, SDE) or late (schedule delay late, SDL). Small finds these penalties to vary systematically with personal and occupational characteristics; on average, the per-minute disutility of SDL is greater than that of travel time which in turn is greater than that of SDE, and the fixed lateness penalty is equivalent to about 5 minutes of travel time (Small, 1982, model 1).

Hendrickson and Plank (1984) also estimate values for SDE and SDL. Their model is based on a mode and departure time logit choice -model. They also include squared terms for SDE and SDL, but no dummy variable for fixed lateness penalty. While their relative values are similar to Small (1982), in that early time is valued less than travel time, and travel time is valued less than late time, their travel time variable is not statistically significant.

Chu (1993) estimates a model of departure time and mode choice which includes schedule delay, similar to Small (1982). Abkowitz (198 1) also analyzes the choice of departure time but without considering schedule delay.

Mannering and Hamed (1990) investigate the work to home departure time decision. Their results show that high levels of congestion are the main cause of delaying the departure decision. Socioeconomic characterstics and the availability of other activities near the work place, while significant, have a much smaller effect. Their study is unique in that it focusses on the work to home trip during the evening peak while most research has analyzed morning departures from home to work.

2. I. 2 Equilibrium Modeling with Endogenous Scheduling

There is an extensive literature on modeling equilibria or dynamic adjustment paths using a simple deterministic demand structure. On the supply side, most such papers use a bottleneck model that is basically that of Vickrey (1969), except usually simplified by making everyone's desired arrival times identical. Arnott et al. (1990a; 1990b) develop such a model that equilibriates the trade-offs between schedule delay and queuing delay; the result is that all commuters face the same costs. They use their model to evaluate various tolling strategies. Hendrickson and Kocur (198 1) and Fargier (1983) develop equilibrium models that analyze departure time decisions and their impact on the timing of congestion.

Extensions to these models include incorporating elastic demand (Ben-Akiva et al., 1986; Arnott et al., 1993), routes through a network (Ben-Akiva et al., 1986; Vythoulkas, 1990; Arnott et al., 1992) and heteregenous commuters with varying desired arrival times (Newell, 1987). Small (1992) provides a detailed review of many of these models.

One author, Henderson (1977; 198 l), uses a supply model which applies a conventional static speed-flow curve to each cohort of travelers. Chu (forthcoming) demonstrates that it is essential to define that cohort by their arrival time at their destination rather than by their departure times from home; otherwise, anomalous possibilities occur and equilibria do not exist. Chu also shows that the Vickrey bottleneck model appears as a limiting case of the Henderson model in which the speed-flow curve becomes kinked (i.e., the elasticity of travel time with respect to vehicle-capacity ratio becomes infinite).

Chu (1993) investigates equilibrium behavior in a model with a Henderson-type supply side, and in which the simple deterministic demand-side specifications just discussed are replaced by a discrete-choice model of scheduling very similar to that of Small (1982). Our research extends Chu's model using stated preference data that includes reliability as an attribute and by generating a distribution of travel times by deterministically randomizing capacity. Equilibration then occurs with people responding to the profile of congestion and, at each clock time, the entire probability distribution of uncertain travel times.

2.1.3 Theoretical and Empirical Research on Travel Reliability

The earliest theoretical work on traveller reactions to uncertain travel times can be attributed to Gaver (1968). Gaver developed a framework based upon utility maximization to demonstrate that commuters (or other travellers with a desired arrival time) will depart with a "head start" time; that is, they anticipate the variance in travel times and plan their departure a little earlier than if travel times were certain. This is similar to the "safety margin" hypothesis proposed by Knight (1974). Polak (1987) adds a concave transformation to Gaver's linear utility function in order to represent risk aversion, while Bates (1990) develops an analytic model to account for shifts to earlier departure times as variance increases.

Jackson and Jucker (198 1) assume that travellers trade off the expected travel time against travel time variance (or standard deviation). This theory ignores any scheduling costs and does not imply any particular functional form for the relationship between cost and unreliability. Most empirical work assumes that cost varies linearly with the standard deviation, as in Jackson and Jucker (198 1). One exception is Senna (1994) who combines the expected utility approach of Gaver (1968) and Polak (1987) with Jackson and Jucker's (1981) mean-variance approach. Senna (1994) defines expected utility in terms of a combined function of travel times and travel time variance allowing for risk aversion (or proneness) to be measured. Empirically he finds that commuters with fixed arrival times are risk prone, that is, they prefer a greater variability in travel times. He attributes this to the absence of lateness penalties. Another possibility is that his modeling approach misses the effects of scheduling costs.

Mirchandi and Soroush (1987) develop a network traffic equilibrium model that incorporates disutility functions for increased travel time variance. They test the model on different networks to demonstrate how travellers shift away from routes with increased travel time variance under congested conditions, but do not consider shifts in scheduling.

The theoretical model developed for this project is an extension of Gaver (1968) and Polak (1987). The additional contribution is that we include a discrete lateness penalty and also take changing levels of congestion into account; i.e., we account for the fact that alternative departure times face a different level of congestion. We also allow a full decomposition of the various cost elements of the morning commute, such as the expected cost of schedule delay, lateness, and travel time. This model will be described in Section 3. Additional detail is available in Noland and Small (1995).

Empirical work on measuring traveller responses to reliability has been slow to develop. Much of the early work was speculative or used proxy measures to account for reliability. Guttman (1979) discusses results that show commuters travelling during peak hours have a greater value of time than off-peak commuters. He attributes this to commuters incorporating the costs of uncertainty into their valuation of travel time. This is certainly a plausible hypothesis given that commuters travelling at peak hours may face greater uncertainty and may also have greater penalties for late arrival. Abkowitz (198 1) defined an expected loss function to represent traveller perceptions of the loss from early or late arrival. He did not find any statistical significance to the loss associated with uncertainty and attributes this to possible inaccuracies in the available data. Abu-Eisheh and Mannering (1988) estimate a departure time and route choice model. Their model includes a variable for the percent of coordinated traffic signals, which they interpret as a proxy for travel time variance. They obtain a negative coefficient on this variable indicating a preference for reduced travel time variance.

Mahmassani and associates (see Mahmassani and Herman, 1989; Mahmassani and Stephan, 1988; Mahmassani and Tong, 1986; and Chang and Mahmassani, 1988) simulate time of day departure choices using hypothetical data collected from actual commuters and fed through a traffic simulation model. These papers focus on day to day variations in travel time as commuters gain experience with the system. While travel times may be uncertain, these simulations emphasize how people learn about the shape of the congestion profile as opposed to uncertainties due to non-recurrent events.

More recent studies utilizing stated preference (SP) techniques have allowed for more explicit determinations of reliability costs and the trade-offs with other attributes. Black and Towriss (1993) performed a detailed SP study in London to measure the effect of travel time reliability. They provided respondents with a set of possible travel times to represent the travel time distribution. We follow this approach in our survey (see Section 4 and Appendix). The results of their estimations show that the standard deviation of travel times is a significant and negative attribute in the travellers utility function. Their stated preference survey did not contain any measures for estimating scheduling costs which we include in the present study.

Abdel-Aty et al. (1994a, 1994b) analyze the impact of travel time variability on route choice. They performed a stated preference survey in Southern California that presented respondents with the choice of route alternatives. One choice was certain arrival time (five days a week) while the other had variability (for example, certain travel time four days a week and the possibility of a longer travel time once a week). In most of the cases presented the route with variability had a total expected travel time less than the route with certain travel times. The results indicate that travellers recognize the disutility of variable travel times. The number of respondents selecting the more variable route diminished significantly when the standard deviation exceeded about 10 minutes (for a journey that regularly would take 20 minutes).

Abdel-Aty et al. (1994a) estimate a binomial logit model that shows standard deviation of travel time as being negative and significant in the choice of route. Abdel-Aty et al. (1994b), using the same data, estimate a Gaussian quadrature model that finds similar results. Unfortunately there is no cost attribute in their models. The ratio of the coefficients of the standard deviation of travel time to that of expected savings in travel time ranges from 0.33 to 1 .O, suggesting that travel time reliability is quite important in route choice decisions.

2.2 Incident Delay and its Effect on Travel Time Variance

Day to day variation in travel times can be caused by many different factors. For example, levels of demand may vary from day to day, or weather conditions may reduce capacity resulting in increased delays. These effects may not be random since commuters may anticipate the daily variation in traffic levels and reduced capacity during adverse weather. Random incidents such as vehicle disablements or accidents result in uncertain travel times. Random incidents cannot be anticipated by the traveller, although they may have some perception of their probability.

Incident related delay accounts for a large fraction of total delay. Giuliano (1989) estimated that about 60% of total congestion is due to non-recurrent incidents. These can range from major accidents that block capacity for an extended period of time to minor incidents such as disabled vehicles along highway shoulders. Lindley (1987) and Scrank et al. (1993) found a similar result for cross-sections of major U.S. metropolitan areas.

An unanswered question is how travel time variance is related to total traffic volume. Intuitively one would expect an increase in standard deviation of travel times during congested conditions, partly because any reduction in capacity during peak hours will have more severe consequences on total travel delay. On the other hand, accidents are probably less severe in slow moving congested conditions than during free-flow conditions. The empirical literature is inconclusive. Newbery (1990) and Bates (1994) posit some empirical relationships showing a power relationship between delay and traffic volume but have little faith in them. Hendrickson and Plank (1984) in an analysis of data from Pittsburgh, find that the coefficient of variation (ratio of standard deviation to mean travel time) is constant at about 0.13 over the peak period. Satterthwaite (198 1) reviews the literature and concludes that accident rates do not necessarily increase with increasing traffic volumes.

The simulations presented in Section 7 will assume constant incident probabilities for peak and off-peak periods. As will be shown, however, this results in a larger standard deviation of travel times (and coefficient of variation) over the peak period compared to off-peak periods. More research is needed to verify this relationship but is beyond the scope of the present study.

2.3 Occupational Categories and Risk Taking

One of the objectives of this study is to examine how socio-economic factors affect departure time choice decisions when travel times are uncertain. The psychological literature on risk-taking behavior (see e.g. Kogan and Wallach, 1964) suggests that certain personality types might prefer risks while others are more risk averse. In terms of commuting behavior this implies that some personality types may dislike travel time variability more than others who are either indifferent to the risk of late arrival or who actually prefer taking risks to minimize their total travel time.

Epstein and O'Brien (1985) suggest that personality traits are only one factor influencing choices in risky situations. Personality traits describe a wide set of attitudes, therefore it is desirable to find an "underlying personality measure" which has predictive power in a wide range of situations. Holland (1985) has hypothesized that a person's personality and occupation are empirically connected. The assumption is that each personality type is a product of a characteristic interaction amongst a variety of cultural and personal forces. From this experience individuals learn to prefer some activities which lead to interests and special competencies. This leads to a personal disposition that results in an individual acting and perceiving with specific tendencies. People search for environments that will let them exercise their skills and abilities, express their attitudes and values, and take on agreeable problems and roles. Therefore, occupational categories generally contain people with similar personality types.

Holland (1958, 1977) developed a Vocational Preference Inventory, a personality inventory based entirely on occupational titles. This inventory measures the individual's interest in different types of vocations. Holland states that these inventories are in fact personality inventories, assessing prior learning, genes, psychological and sociological influences, or the behavioral repertoires that such influences create. Consequently people in a vocational group will have similar personalities, and they will respond to many situations and problems in a similar way.

The theory is interactive in that it assumes that many career and social behaviors are the outcome of people and environments acting on one another. On the one hand people gravitate towards their optimal vocation and on the other the work environment molds them towards those personalities typical of their vocation.

The Holland occupational groups are separated into six categories. These are defined as "realistic", "investigative", "artistic", "social", "enterprising", and "conventional" occupational types. We now define each in terms of their major characteristics.

The **realistic** type prefers activities that entail the explicit, ordered, or systematic manipulation of objects, tools, machines, and animals and has an aversion to educational and therapeutic activities. These tendencies lead to the acquisition of manual, mechanical, agricultural, electrical, and technical competencies and to a deficit in social and educational competencies. The realistic person values concrete things or tangible personal characteristics such as money, power, and status.

The realistic person is apt to be:

Asocial	Materialistic	Self-effacing
Conforming	Natural	Inflexible
Frank	Normal	Thrifty
Genuine	Persistent	Uninsightful
Hard-headed	Practical	Uninvolved

The **investigative** type prefers observational, symbolic, systematic, and the creative investigation of physical, biological, and cultural phenomena in order to understand and control such phenomena, and has an aversion to persuasive, social, and repetitive activities. These tendencies lead to the acquisition of scientific and mathematical competencies and to a deficit in persuasive competencies. The investigative type values science.

The investigative type is apt to be:

Analytical	Independent	Rational
Cautious	Intellectual	Reserved
Critical	Introspective	Retiring
Complex	Pessimistic	Unassuming
curious	Precise	Unpopular

The **artistic** type prefers ambiguous, free, unsystematized activities that entail the manipulation of physical, verbal, or human materials to create art forms or products, and has an aversion to explicit, systematic, and ordered activities. These tendencies lead to the acquisition of competencies in language, art, music, drama, and writing, and to a deficit in clerical or business competencies. Artistic types value esthetic qualities.

The artistic type is apt to be:

Complicated	Imaginative	Intuitive
Disorderly	Impractical	Nonconforming
Emotional	Impulsive	Original
Expressive	Independent	Sensitive
Idelistic	Introspective	Open

The **social** type prefers manipulation of others to inform, train, develop, cure, or enlighten, and has an aversion to explicit, ordered, systematic, activities involving materials, tools, and machines. These tendencies lead to the acquisition of interpersonal and educational competencies and to a deficit in manual and technical competencies. The social type values social end ethical activities and problems.

The social type is apt to be:

Ascendant	Helpful	Responsible
Cooperative	Idealistic	Sociable
Patient	Empathic	Tactful
Friendly	Rind	Understanding
Generous	Persuasive	Warm

The **enterprising** type prefers the manipulation of others to attain organizational goals or economic gain, and has an aversion to observational, symbolic, and systematic activities. These tendencies lead to the acquisition of leadership, interpersonal, and persuasive competencies, and to a deficit in scientific competencies. The enterprising type values political and economic achievement.

The enterprising type is apt to be:

Acquisitive	Energetic	Flirtatious
Adventurous	Exhibitionistic	Optimistic
Agreeable	Exitement	Self-confident
Ambitious	seeking	Sociable
Domineering	Extroverted	Talkative

The **conventional** type prefers explicit, ordered, systematic manipulation of data, such as keeping records, filing materials, reproducing materials, organizing written and numerical data according to a predescribed plan, operating business machines and data processing machines to attain organizational or economic goals, and has an aversion to ambiguous, free, exploratory, or unsystematized activities. These tendencies lead to the acquisition of clerical, computational, and business system competencies and to a deficit in artistic competencies. Conventional types value business and economic achievement

The conventional type is apt to be:

Careful	Inflexible	Persistent
Conforming	Inhibited	Practical
Conscientious	Methodical	Prudish
Defensive	Obedient	Thrifty
Efficient	Orderlv	Unimaginative

The demand models presented in section 6 will attempt to measure the influence of Holland's specific occupational groupings on preferences for reliable commuting. These occupational groups are defined in Holland (1985) as realistic, conventional, artistic, enterprising, social, and conventional. We summarize the main characteristics of each group in section 5.2.

3. DEVELOPMENT OF THEORETICAL MODEL

The theoretical model outlined here is a slightly generalized version of that in Noland and Small (1995), where it is described more fully. Here we present a brief description of the model and emphasize its relation to the empirical work described in Section 6.

We begin with a theory of scheduling costs under uncertain travel times. As mentioned above, we build upon prior work by Gaver (1968) Polak (1987), and Bates (1990) by postulating a cost function for a commuter with a particular preferred arrival time at work, which empirically is taken to be the official work start time, t_w. If the commuter leaves home at time t_h and the travel time on a particular day is T, then the commuter will arrive early if $t_h + T < t_w$ and late if $t_h + T > t_w$. Small (1982) defines variables to measure how early or late this is: schedule delay early (SDE) is defined as $t_w - (t_h + T)$ if the commuter is early, and zero otherwise; while schedule delay late (SDL) is $(t_h + T) - t_w$ if the commuter is late and zero otherwise. This scheduling cost function, C_s, is postulated to be:

$$C_s = \alpha T + \beta(SDE) + \gamma(SDL) + \theta D_L \tag{1}$$

where DL is equal to 1 when SDL > 0 and 0 otherwise. The coefficient a is the cost of travel time, β and γ are the costs per minute of arriving early and late, respectively, and θ is an additional discrete lateness penalty.

We define three elements of total commute time, T. The first is the free-flow travel time, T_f, which occurs if the highway has no congestion. The extra travel time due to congestion is defined as T,. This is minimum congested travel time that the commuter knows will occur, i.e., recurrent congestion. The added time due to non-recurrent congestion, due for example to incident related delays (Lindley, 1987; Scrank et. al, 1993), is defined as T,, a random variable. We define a probability distribution with a mean and standard deviation for this variable; for simplicity we assume it is independent of the amount of recurrent congestion and of the time of day of travel.

These elements are used to define the maximum early arrival time, T,:

$$T_e = t_w - t_h - T_f - T,. \tag{2}$$

This is the "head start" time, originally defined by Gaver (1968). This enables us to rewrite the cost function as follows:

$$C_S(T_r) = \alpha[T_f + T_X + T_r] + \beta(1 - D_L)[T_e - T_r] + \gamma D_L[T_r - T_e] + \theta D_L. \tag{3}$$

The next step is to calculate the expectation of this cost function using a specified distribution function. Many authors, including Richardson & Taylor (1978), have fit log-normal curves to travel-time variance data; Giuliano (1989) has verified that non-recurrent congestion follows a log-normal distribution. Unfortunately, the log-normal distribution is analytically intractable. Instead we calculate it here for a uniform distribution (like Polak, 1987) and an exponential distribution (like Gaver, 1968). (Our empirical model uses neither of these distributions, but instead generates T from a supply model with random capacity reductions, as specified below).

The uniform distribution for Tr is defined by the probability density function $f(T_r)=1/T_m$ for $0 \leq Tr \leq Tm$ and $f(T_r)=0$ otherwise. Its mean is $\frac{1}{2}T_m$ and its standard deviation is $T_m/\sqrt{12}$. The expected cost is

$$EC, = \frac{1}{T_m}\int_0^{T_m} C(T_r)dT_r \tag{4}$$

Assuming that $0 \leq T_e \leq T_m$, the chosen departure time can lead to either early or late arrival depending on the realization of the random variable Tr; expected cost is then

$$EC, = \alpha(T_f + T_x + \frac{T_m}{2}) + \frac{1}{T_m}\int_0^{T_e}\beta(T_e - T_r)dT_r + \frac{1}{T_m}\int_{T_e}^{T_m}[\gamma(T_r - T_e) + \theta]dT_r \tag{5}$$

$$= \alpha\left[T_f + T_x + \frac{T_m}{2}\right] + \frac{1}{T_m}[\theta(T_m - T_e)] + \frac{1}{2T_m}\left[\beta T_e^2 + \gamma(T_m - T_e)^2\right] \tag{6}$$

$$= aE(T) + \beta E(\text{SDE}) + \gamma E(\text{SDL}) + \theta P_L, \tag{7}$$

where P_L = (T, - T,) / T_m is the probability of arriving late. We see that for any given choice T_e of travel schedule, expected scheduling cost is simply the sum of expected costs of travel time, schedule delay early, schedule delay late, and lateness penalty. Note that since randomness in T_r makes either early or late arrival possible, all four terms can be positive.

When $T_e < 0$ or $T_e >$ T,, Noland and Small (1995) show that equation (7) still holds, although certain terms are then equal to zero because E(SDE)=0 in the case $T_e < 0$, and E(SDL) = P_L = 0 in the case $T_e >$ T,. What this means is simply that with the uniform distribution it is possible to choose the head start so as to guarantee early arrival or so as to guarantee late arrival.

The exponential distribution for T_r is defined by the probability density function,

$$f(T_r) = \frac{1}{b} e^{\left(-T_r/b\right)}, \tag{8}$$

which applies for 0 ≤ T,. The parameter b is the mean and the standard deviation of the distribution. Assuming that $T_e \geq 0$,[1] expected cost is:

$$EC, = \frac{1}{b}\int_0^{T_e} C(T_r)e^{-T_r/b}dT_r + \frac{1}{b}\int_{T_e}^{\infty} C(T_r)e^{-T_r/b}dT_r. \tag{9}$$

$$= \alpha(T_f + T_x + b) + \beta(T_e - b) + e^{-T_e/b}(\theta + b\beta + b\gamma), \tag{10}$$

$$= \alpha(T_f + T_x + b) + \beta(T_e - P_E b) + P_L(\theta + b\gamma). \quad (19$$

By taking the conditional expectation of Tr, conditional on Tr < T_e or $T_r > T_e$, one can rewrite (11) as:

$$EC, = \alpha E(T) + \beta E(\text{SDE}) + \gamma E(\text{SDL}) + \theta P_L, \tag{12}$$

where $P_L = e^{-T_e/b}$ is the probability of arriving late. Equation (12) is identical to (7).

‘Noland & Small (1995) provide more detail on cases when $T_e < 0$.

In addition to producing mis-matched schedules, travel time uncertainty may also impose an inconvenience due to the inability to plan one's activities exactly. We call this "planning cost", C_p, and assume it is a function of the standard deviation S of uncertain travel time Tr, with coefficient cr. Total expected cost is therefore

$$EC = EC_S + C_P \tag{13}$$

$$= \alpha E(T) + \beta E(SDE) + \gamma E(SDL) + \theta P_L + \sigma f(S). \tag{14}$$

This is the basic model that we estimate in section 6. Our expectation is that $\beta < a < \gamma$ and that all coefficients are positive.[2]

In Noland and Small (1995), we permit head-start T_e to be chosen to minimize expected scheduling cost, EC,. However, here we assume instead that head-start is chosen from a random utility model in which disutility is proportional to EC. We expect this to lead to similar qualitative behavior, such as a shift toward earlier schedules in response to increased standard deviation of travel time.

2Since the estimation procedure is based on utility maximization the coefficients would all be negative when specified in a utility function.

4. SURVEY DESIGN AND DATA COLLECTION PROCESS

In order to empirically estimate the trade-offs among reliability, mean travel time, and scheduling decisions, we developed a stated-preference survey and administered it to a sample of 677 commuters in the Los Angeles region who had already taken part in a recent panel study undertaken by David Brownstone and Thomas Golob. This strategy enabled us to take advantage of information already compiled about employer, work start time, and travel conditions. It also provided an 80 percent response rate, ultimately resulting in 543 usable questionnaires.

The questionnaire is divided into three parts. The first concentrates on the respondent's occupation and related work characteristics. The second measures the daily work and individual constraints on the timing of the commute. The third consists of questions about current commuting experiences and reactions to hypothetical changes in it.

This third part includes a set of nine stated preference choices. Each choice is between two alternative commutes to work, each with a specified distribution of travel times and a specified departure time from home. Departure time is presented in minutes prior to the "usual arrival time," which was ascertained from a question in the previous panel about the commuter's actual commuting situation and which here takes the role of work start time in the theory developed above. The travel mode is not specified. A sample question is shown in Figure 4-l; see Appendix A for a sample copy of the complete survey including the SP questions. Our empirical demand model, discussed in section 6, is estimated from the answers to the SP questions (based on nine repeated measures given to each respondent).

The question format is a compromise between the need to describe a travel time distribution that would be realistic to the respondent, and the need to keep the question simple enough to be understood. Based on the experience of Black and Towriss (1993), who studied different question formats with this tradeoff in mind, the travel time distribution in the current study is described as a five point discrete distribution, where each possible travel time has an equal probability. The possible travel times were determined by choosing a log-normal distribution with a given mean and standard deviation, then picking the lst, 3rd, 5th, 7th, and 9th decile points, each rounded to the nearest minute. The standard deviation was chosen to be larger for those commuters whose current actual travel time was longer.

To represent a travel time distribution as a discrete distribution is clearly a simplification. Two aspects could be problematic. First, it restricts the domain of the probability distribution, creating an artificial certainty as to the maximum possible delay that could occur. Second, one cannot adequately capture the skewness of the underlying distribution using only five points. To counteract any hidden skewness effects, all the sets of travel times we presented to respondents are derived from distributions with the same skewness, which means we cannot study the effects of third or higher moments of the travel time distribution.

In order to reduce some of the problems that have been identified in stated preference questions (Bonsall, 1985; Bradley and Kroes, 1990), the questions were designed to be realistic and relevant to the respondents. For example, the distributions presented were customized so as not to deviate too far from the respondent’s current mean travel time. In order to avoid “affirmation bias,” the questions were designed as abstract alternatives with no obvious way to promote any particular political philosophy through the answer. Finally, following a pilot study in which questions about tolls elicited responses that were clearly political statements, the price attribute was dropped from the design; this means that we can measure ratios of cost coefficients but not the actual costs.

As for the design of the independent variables, Hensher and Barnard (1990) demonstrate that an orthogonal design will contain some combinations of attribute levels for which one alternative completely dominates another, making that choice not very informative and possibly boring the respondent. As an alternative to orthogonal statistical design, we selected from a complete factorial design the largest subset of non-dominated alternatives in order to form the choice sets.

The three attributes specified in the SP design were assigned three levels (high, medium, and low), leading to a 33 matrix of attribute combinations. Out of this matrix of 27 attribute combinations the largest subset of non-dominated attribute combinations was chosen. This subset consists of seven attribute combinations, which are presented in Table 4- 1.

Randomly drawn pairs of the three attribute levels were assigned to each individual to create nine repeated measure SP questions. Respondents were not presented the same pair twice. The respondents were also divided into 5 groups based on their usual commuting time from home to work with each group having a separate set of attribute combinations designed for it. The 5 travel time groups and their attribute levels are listed in Table 4-2. Departure time levels were calculated as a linear combination of the mean travel time and the standard deviation to determine three departure time levels. The lowest of the three levels was the departure time being equal to the expected travel time. The medium level was the expected travel time plus one standard deviation, while the highest level was the expected travel time plus two standard deviations.

As mentioned above, the 5 travel times were computed by choosing a log-normal distribution. The variance of the corresponding normal distribution was assumed to be constant at 0.3. The 5 points were chosen as the 1st 3rd, 5th, 7th, and 9th deciles of the chosen log-normal distribution. The actual values presented were, however, approximate due to rounding to zero decimal places. During our estimations (see Section 6) we recalculate the standard deviation based on the actual rounded values presented to the respondent. Table 4-3 displays the complete set of alternatives for each travel time group.

FIGURE 4-l

SAMPLE STATED PREFERENCE QUESTION

Time : minutes
12 13 14 16 20

Time : minutes
5 7 9 12 18

Departure 15 minutes before your usual arrival time

Departure 10 minutes before your usual arrival time

Please circle
your choice: A B

TABLE 4-l

DESIGN OF ATTRIBUTE LEVELS FOR SP QUESTIONS

mean travel time	Standard deviation of travel time	departure time
high	medium	low
medium	high	low
high	low	medium
medium	medium	medium
low	high	medium
medium	low	high
low	medium	high

TABLE 4-2

ATTRIBUTE LEVELS FOR EACH TRAVEL TIME GROUP

Travel time group	Mean travel time			Standard deviation of travel time		
	Low	Medium	High	Low	Medium	High
Less than 20 minutes	7	10	15	1	3	5
20 - 29 minutes	20	25	30	1	4	6
30 - 39 minutes	30	35	40	1	5	8
40 - 54 minutes	40	45	55	1	5	9
55 minutes or more	55	60	70	1	6	11

TABLE 4-3

STATED PREFERENCE CHOICES, BY TRAVEL TIME GROUP

Travel time group	Mean travel time	Standard deviation of travel time	Departure time	Possible travel times 1st decile	2nd decile	3rd decile	4th decile	5th decile
Less than 20 minutes	15	3	15	12	13	14	16	20
	10	5	10	5	7	9	12	18
	15	1	16	14	14	15	15	17
	10	3	16	7	8	9	11	15
	7	5	12	2	4	6	9	15
	10	1	12	9	9	10	10	12
	7	3	13	4	5	6	8	12
20 - 29 minutes	30	4	30	26	27	29	32	38
	25	6	25	19	21	24	27	34
	30	1	31	29	29	30	30	32
	25	4	29	21	22	24	26	31
	20	6	26	14	16	19	22	29
	25	1	27	24	24	25	25	27
	20	4	28	16	17	19	21	26
30 - 39 minutes	40	5	40	35	37	39	42	48
	35	8	35	27	30	33	38	47
	40	1	41	39	39	40	40	42
	35	5	40	30	32	34	37	44
	30	8	38	22	25	28	33	42
	35	1	37	34	34	35	35	37
	30	5	40	25	27	29	32	39
40 - 54 minutes	55	5	55	50	52	54	57	63
	45	9	45	36	39	43	48	59
	55	1	56	54	54	55	55	57
	45	5	60	40	42	44	47	54
	40	9	49	31	34	38	43	54
	45	1	47	44	44	45	45	47
	40	5	50	35	37	39	42	48
55 minutes or more	70	6	70	64	66	69	72	79
	60	11	60	48	53	58	64	77
	70	11	71	69	69	70	70	72
	60	6	66	54	56	59	62	69
	55	11	66	43	48	53	59	72
	60	1	62	59	59	60	60	62
	55	6	77	49	51	54	57	64

5. SUMMARY STATISTICS AND ANALYSIS OF OCCUPATIONAL CATEGORIES

5.1 Demographics of Sample

Table 5-l shows the distribution of ages by gender in the sample. There were slightly more males (53.2%) in our sample, than females and more than 25% of the sample was over the age of 50, while the bulk were between the ages of 30 and 49. These are prime working years and since we are concerned with commuting trips, this bias is acceptable.

Tables 5-2 and 5-3 show the income distribution of the sample both by personal earned income and total household income. The sample has a higher median income than average, which is not uncommon for mail surveys.

5.2 Occupational Variables

Table 5-4 shows that most of the respondents received benefits in their employee compensation packages. Only 3.5% of employees did not receive benefits and 4.1% were self-employed. Most of the employees in our sample also had a fixed monthly salary (see Table 5-5). This may indicate that our sample is underrepresenting people employed in less secure and transitory job occupations.

Table 5-6 shows the distribution of industry types in our sample. The largest category was "manufacturing, durable goods" with a share of 22.1% followed by "health services" with a 15.8% share.

The survey respondents were allocated to occupational groups by their answers to question 6 (What is your title in your work organization?) and question 7 (What is your occupation?). We spent considerable effort to accurately determine occupational codings for the survey respondents. Answers to questions 6 and 7 were compared to titles in Holland's occupational dictionary. This dictionary lists all the occupational titles in U.S. Employment

Service (1977) and gives their codes according to the Holland classification scheme outlined above. If the occupational title was not listed in the Holland dictionary, we matched it with the Department of Labor Occupational Dictionary (U.S. Employment Service, 1977), which gives descriptions of all occupational titles and a title of similar activities. We chose similar job titles if the respondent's occupation was not listed in the Holland code book. Some of the respondents were personally contacted to clarify their job titles.

Table 5-7 shows the distribution of the Holland occupational categories in our sample. A surprisingly high number of respondents were in the "enterprising" category (34.9%). This may be a sampling bias indicating that these type of individuals are more likely to fill out surveys; in any case we obtained a good sampling from all the occupational categories, except "artistic" and our statistical methodology allows us to control for the effect of different occupational categories (see section 6.2).

5.3 Work Related Time Constraints, Lateness Penalties, and Slack Time

The next set of tables explores in detail the nature of the constraints and preferences commuters have regarding the timing of their travel to work. These questions reveal great variety in how people's employment situation accomodate the vagaries of commute time. There are systematic differences among occupational groups, although generally less than the differences within each occupational group. In each table, the occupational differences are shown by presenting the actual count of respondents in each cell of the table, and below that the expected count that would occur if members of that occupational group had the same distribution of answers as the entire sample (the expected count is therefore the "row total" multiplied by the "column percent").

Different occupational groups place different time requirements on employees. Employees in Realistic and Conventional occupations tend to have the strictest arrival time requirements. Respondents in these two categories have a greater frequency of indicating that it is important to arrive on time every day. At the other extreme, people in Investigative occupations tend to have work requirements where it is practically never important to arrive at work at a particular time. People in Enterprising occupations tend to report that it is important to arrive on time only on some days (See Table 5-8).

Different employers have different rules and conditions affecting whether employees are able to begin work if they arrive before the official work start time. This can result in different occupational categories having different values for schedule delay early (SDE). Employers of people in Realistic and Conventional occupations tend to not want their employees to start work earlier than the official time, while employers of people in Investigative and Enterprising occupations appear less likely to object (Table 5-9).

Similar patterns are apparent with regard to working late and taking work home. It tends to not occur in Realistic and Conventional occupations, but does occur in Enterprising occupations (see Tables 5-10 and 5-l 1). Additional analysis (not shown) showed similar relationships when we consider the employee’s ability to change work constraints. This may indicate that the constraints are primarily set by the employers.

When asked if there would be “negative consequences” from arriving late, 10.5% of the respondents answered that they would be paid less, 49.4% felt that their reputation would suffer, 24.5% would have stress from rushing things, 13.8% stated that there would be some other kind of negative consequences, while 3 1.1% stated that there would not be any negative consequences, (The percentages do not add up to 100 because some respondents gave more than one answer).

People most likely to lose earnings due to lateness are in Realistic and Conventional occupations, while people least likely to lose earnings due to lateness are in Investigative and Enterprising occupations (see Table 5- 12).

Arriving at work late can cause a loss of reputation to the employee. This tends to be more prevalent among those in the Realistic occupational group, but not for the Artistic and Social groups (see Table 5-13). About one-fourth of the individuals in all occupational groups experience greater stress and feel more rushed when they arrive at work late (see Table 5-14), with the Pearson Chi-square test indicating no statistical difference between the occupational categories.

People in Realistic occupations have the lowest likelihood of avoiding negative consequences due to lateness, while those working in Artistic and Enterprising occupations report avoiding negative consequences more often than those in other occupational groups (Table 5-15). When asked if it is OK to arrive 15 minutes late, people in Realistic and Social occupations answer ‘no’, while those in Enterprising and Investigative occupations tend to indicate that they can arrive 15 minutes late (see Table 5-16). The method of how an employee is paid (e.g. a fixed monthly salary versus an hourly wage) should be a good indicator of whether one experiences negative consequences from arriving late. This is confirmed in Table 5-17; hourly wage-earners are more likely to answer that they have negative consequences from lateness than salaried employees or people who are paid on comission.

One way to avoid lateness penalties from late arrival is to leave home earlier and allow for some slack time at one’s destination. As is expected, workers in those occupational categories that are least tolerant of late arrival are more likely to budget some slack time into their schedule. This is shown in Table 5- 18. Realistic, Social, and Conventional occupational groups are more likely to budget slack time into their schedule, while Investigative and Enterprising occupational groups are less likely to. We also found that when commutes are lengthier individuals do not budget any additional slack time into their schedules, as can be seen by the insignificant chi-square test in Table 5-19.

5.4 Reported Reactions to Congested Traffic Conditions

We presented the survey respondents with several questions which posed hypothetical situations involving increases in congested traffic. For example, respondents were asked what their response would be if congested conditions leading to at least a 15 minute delay occurred twice as frequently as under current conditions. Results are shown in Table 5-20. We found that half would reserve more time for commuting, whereas 44% reported that they would not change their current commuting habits. Changes in residence or work location were minimal, and about 10% indicated that they would be willing to pay a toll to guarantee an on-time arrival.

We increased the severity of the hypothetical situation by asking what the response would be if the 15 minute delay were permanent. Surprisingly we obtained a poor response rate for this question. This may be attributable to the omission of the choice 'not change your commuting habits'. Probably the most interesting result from this question is that again about 10% of those who responded would be willing to pay a toll to guarantee on-time arrival. About half of these 10% had also indicated that they would pay a toll for occasional delays (Table 5-20) Therefore, some people will pay a toll for occasional delay but will seek other options if delays are permanent, while others will not pay a toll for occasional delay but will if delays are permanent. These results are not conclusive but do indicate that one may get different behavioral responses to recurrent as opposed to non-recurrent congestion.

We also presented the hypothetical situation where one expects to be stuck in immobile traffic for at least 30 minutes and is then given the choice of using a bypass for a fee. 85 % of the respondents indicated that they would be willing to pay a fee, and the willingness to pay was dependent on income. People in higher income groups are more willing to pay a fee, and the fee that they are willing to pay is higher (See Table 5-21). People in different occupations have different levels for their willingness to pay a fee: people in Realistic, Investigative, and Conventional occupations are more likely to not pay anything, whereas people in Social and Enterprising occupations are more willing to pay a fee (Table 5-22). The willingness to pay a fee was not dependent on commuting distance or time, household income, form of employment contract (i.e., hourly wage versus monthly salary), or carpooler status.

5.5 Summary of Preliminary Analysis

These results suggest that there are differences in the behavior of individuals dependent on the type of occupational category in which they are employed. While it is unclear whether these constraints are imposed by the employer or are determine by specific individual traits, the theory proposed by Holland (1985) is that invididual characteristics will be partly determined by the environment of the type of occupation selected, as well as determining the occupation selected. Therefore, it is not surprising to find some differences in scheduling considerations for different occupational categories.

In summary, we found the Enterprising and Investigative occupational groups to be less sensitive to timing and work place constraints. These occupational groups tend to be composed of professional and entrepreneurial individuals; they may seek more control over their work schedules and therefore these type of jobs allow for more flexibility. In our demand models that follow (see Section 6.2) we pursue these relations more explicitly using the stated preference questions in our survey.

TABLE 5-l

AGE AND GENDER DISTRIBUTIONS

Age	Male	Female	Row Total	Row Percent
20-29	15	17	32	6.1%
30-39	75	81	156	29.8%
40-49	94	91	185	35.3%
50-59	59	46	105	20.0%
60-69	32	9	41	7.8%
70-100	4	1	5	1.0%
Column Total	279	245	524	100%
Column Percent	53.2%	46.8%		

TABLE 5-2

PERSONAL EARNED INCOME DISTRIBUTION

Earned income r>er vear	Frequency	Percent
Less than $ 10,000	6	1.1%
$ 10,000 to $ 14,999	7	1.3%
$ 15,000 to $ 19,999	9	1.7%
$20,000 to $24,999	19	3.5%
$25,000 to $29,999	35	6.4%
$30,000 to $34,999	45	8.3%
$35,000 to $39,999	60	11.0%
$40,000 to $44,999	50	9.2%
$45,000 to $49,999	52	9.6%
$ 50,000 to $ 54,999	56	10.3%
$ 55,000 to $59,999	36	6.6%
$ 60,000 to $ 64,999	37	6.8%
$65,000 to $ 69,999	26	4.8%
$ 70,000 to $ 74,999	14	2.6%
$75,000 to $ 84,999	17	3.1%
$ 85,000 to $94,999	19	3.5%
$ 95,000 to $ 119,999	19	3.5%
$ 120,000 or more	12	2.2%
Missing	24	4.4%
Total	543	100%

TABLE 5-3

HOUSEHOLD INCOME DISTRIBUTION

Household's annual gross income	Frequency	Percent
Less than $ 15,000	6	1.1%
$ 15,000 to $24,999	8	1.5%
$25,000 to $34,999	25	4.6%
$35,000 to $44,999	50	9.2%
$45,000 to $54,999	67	12.3%
$ 55,000 to $64,999	46	8.5%
$65,000 to $ 74,999	59	10.9%
$75,000 to $ 84,999	66	12.2%
$85,000 to $94,999	58	10.7%
$95,000 to $ 119,999	62	11.4%
$ 120,000 to $ 149,999	46	8.5%
$ 150,000 or more	30	5.5%
Missing	20	3.7%
Total	543	100%

TABLE 5-4

FORM OF EMPLOYEE COMPENSATION

Form of compensation	Frequency	Percent
An employee with benefits	487	89.7%
An employee without benefits	19	3.5%
An independent contractor within a company	7	1.3%
Self-employed / An entrepreneur	22	4.1%
Other	7	1.3%
Missing	1	0.2%
Total	543	100%

TABLE 5-5

TYPE OF PAYMENT OF EARNED INCOME

Type of Payment	Frequency	Percent
A fixed monthly salary	**387**	**71.3%**
An hourly wage	131	**24.1%**
Comission	11	**2.0%**
Missing	14	**2.6%**
Total	**543**	100%

TABLE 5-6

DISTRIBUTION OF INDUSTRY CATEGORIES

Industry	Frequency	Percent
Mining	1	**0.2%**
Construction	**18**	**3.3%**
Manufacturing, nondurable goods	**52**	**9.6%**
Manufacturing, durable goods	**20**	**22.1%**
Transportation	**19**	**3.5%**
Public utilities, Post, Telecommunications	**16**	**2.9%**
Wholesale trade	**18**	**3.3%**
Retail trade	**12**	**2.2%**
Finance, Insurance, Real Estate	**53**	**9.8%**
Business and Repair services	**7**	**1.3%**
Personal Services	**5**	**0.9%**
Entertainment and Recreation	**9**	**1.7%**
Health services	**86**	**15.8%**
Educational services	**28**	**5.2%**
Other professional services	**79**	**14.5%**
Public administration	**8**	**1.5%**
Missing	**12**	**2.2%**
Total	**543**	100%

TABLE 5-7

DISTRIBUTION OF HOLLAND OCCUPATIONAL CATEGORIES

Holland Occupational Categories	Frequency	Percent
Realistic	79	15.5
Investigative	100	19.6
Artistic	16	3.1
Social	80	15.7
Enterprising	178	34.9
Conventional	57	11.2
Total	510	

TABLE 5-8

FREQUENCY OF IMPORTANCE OF ON-TIME ARRIVAL BY OCCUPATIONAL GROUPS

Survey Question: HOW OFTEN IS IT IMPORTANT THAT YOU ARRIVE AT A PRECISE PRE-DETERMINED TIME ?

Holland Occupational Categories	Practically never	Once a month or less	Two to four times a month	Two to four times a week	Every day	Row Total	Row Percent
Realistic	17	3	7	10	47	84	15.8%
	24.5	2.8	10.1	13.0	33.5		
Investigative	47	3	13	16	28	107	20.2%
	31.2	3.6	12.9	16.5	42.7		
Artistic	4	0	3	3	7	17	3.2%
	5.0	0.6	2.0	2.6	6.8		
Social	17	4	9	15	36	81	15.3%
	23.6	2.7	9.8	12.5	32.3		
Enterprising	57	7	30	33	57	184	34.7%
	53.7	6.2	22.2	28.4	73.5		
Conventional	13	1	2	5	37	58	10.9%
	16.9	2.0	7.0	9.0	23.2		
Column Total	155	18	64	82	212	531	
Column Percent	29.2%	3.4%	12.1%	15.4%	39.9%		100%

Pearson Chi-Square (49.65, 20); p = 0.00025

Top number in cell is actual count, bottom number is expected count if that occupational group had the same distribution of answers to the question as the entire sample.

TABLE 5-9

FLEXIBILITY TO ARRIVE AT WORK EARLY, BY OCCUPATIONAL GROUPS

Survey Question: DOES YOUR EMPLOYER ALLOW YOU TO ARRIVE AND START WORK BEFORE YOUR NORMAL WORKING HOURS ?

Holland Occupational Categories	Yes - can start work earlv	No - cannot start work earlv	Row Total	Row Percent
Realistic	54 65.8	**29** 17.2	83	15.7%
Investigative	88 84.1	18 21.9	106	20.1%
Artistic	13 13.5	4 3.5	17	3.2%
Social	65 64.2	16 16.8	81	15.4%
Enterprising	158 144.4	24 37.6	182	34.5%
Conventional	40 46.0	18 12.0	58	11.0%
Column Total Column Percent	418 79.3%	109 20.7%	527	100%

Pearson Chi-Square (21.32,5), p = .00071

Top number in cell is actual count, bottom number is expected count if that occupational group had the same distribution of answers to the question as the entire sample.

TABLE 5-10

FLEXIBILITY TO WORK LATE, BY OCCUPATIONAL GROUPS

Survey Question: DOES YOUR EMPLOYER ALLOW YOU TO STAY AND CONTINUE WORKINGAFTER YOUR NORMAL WORKING HOURS?

Holland Occupational Categories	Yes - can work late	No - cannot work late	Row Total	Row Percent
Realistic	61 72.0	22 11.0	83	15.8%
Investigative	93 91.9	13 14.1	106	20.2%
Artistic	14 14.7	3 2.3	17	3.2%
Social	74 70.2	7 10.8	81	15.4%
Enterprising	172 158.6	11 24.4	183	34.8%
Conventional	42 48.5	14 7.5	56	10.6%
Column Total Column Percent	456 86.7%	70 13.3%	526	 100%

Pearson (Chi-Square (29.52, 5) p = .00002

Top number in cell is actual count, bottom number is expected count if that occupational group had the same distribution of answers to the question as the entire sample.

TABLE 5-11

FLEXIBILITY TO WORK AT HOME, BY OCCUPATIONAL GROUPS

Survey Question: DOES YOUR EMPLOYER ALLOW YOU TO TARE WORK HOME AFTER YOUR NORMAL HOURS OR WORK AT HOME INSTEAD OF AT YOUR WORK SITE?

Holland Occupational Categories	Yes - can work at home	No - cannot work at home	Row Total	Row Percent
Realistic	30 44.4	55 40.6	85	16.3%
Investigative	61 54.3	43 49.7	104	19.9%
Artistic	12 8.9	5 8.1	17	3.3%
Social	41 41.8	39 38.2	80	15.3%
Enterprising	111 93.4	68 85.6	179	34.2%
Conventional	18 30.3	40 27.7	58	11.1%
Column Total Column Percent	273 52.2%	250 47.8%	523	 100%

Pearson Chi-Square (3 1.12, 5), p = .00001

Top number in cell is actual count, bottom number is expected count if that occupational group had the same distribution of answers to the question as the entire sample.

TABLE 5-12

LOST PAY DUE TO ARRIVING AT WORK LATE, BY OCCUPATIONAL GROUPS

Holland Occupational Categories	Yes - I get paid less	No - I do not get paid less	Row Total	Row Percent
Realistic	15 8.9	70 76.1	85	15.9%
Investigative	7 11.2	100 95.8	107	20.1%
Artistic	2 1.8	15 15.2	17	3.2%
Social	11 8.5	70 72.5	81	15.2%
Enterprising	8 19.4	177 165.6	185	34.7%
Conventional	13 6.1	45 51.9	58	10.9%
Column Total Column Percent	56 10.5%	477 89.5%	533	 100%

Pearson Chi-Square (23.5 1, 5), p = .00027

Top number in cell is actual count, bottom number is expected count if that occupational group had the same distribution of answers to the question as the entire sample.

TABLE 5-13

LOSS OF REPUTATION DUE TO ARRIVING AT WORK LATE, BY OCCUPATIONAL GROUPS

Holland Occupational Categories	Yes - my reputation suffers	No - my reputation does not suffer	Row Total	Row Percent
Realistic	50 42.3	35 42.7	85	15.9%
Investigative	56 53.2	51 53.8	107	20.1%
Artistic	3 8.5	14 8.5	17	3.2%
Social	35 40.3	45 40.7	81	15.2%
Enterprising	90 92.0	95 93.0	185	34.7%
Conventional	30 28.8	28 29.2	58	10.9%
Column Total Column Percent	265 49.7%	268 50.3%	533	 100%

Pearson Chi-Square (11.19, 5), p = .04782

Top number in cell is actual count, bottom number is expected count if that occupational group had the same distribution of answers to the question as the entire sample.

TABLE 5-14

INCREASED STRESS AND RUSHING DUE TO LATENESS, BY OCCUPATIONAL GROUPS

Holland , Occupational Categories	Yes - I feel more stress	No - I don't feel more stress	Row Total	Row Percent
Realistic	20	65	85	15.9%
	21.2	63.8		
Investigative	23	84	107	20.1%
	26.7	80.3		
Artistic	4	13	17	3.2%
	4.2	12.8		
Social	28	53	81	15.2%
	20.2	60.8		
Enterprising	46	139	185	34.7%
	46.2	138.8		
Conventional	12	46	58	10.9%
	14.5	43.5		
Column Total	133	400	533	
Column Percent	25.0%	75.0%		100%

Pearson Cl&Square (5.36, 5) p = .37400

Top number in cell is actual count, bottom number is expected count if that occupational group had the same distribution of answers to the question as the entire sample.

TABLE 5-15

NO NEGATIVE CONSEQUENCIES DUE TO LATENESS, BY OCCUPATIONAL GROUPS

Holland Occupational Categories	Negative consequences from late arrival	No negative consequences from late arrival	Row Total	Row Percent
Realistic	69 58.4	16 26.6	85	15.9%
Investigative	69 73.5	38 33.5	107	20.1%
Artistic	8 11.7	9 5.3	17	3.2%
Social	59 55.6	22 25.4	81	15.2%
Enterprising	121 127.0	64 58	185	34.7%
Conventional	40 39.8	18 18.2	58	10.9%
Column Total Column Percent	366 68.7%	167 31.3%	533	 100%

Pearson Chi-Square (12.31, 5) p = .03073

Top number in cell is actual count, bottom number is expected count if that occupational group had the same distribution of answers to the question as the entire sample.

TABLE 5-16

ABILITY TO ARRIVE AT WORK 15 MINUTES LATE, BY OCCUPATIONAL GROUPS

Survey Question: IS IT OK TO ARRIVE 15 MINUTES LATE?

Holland Occupational Categories	Yes - it is OK to arrive 15 min. late	No - it is not OK to arrive 15 min. late	Not Applicable	Row Total	Row Percent
Realistic	37 43.8	42 30.2	5 10.0	84	15.9%
Investigative	68 55.8	26 38.4	13 12.7	107	20.2%
Artistic	10 8.9	6 6.1	1 2.0	17	3.2%
Social	28 42.3	40 29.1	13 9.6	81	15.3%
Enterprising	103 95.5	52 65.7	28 21.8	183	34.6%
Conventional	30 29.7	24 20.5	3 6.8	57	10.8%
Column Total Column Percent	276 52.2%	190 35.9%	63 11.9%	**529**	100%

Pearson Chi-Square (33.57, 10), p =.00022

Top number in cell is actual count, bottom number is expected count if that occupational group had the same distribution of answers to the question as the entire sample.

TABLE 5-17

NEGATIVE CONSEQUENCES FROM LATE ARRIVAL, BY METHOD OF EMPLOYEE COMPENSATION

Survey Question: ANY NEGATIVE CONSEQUENCES FROM LATENESS?

Method of Compensation	Yes - there are negative consequences	No - there are no negative consequences	Row Total	Row Percent
Fixed Monthly Wage	140 122.2	247 264.8	387	73.2%
Hourly Wage	22 41.4	109 89.6	131	24.8%
Commission	5 3.5	6 7.5	11	2.1%
Column Total Column Percent	167 31.6%	362 68.4%	529	100%

Pearson Chi-Square (18.02, 2) p = .00012

Top number in cell is actual count, bottom number is expected count if that group had the same distribution of answers to the question as the entire sample.

TABLE 5-18

SLACK TIME, BY OCCUPATIONAL GROUP

Survey Question: HOW MANY MINUTES BEFORE ;YOU ACTUALLY STARTED WORK DID YOU ARRIVE AT YOUR WORK PLACE?

Holland Occupational Categories	No slack time	Slack time	Row Total	Row Percent
Realistic	37 48.2	48 36.8	85	15.9%
Investigative	66 60.6	41 46.4	107	20.1%
Artistic	9 9.6	8 7.4	17	3.2%
Social	41 45.9	40 35.1	81	15.2%
Enterprising	120 104.8	65 80.2	185	34.7%
Conventional	29 32.9	29 25.1	58	10.9%
Column Total	302	231	533	
Column Percent	56.7%	43.3%		100%

Pearson Chi-Square (14.49, 5), p = .01280

Top number in cell is actual count, bottom number is expected count if that occupational group had the same distribution of answers to the question as the entire sample.

TABLE 5-19

SLACK TIME, BY COMMUTE DISTANCE

Survey Question: HOW MANY MINUTES BEFORE YOU ACTUALLY STARTED WORK DID YOU ARRIVE AT YOUR WORK PLACE?

Holland Occupational Categories	No slack time	Slack time	**Row** Total	Row Percent
5 miles or less	54 52.1	39 40.9	93	17.1%
6- 10 miles	50 59.9	57 47.1	107	19.7%
11 -15 miles	67 63.3	46 49.7	113	20.8%
16 - 25 miles	62 59.3	44 46.7	106	19.5%
more than 25 miles	62 63.3	51 49.7	113	20.8%
missing	9	2	11	2.0%
	6.2	4.8		
Column Total Column Percent	304 56.0%	239 44.0%	543	**100%**

Pearson Chi-Square (7.69, 5), p = .17409

Top number in cell is actual count, bottom number is expected count if that travel distance group had the same distribution of answers to the question as the entire sample.

TABLE 5-20

REACTIONS TO INCREASED PROBABILITY OF TRAVEL DELAY

	Number	Percent
Start to car-pool if you now drive alone.	27	5.0%
Start to drive alone if you now carpool.	4	0.7%
Change work and commuting hours.	81	14.9%
Change your residence.	19	3.5%
Change your work place.	15	2.8%
Be willing to pay a road toll to guarantee timely arrival.	56	10.3%
Reserve more time for commuting.	269	49.5%
Not change your commuting habits.	237	43.6%
Other	45	8.3%

Note: percent totals do not sum to 100 due to respondents selecting multiple answers.

TABLE 5-21

PRICE ONE IS WILLING TO PAY TO BYPASS A 30 MINUTE TRAFFIC JAM, BY INCOME LEVEL

	Less than $25,000	$25,000 - $49,999	$50,000 - $64,999	$65,000 - $94,999	$95,000 and above	ROW Total	Row Percent
Nothing	12	26	31	6	1	76	15.0%
	5.7	27.9	26.4	11.3	4.7		
$0.50	9	57	30	12	6	114	22.5%
	8.6	41.9	39.7	16.9	7.0		
$1.00	8	60	58	24	7	157	31.0%
	11.8	57.7	54.6	23.3	9.6		
$2.00	5	20	29	14	9	77	15.2%
	5.8	28.3	26.8	11.4	4.7		
$3.00	1	13	16	7	5	42	8.3%
	3.2	15.4	14.6	6.2	2.6		
$5.00	3	10	12	12	3	40	7.9%
	3.0	14.7	13.9	5.9	2.5		
Column Total	38	186	176	75	31	506	
Column Percent	7.5%	36.8%	34.8%	14.8%	6.1%		100%

Pearson Chi-Square (19.45, 10). p = 0.03489

Top number in cell is actual count, bottom number is expected count if that income group had the same distribution of answers to the question as the entire sample.

TABLE 5-22

PRICE ONE IS WILLING TO PAY TO BYPASS A 30 MINUTE TRAFFIC JAM, BY OCCUPATIONAL GROUP

	Realis-tic	Investi-gative	Artistic	Social	Enter-prising	Conven-tional	Row Total	Row Percent
Nothing	22	19	1	6	22	11	81	15.5%
	12.7	16.2	2.6	12.1	28.5	8.9		
$0.50	21	18	1	23	46	10	119	22.8%
	18.7	23.8	3.9	17.8	41.8	13.0		
$1.00	16	26	5	27	60	26	160	30.7%
	25.2	31.9	5.2	24.0	56.2	17.5		
$2.00	14	19	9	7	27	3	79	15.2%
	12.4	15.8	2.6	11.8	27.7	8.6		
$3.00	7	9	1	7	14	4	42	8.1%
	6.6	8.4	1.4	6.3	14.8	4.6		
$5.00	2	13	0	8	14	3	40	7.7%
	6.3	8.0	1.3	6.0	14.0	4.4		
Column Total	82	104	17	78	183	57	521	
Column Percent	15.7%	20.0%	3.3%	15.0%	35.1%	10.9%		100%

Pearson Cl-G-Square (60.37, 25), p = 0.00009

Top number in cell is actual count, bottom number is expected count if that occupational group had the same distribution of answers to the question as the entire sample.

6. ESTIMATION OF DEMAND MODELS

6.1 Discrete Choice Model Estimation

The estimation procedure used to analyze our data set is a multinomial logit model. This is a qualitative choice model, applicable to situations where the dependent variable is discrete, i.e. the set of choice alternatives is limited and exhaustive and the alternatives are mutually exclusive. The model calculates a probability that the decision maker will choose a particular alternative from the set of alternatives, given the observed data.

Each individual is assumed to choose the alternative which gives the highest utility. The utility of an alternative, i, is divided into two components, observed, V_i, and random utility, ei. The observed utility is derived from the data, and the random component accounts for all the unobserved characteristics of the individual and both unobserved alternatives and independent variables. The probability that individual, n, will choose alternative, i, from a set of alternatives, C_n, is,

$$P_{in} = \Pr\left[V_{in} + e_{in} > V_{jn} + e_{jn}, \quad j \neq i\right] \tag{15}$$

Different choice models can be estimated based on assumptions made about the random component, e. If a normal distribution is assumed, the choice model is probit An extreme value distribution results in a logit model. For practical purposes there is generally little difference in the results. Logit models are more commonly used and are used in our estimations. Ben-Akiva and Lerman (1985) provide details on estimation procedures.

The formula for probability of choosing alternative i in a logit model is

$$P_n(i) = \frac{e^{V_{in}}}{\sum_{j \in C_n} e^{V_{jn}}} \tag{16}$$

In our application, there are only two alternatives in the choice set.

The results of logit estimations can be interpreted by examining the t-statistics as in conventional regression analysis. The repeated measures approach taken in our SP survey, however, results in upward biased t-statistics because some of the observations are not statistically independent of each other. Unfortunately, there are no easy procedures for correcting this bias. Instead, we note that the true t-statistic (i.e. true standard error divided by estimated coefficient) lies between the reported t-statistic and an "adjusted t-statistic" which treats the repeated observations as though their error were perfectly correlated. The adjusted t-statistic is found, as suggested by Louviere and Woodworth (1983) by dividing the reported t-statistic by the square root of the number of repeated measures ($\sqrt{9}$ in our data set).

We also use the $\bar{\rho}^2$ measure as defined in Ben-Akiva and Lerman (1985),

$$\bar{\rho}^2 = 1 - \left(L\left(\hat{\beta}\right) - K\right) / L(O) \qquad (17)$$

$L(\hat{\beta})$ is the log-likelihood at its maximum value, K is the number of parameters estimated, and L(0) is the log-likelihood when all the parameters are zero. This measure is similar (although not analogous) to the adjusted R^2 in regression analysis and allows us to compare alternative model specifications using the same data.

6.2 Results of Estimations

We now present the results of the demand models estimated with the data. First, we describe a series of basic models without socio-economic or other dummy variables included. These give some interesting comparisons with previous work and also allow us to highlight the basic behavioral trade-offs between the various attributes. We then explore the interactions of various socio-economic and other dummy variables to develop a comprehensive demand model.

6.2. I Basic Models

The basic models estimated in this section focus on the information obtained from the stated preference questions in our survey. Those questions, as discussed in section 4 (see Figure 4-l), provide trade-offs between mean travel time, departure time choices, and the distribution of travel times. To correspond with our analytical model (equation 14) we need to determine the expected schedule delay (both early and late) and the lateness probability from these questions.

Schedule delay, early and late, were defined in Section 3. We modified that framework slightly in order to match the format of the question shown in Figure 4-1, in which we used the words “usual arrival time” instead of “official work start time” as the basis for representing people’s most preferred arrival time; we did this to avoid having to make elaborate descriptions of how to count time in the elevator, walking through the office, and so forth. The stated-preference question format specifies “departure $[T_a]$ minutes before your usual arrival time”, where a specific number is inserted for T_a; that number is therefore taken to be a measure oft, - th in the notation of section 3. (The notation Ta indicates minutes ahead of desired arrival time.) The definition of early and late schedule delay given just prior to equation (1) is therefore the following in the current notation:

$$SDL_i = \begin{cases} T_a - T_i, \text{if} > 0, \\ 0 \text{ otherwise;} \end{cases} \qquad (18)$$

$$SDE_i = \begin{cases} T\text{-}T,, \text{ if} > 0, \\ 0 \text{ otherwise.} \end{cases} \qquad (19$$

T_a and the five values of T_i are stated directly in the question. The expectations of T, SDE and SDL are derived by summing, over the five possible values and dividing T_i, SDE, or SDL, by five. For example, using the sample question in Figure 4-1, for choice A we have three possibilities of arriving early since the departure time is 15 minutes before usual arrival time, (i.e. T_a is 15 minutes) and travel times (T_i) are 12, 13, 14, 16, and 20. In three cases one can arrive early, by 3, 2, and 1 minute. Therefore to calculate E(SDE) we sum the early arrivals (3 + 2 + 1 + 0+ 0) and divide by 5 to get a value of E(SDE) equal to $6/5$ = 1.2 minutes. In choice B, E(SDE) is 1.8 minutes. E(SDL) is calculated in a similar manner and would be 1.2 minutes in choice A and 2 minutes in choice B.

The lateness probability is determined discretely by counting the number of possible travel times that will result in a late arrival and dividing by 5. Using the sample question in Figure 4-1, choice A has 2 possibilities of arriving late (16 and 20 minute travel times) which result in a 40% lateness probability (P_L = 0.40). Choice B also has a 40% lateness probability (P_L = 0.40). The design of the SP questions provided only three discrete levels of lateness probability: 0%, 20%, and 40%.

The standard deviation of the travel time is defined in the usual way as the sum of five terms $[T_i - E(T)]^2$ divided by 5.

Our first step in analyzing the results is to estimate a simple model that contains only the trade-off between mean travel time and the standard deviation of travel time. The result is shown in Table 6- 1, column 1. Both attributes are highly significant in explaining choice and both estimated coefficients have the expected negative sign (i.e., the larger the travel time and/or the standard deviation, the less desirable the alternative). For comparison, column 2 shows the results of Black and Towriss (1993). They also include money in their estimations.

A useful comparison is the ratio of the coefficient of standard deviation to that of E(T). We find the ratio to be 1.32 while Black and Towriss have a ratio of 0.55. Thus our estimation indicates that each minute of standard deviation is about 30% more costly than each minute of mean travel time. One of the key differences between our study and Black and Towriss is that they did not specify the head start time as we do; therefore it is natural that they found people less averse to travel time variation because in the survey people can anticipate its effects by adjusting their schedules.[3] We can also take that into account, but to do so we need to estimate the full model of equation (14). MVA Consultancy (1992) suggest that the most plausible value for the ratio is between 1.1 and 2.2, based on the extremely limited empirical information available.

[3]Black and Towriss (1993) did include a money cost in their survey. As mentioned previously, we found a large politically motivated bias in our pre-test and so excluded a cost variable from our final survey design.

Table 6-2 shows the result of estimating the full model of equation (14) with planning cost assumed proportional to the standard deviation of travel time. Planning cost has a positive and significant coefficient, which is contrary to the theory. The coefficient for the mean travel time is also less than that for E(SDE), which implies that people prefer to be in traffic than to arrive early. As an alternative we specify planning cost as proportional to the coefficient of variation (standard deviation divided by mean travel time) and find that while this is statistically insignificant, it does have the appropriate sign. This is shown in Table 6-3, column 1, and henceforth will be referred to as our "Basic Model".

All coefficients in the basic model have the expected negative signs. They also have the expected relative magnitudes: E(SDE) is less onerous than E(T) which is less than E(SDL). However, we were surprised that the relative magnitude of E(SDL) was not much greater than E(T). In fact, the adjusted T-Stat implies that it may not even be significant. The adjusted T-Stats for the lateness probability and the coefficient of variation are also not significant.

It is possible that E(SDL), P_L, and the coefficient of variation are too highly correlated to distinguish their effects seperately. Column 2 (Table 6-3) shows that when P_L is removed the coefficients of the other two increase, and the ordinary T-Stat (though not the adjusted T-Stat) of the coefficient of variation becomes significant.

When the coefficient of variation is removed from the model (Table 6-3, column 3) the other coefficients do not noticeably change. The coefficient on lateness probability does increase slightly, indicating that it is picking up some of the explanatory power of the coefficient of variation. This result seems to suggest that our hypothesized "planning cost" is not as important a variable in the commuters' choice as the other variables. Alternatively, we may not have specified an appropriate functional form for planning cost. In any case, it appears that much of the uncertainty inherent in unreliable commuting trips is better explained by the schedule delay and lateness probability variables. Table 6-3, Column 4 shows a specification in which lateness probability is entered as a dummy variable equal to 1 when $P_L > 0$; our other coefficients maintain the same relative magnitude, but this specification does not fit nearly as well as the model of column (3) which specified P_L directly.

The relative importance of the schedule delay variables with respect to travel time was first detected by Small (1982). We present his model for comparison in column 5. This model contained no uncertainty in travel time, and therefore no planning cost (coefficient of variation).

The bottom of Table 6-3 shows the ratios of the coefficients for E(SDE) and E(SDL) relative to travel time for each model. As can be seen, when the lateness probability is not included, we get very similar results to the model that Small estimated. This is an encouraging result, as it indicates that the respondents to the questionnaire interpreted the trade-offs in the SP questions appropriately.

These models show that all the components of the scheduling cost, C,, in equation (14) are important determinants of the travel choices individuals make. We believe these are the underlying factors behind the aversion to travel time uncertainty found by other researchers, such as Black and Towriss (1993). Whether planning cost is a significant factor when scheduling variables are taken into account remains unproven due to the statistical insignificance of the coefficient of variation in our basic model. It may be that it is a lesser factor whose importance is too small for us to measure.

The model with the highest $\bar{\rho}^2$ (and the largest likelihood function) and that matches our theoretical formulation is the basic model in column 1 of Table 6-3. For this reason we will utilize this model in the simulations presented in section 7. The next section expands our understanding of individual demand by adding various socio-economic factors into the basic demand model.

TABLE 6-1

SIMPLE MODEL COMPARED WITH BLACK AND TOWRISS MODEL

	Simple Model	Black and Towriss model (cars only) (1993)
	(1)	(2)
E(trave1 time)	-0.0996	-0.0635
T-Stat	(-17.517)	(-8.90)
Adj. T-Stat	(-5.839)	
standard deviation	-0.1263	-0.0352
T-Stat	(-12.669)	(-3.17)
Adj. T-Stat	(4.223)	-
Money		-0.0082
T-Stat		(-6.34)
N = 4340		
$L(\beta)$	-2826.5	
$\bar{\rho}^2$	0.0598	

Note: The measure of fitness was computed as $\bar{\rho}^2 = 1-(L(\beta)-K)/L(0)$, where K equals the number of estimated parameters, L(B) is the log-likelihood value evaluated at the estimated parameters, and $L(0)$ = -3008.3 is the log-likelihood value evaluated setting all coefficients equal to zero. Sample size is equal to N above. .

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TABLE 6-2

MODEL WITH PLANNING COST PROPORTIONAL TO STANDARD DEVIATION

E(travel time)	**-0.0556**
T-Stat	**(-4.656)**
Adj. T-Stat	**(-1 .552)**
E(SDE)	**-0.1311**
T-Stat	**(-11.386)**
Adj. T-Stat	**(-3.795)**
E(SDL)	**-0.3036**
T-Stat	**(-5.085)**
Adj. T-Stat	(-1.695)
lateness probability	**-2.564**
T-Stat	**(-6.426)**
Adj. T-Stat	**(-2.142)**
standard deviation	**0.1510**
T-Stat	**(5.098)**
Adj. T-Stat	**(1.699)**
N = 4340	
$L(\beta)$	**-2747.3**
$\bar{\rho}^2$	**0.085 1**

TABLE 6-3

RESULTS OF MODEL ESTIMATIONS

	Basic Model (1)	without lateness probability (2)	without coefficient of variation (3)	with lateness probability dummy (4)	Small (1982), model 1* (5)
E(trave1 time)	-0.1051	-0.1285	-0.0976	-0.1133	-0.106
T-Stat	(-10.148)	(-15.451)	(-11.052)	(-14.442)	(-2.79)
Adj. T-Stat	(-3.383)	(-5.150)	(-3.684)	(-4.814)	
E(SDE)	-0.093 1	-0.0966	-0.0945	-0.1000	-.065
T-Stat	(-10.606)	(-11.004)	(-10.854)	(-11.544)	(-9.29)
Adj. T-Stat	(-3.535)	(-3.668)	(-3.618)	(-3.848)	
E(SDL)	-0.1299	-0.2807	-0.1280	-0.2856	-0.254
T-Stat	(-2.694)	(-10.594)	(-2.656)	(-10.683)	(-8.47)
Adj. T-Stat	(-0.898)	(-3.531)	(-0.885)	(-3.561)	
lateness probability	-1.3466		-1.529		-0.58
T-Stat	(-3.704)		(-4.495)		(-2.76)
Adj. T-Stat	(-1.235)		(-1.498)		
coef. of variation	-0.3463	-0.6674			
T-Stat	(- 1.403)	(-2.908)			
Adj. T-Stat	(-0.467)	(-0.969)			
lateness probability dummy	-			-0.1466	
	-			(-2.469)	
	-			(-0.823)	
N = 4340					
$L(\beta)$	-2759.6	-2766.5	-2760.6	-2767.7	
$\bar{\rho}^2$	0.0810	0.0790	0.0810	0.0786	
Coeffkient Ratios					
E(SDE) / E(T)	0.886	0.752	0.968	0.883	0.613
E(SDL) / E(T)	1.236	2.184	1.311	2.521	2.396

* Small's model also contains coefficients to adjust for rounding errors in reported measurements. The variable definitions are somewhat different also. The travel time, SDE and SDL variables are actual reported values as opposed to expected values; the lateness probability was a dummy variable for those choices involving actually arriving at work late, whose expectation would be the lateness probability in the context of the present paper.

6.2.2 Inclusion of Occupational and Socio-Economic Factors

As discussed previously, we hypothesize that various personality traits, as identified by occupational decisions, may influence travel behavior, especially with regard to risk taking and uncertain travel times. We developed a demand model that includes these occupational categories plus other socio-economic factors.

We analyzed various socio-economic factors that are generally important in travel decisions. In particular, household income and personal income may influence the value of reliability; however, we found that these variables were not significant in our sample. Probably this is because we do not include a cost variable. Having school age children may also increase the valuation of reliability, due mainly to increased scheduling concerns (i.e., the need to chaffeur children to school and other activities). We found some significance to this effect as will be discussed further below.

Variables associated with the commute itself may also influence the value of travel time variability. For example, people with longer commutes may tolerate larger deviations in travel time, whereas carpoolers may value reliability more due to the need for schedule coordination; in both cases, however, we found no significant effects. Given the lack of any significant differences between those who car-pool and single occupant drivers, we do not pursue any additional analysis of the effect of car-pooling in our congestion simulations.[4]

We attempted to first find a robust, sparse demand model which would capture the essence of the effects of unreliable travel time without hard to measure variables or variables whose values depend on the subjective assessments of the respondent (such as whether employers impose sanctions for late arrival), These models are reported in table 6-4; selected coefficient ratios (marginal rates of substitution) are shown in table 6-5.

Model (6) is the basic model (1) with the addition of the wage-earner indicator interacted with the time and scheduling variables. The coefficient of variation of the travel time (standard

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[4] Given the lack of any significant differences between those who carpool and single occupant drivers, we do not pursue any additional analysis of the effect of carpooling in our congestion simulations.

deviation of travel time divided by mean travel time) is interacted with the dummy variable for school-aged children in the household.

The results indicate that wage earners are less sensitive than salaried employees to time spent traveling, time early, or time late. (These are indicated by the positive coefficients on the wage-earner interactions, which partly offset the negative coefficients of the corresponding non-interacted variables.) Wage earners are more sensitive than salaried workers, however, to the probability of being late (although this difference is not statistically significant). These seem plausible descriptions of workers who value time less but are more subject to sanctions when late.

Since the schedule-delay-late variable seemed to covary with the probability of lateness, we dropped one of them in model (7) and the other in model (9). Model (7) indicates a greater aversion towards schedule delay early for both salaried workers and wage-earners, but a twice as large aversion towards schedule delay late for wage-earners than for salaried persons. Model (9), which uses lateness probability P_L to proxy all effects of late arrivals, fits considerably better than model (7) according to the log-likelihood.

We then added one subjective variable to each of specifications (7) and (9), forming (8) and (10) respectively. The new variable is a dummy called "penalty," which takes a value of one if the respondent indicates that he or she cannot arrive late without negative consequences. This variable is intended to capture the employer's policy toward lateness, and so is interacted with either expected schedule delay late or lateness probability. In both cases it produces a negative coefficient, one that is marginally significant in model (8) but not significant in model (10). We do not pursue this variable further because of the danger that it is endogenous, possibly being used to justify behavior that is chosen for other reasons,

Table 6-6 shows the results of adding dummy variables for various occupational groups. We first repeat model (9) of the previous tables as a starting point. This seems to be a well performing model, sparse enough to support adding additional interactions. Model (11) then adds occupational variables determined as follows.

The six Holland occupational groups are Realistic, Investigative, Artistic, Social, Enterprising, and Conventional (as discussed in detail in Section 2). Preliminary exploration discussed in section 5 indicated that the realistic and conventional groups are somewhat similar and we combine them into one group; the artistic group behaves quite unlike any others (possibly due to its small numbers in this sample). The other three groups, which involve personal and intellectual skills and perhaps a greater degree of initiative on the job, seemed similar enough to group together; we take those as the base group with respect to which the others are measured. The result of this approach is model (11). It indicates that people in realistic-conventional occupations tend not to mind long commutes, scheduled early arrival or even the probability of arriving late as much as people in other occupations. The coefficients for Artistic occupations indicates similar tendencies, but the coefficients are not significant.

On the whole, it appears that the wage-earner indicator does a better job than the Holland occupational codes of separating people according to their response to scheduling considerations.

TABLE 6-4

RESULTS OF TRAVEL DEMAND MODEL ESTIMATIONS

	Basic Model with socio-economic variables (6)	without PL variables (7)	without P_L variables, with penalty (8)	without E(SDL) variables (9)	without E(SDL) variables, with penalty (10)
E(trave1 time)	-0.1239	-0.1444	-0.1448	-0.1091	-0.1089
T-stat	-10.657	-15.054	-15.056	-10.649	-10.617
E(trave1 time) x wage earner	0.0797	0.0675	0.0668	0.0696	0.0692
T-stat	3.866	3.857	3.817	3.972	3.946
E(SDE)	-0.1041	-0.1067	-0.1071	-0.0962	-0.0966
T-stat	-9.970	-10.231	-10.250	-9.701	-9.725
E(SDE) x wage earner	0.0567	0.0525	0.052 1	0.0512	0.05 14
T-stat	2.841	2.653	2.633	2.699	2.707
E(SDL)	-0.1491	-0.2720	-0.1902		
T-stat	-2.667	-9.172	-4.617		
E(SDL) x wage earner	0.1026	-0.0107	0.0128		
T-stat	0.897	-0.201	0.238		
E(SDL) x wage earner			-0.1289		
T-stat	-		-2.824		
PL	-1.1293			-2.0730	-1.815
T-stat	-2.721			-9.375	-6.416
PL x wage earner	-0.8765			-0.2306	-0.1430
T-stat	-1.088			-0.62 1	-0.380
PL x penalty					-0.4333
T-stat					-1.450
coef. of variation	-0.2922	-0.6082	-0.6165	-0.2811	-0.2744
T-stat	-1.104	-2.449	-2.481	-1.058	-1.032
coef. of variation x child6-15	-0.6580	-0.6828	-0.6486	-0.6479	-0.6313
T-stat	-1.577	-1.647	-1.564	-1.546	-1.506
N = 4258 $L(\beta)$	-2702.0	-2709.3	-2705.3	-2705.7	-2704.6
$\bar{\rho}^2$	0.0809	0.079 1	0.0803	0.080 1	0.0804

Notes: In each case, the t-statistic shown may be divided by 3 to obtain the "adjusted" or lower-bound t-statistic (see text).

The measure of fitness was computed as $\bar{\rho}^2 = 1-(L(\beta)-K)/L(0)$, where K equals the number of estimated parameters, $L(\beta)$ is the log-likelihood value evaluated at the estimated parameters, and L(O)=-295 1.4 is the log-likelihood value evaluated setting all coefftcients equal to zero. Sample size for the socio-economic models is 4,258.

TABLE 6-5

COEFFICIENT RATIOS OF TRAVEL DEMAND MODELS

	Basic Model with socio-economic variables (6)	without PL variables (7)	without PL variables, with penalty (8)	without E(SDL) variables (9)	without E(SDL) variables, with penalty (10)
Salaried:					
E(SDE) / E(T)	0.840	0.739	0.740	0.882	0.887
E(SDL)/E(T)	1.203	1.884	1.314		
P_L/E(T)	9.115			19.001	16.667
Wage-earners:					
E(SDE)/B(T)	1.072	0.705	0.705	1.139	1.139
E(SDL)/E(T)	0.889	3.676	2.274		-
P_L/E(T)	45.380			58.3 19	49.320
Salaried with lateness penalty:					
E(SDL)/E(T)			2.204		
P_L/E(T)	-				20.646
Wage-earners with lateness penalty:					
E(SDL)/E(T)			3.927		
P_I/E(T)					60.234

TABLE 6-6

TRAVEL DEMAND MODEL WITH OCCUPATIONAL VARIABLES

	Coefficient	T-Stat
E(T)	-0.1217	-10.973
E(T) x wage earner	0.0620	3.454
E(SDE)	-0.1170	-10.519
E(SDE) x wage earner	0.0334	1.702
P_L	-2.270	-9.508
P_L x wage earner	-0.4238	-1.107
coef. of variation	-0.2744	-1.029
coef. of variation x child 15	-0.6083	-1.444
E(T) x realistic-conventional	0.0460	2.628
E(T) x artistic	0.0897	1.586
E(SDE) x realistic-conventional	0.0834	4.395
E(SDE) x artistic	0.0847	1.181
P_L x realistic-conventional	0.7768	2.096
P_L x artistic	0.5247	0.568
N = 4258		
$L(\beta)$	-2694.1	
$\bar{\rho}^2$	0.0824	

7. SIMULATIONS WITH ENDOGENOUS CONGESTION

We now combine the demand analysis of the basic model of Table 6-3, column **1,** with a supply side model of a congested highway corridor to simulate the effect of non-recurrent events on actual congestion patterns. This procedure will allow us to examine scheduling shifts due to either a reduction in incident probabilities or an expansion of capacity. We also examine the expected costs to commuters of these policy options.

First we discuss the basic simulation procedure and methodology. We then briefly present the travel conditions generated by the simulations. This is followed by an analysis of the pattern of scheduling shifts and the relative components of total travel costs.

7.1 Simulation Methodology

A simulation was performed to determine how uncertain capacity will affect the equilibrium pattern of congestion, total commuter costs, and the per person average travel delay. The simulation model used is essentially that of Chu (1993) but modified to account for random events that reduce the capacity of the highway facility. We also substitute our demand model for his. Capacity reducing events result in non-recurrent congestion and may be due to accidents, minor incidents such as breakdowns, or adverse weather conditions. The probability of a capacity reducing incident occurring can be considered an exogenous policy variable. For example, specific measures to reduce the probability of an incident may include a state vehicle inspection program or increased enforcement of traffic regulations. The simulations analyzed in this report focus on changes in this variable and the level of capacity.

The simulation is an iterative process that balances the demand model with a supply side model of congestion. The demand model is applied to a synthetic sample of 5000 individuals. Their “work start” times (actually departure times from the congested highway) were generated randomly from a normal distribution with mean = 8:00 am and standard deviation = 60 minutes; their free flow times were generated from a distribution with mean = 20 minutes and standard deviation = 5 minutes.5 Although our respondents faced only two choices in the SP questions, we assume that when faced with a larger choice set they would apply a multinomial logit choice rule to that larger set using the same estimated utility function. In our simulation there are eleven choices, ranging from $E(\mathrm{SDE})$ = 20 minutes to $E(\mathrm{SDL})$ = 20 minutes. The intermediate values for both $E(\mathrm{SDE})$ and $E(\mathrm{SDL})$ are 15, 10, 5, and 3 minutes, as well as the expectation of arriving on-time (0 minutes). Alternatively, we can express this as a choice of $E(\mathrm{SD})$ ranging from -20 to +20.

For each member of the synthetic sample, the demand model determines the probabilities of each of the eleven possible values of $E(\mathrm{SD})$. Each of these choice probabilities is then allocated to a 10 minute clock time increment using that individual's "work start" time. For example, if an individual has a work start time of 8:30 am (540 minutes), then we sum the probability of $E(\mathrm{SD})$ into the absolute time slots which precede this work start time (e.g., the summation of the probabilities that expected $E(\mathrm{SD})$ is -20 minutes would be allocated to the time increment between 8: 10 and 8:20 am). Sample enumeration, which consists of summing the choice probabilities for each individual in the synthetic sample, allows us to determine the estimated traffic volume for each 10 minute time slot.

Our supply model applies the following simple speed-flow relationship to each time slot:

$$\mathrm{T} = \ell \cdot \left[\mathrm{T}^0 + \mathrm{T}^1 \left(\frac{\mathrm{V}}{\mathrm{C}} \right)^{\varepsilon} \right] \tag{20}$$

where T is the travel time in minutes, V is the number of vehicles leaving the highway per hour, C is the capacity of the facility, ε is the elasticity parameter, l is the length of the facility (assumed to be equal to 5 miles), and T^0 and T^1 are constants. The supply model of equation (20) has a long history in transportation engineering and economics, dating back at least to the U.S. Bureau of

[5] Work start times are usually at discrete intervals, such as 8:00 am, 8:30 am, etc. Our "work start" times represent the point at which individuals depart the highway facility. Presumably they would have some extra travel after they have left the highway to get to their final job location, and this would vary across the population, smoothing the distribution of "work start" times.

Public Roads (1964). It was incorporated into the Urban Transportation Planning Process computer software used widely in the U.S. (Branston, 1976, p. 230) and has also been used in many economic models of congestion including Vickrey (1963), Mohring (1979), and Kraus (1981), with values of ε ranging from 2.5 to 5. Small (1992, pp. 70-73) finds that equation (2) fits quite well the data from a dynamic simulation of city streets in Toronto (with ε = 4.08) and the data from an aggregate analysis of Boston express roads (with ε = 3.27). Since the precise function is less important for our purposes than its general ability to measure rapidly increasing congestion, we forego an extensive empirical estimation and simply used the parameters of U.S. Bureau of Public Roads (1964) namely: $\varepsilon = 4$ and $T^1/T^0 = 0.15$. We also set $T^0 = 1.0$ minutes/mile to represent a free-flow speed of 60 miles per hour.

It is assumed that the volume used in (20) is calculated at the point where the flow leaves the highway, as defined by Chu (1995). The capacity is assumed equal to 1200 vehicles/hour except for random reductions due to incidents. It is these random capacity reductions that make T stochastic.

We assume that the probability of an incident is the same for every 10 minute increment of clock time. We also assume that each incident is independent of other incidents, except that for simplicity, we assume that only one incident can occur within a given time interval. We also assume that no additional incidents occur during the time when the capacity is reduced. The probability of a capacity reduction is assumed independent of traffic volume; although, as we will show, the resulting standard deviation of travel times varies and is higher over the peak period.

Three levels of incident severity were defined, given that an incident had occurred. These were based on the fraction of capacity blocked. We specify three levels of capacity reduction: 50%, 30%, and 10%, occurring with conditional probabilities of 10%, 20%, and 70%, respectively.[6]

[6] Analysis of variations in severity level and probabilities found no substantive differences to variations in incident probabilities.

The duration of each reduction in capacity must also be specified. Incident durations have been determined to occur with a log-normal distribution (Giuliano, 1989; Golob et al., 1987). We instead set three levels based on the clock time intervals. The probability that the incident lasted for only 10 minutes (1 interval) was set to 50%, for 20 minutes (2 intervals), 30%, and for 30 minutes (3 intervals) 20%. These durations result in a given individual facing the possibility of a capacity reduction with a probability equal to 1.7 times the specified incident probability for a given 10 minute interval. Therefore, variation in incident durations are essentially equivalent to variations in the incident probability for a given period.

For the sake of exposition, we calculated the distribution of travel time values assuming 10,000 trips. This allowed us to calculate travel time values given a range of incident probabilities and the specified severity probabilities. For example, if we assumed a 2% incident probability, then there would be 200 trips with some reduction in capacity. If for each incident there was a 50% chance of a 10% reduction in capacity, then 100 trips would have capacity reduced by this amount in the calculation of the travel time using the speed-flow equation (20) above. This was done for each 10 minute clock interval, resulting in a complete description of the the travel time distribution for that time interval, including the mean travel time and the standard deviation of travel time.[7]

This distribution was then fed back into the demand model. This allows us to calculate a new distribution of expected schedule delays for each individual. The demand model also uses the ratio of standard deviation to the mean travel time, the latter also includes the free flow travel time for each individual. From this the demand model allocates each individual stochastically to a clock time interval and we can enumerate over the entire synthetic sample. This process continues until the number of individuals in each time interval remains essentially constant (or changes by a very small amount) from one iteration to the next. We then evaluate the congestion profile, the average travel delay, and the total cost.

[7] We initially used a random monte carlo process to generate incident probabilities and duration levels. However, we found that given the constraints of processing time we could not eliminate random fluctuations which created large deviations in our results.

7.2 Travel Conditions Generated by Simulations

The travel conditions generated by the simulations are a function of our assumptions about incident probability levels, the severity of those incidents, the probability of a given level of severity occuring, and the incident duration. The travel conditions give the values that are used in the demand model and that represent the equilibirium level of the system. Here we review these values and briefly discuss their realism and the rationale behind how they are generated.

Figure 7-l graphs the average travel time generated for each ten minute clock interval, for each of four alternate values for the incident probability. This travel time includes the minimum 5 minute free-flow time to travel along the 5 mile corridor which is simulated, but does not include the average of individual free-flow times (which averaged an additional 15 minutes). The amount above the 5 minute free-flow time is the extra travel time for each interval due to normal congestion and non-recurrent congestion. The graph shows that as the incident probability increases, the travel time at the peak will also increase while off-peak times stay at the free-flow speed. This is because the capacity reduction does not result in any congestion during the off-peak periods. Figure 7-2 shows the travel delay which occurs only because of non-recurrent congestion, ranging from peaks of about 2.5 minutes up to 5.5 minutes in our simulations.

The standard deviation of travel time and the coefficient of variation vary over the peak also (see Figure 7-3 and Figure 7-4). The maximum standard deviation and coefficient of variation occur at the most congested time. This is because any reduction in capacity at this time will have a much greater impact on travel times than a capacity reduction when traffic volumes are less. Incidents during off-peak hours will not have any impact on travel times since there is ample capacity, even after an incident causes a reduction in capacity. The increase in standard deviation (and the coefficient of variation) over the peak occurs despite modelling a constant incident probability for each clock interval. The coefficient of variation ranges up to about 0.14 which matches empirical measurements ranging from 0.08 to 0.2 as reported by Bates (1990)

The probability of arriving at work late for any given choice of schedule shows an expected pattern. As the probability of a capacity reduction increases, lateness probability increases. Figures 7-5, 7-6, and 7-7 show this pattern for four different values of incident probability if one chooses departure time to to have *E*(SDE) = 0 (on-time arrival), *E*(SDE) = 5, and *E*(SDE) = 20, respectively. The simulations generate a maximum lateness probability of slightly over 40% in the on-time case (with a 25% incident probability); this is a good match to the range of lateness probabilities in our stated preference questions which had three levels of 0%, 20%, and 40%. As can be seen by the three graphs, the lateness probability only occurs when there is traffic congestion; when the capacity reduction generates any excess congestion within a given clock interval then lateness probability increases abruptly from the 0% level. However, the commuter can lower their lateness probability considerably by leaving earlier.

7.3 Travel Delay and Scheduling Shifts from Incident Reduction and Capacity Expansion

Reductions in non-recurrent delay (expressed as incident probabilities) can decrease average travel times. Increases in capacity can have a similar effect. Both may also have an impact on scheduling choices which may reduce the benefits of reductions in peak travel time by allowing more commuters to travel during peak hours. There may be reductions in scheduling costs associated with any shift to the peak.

Figure 7-8 shows how average travel delay is reduced as the incident probability decreases. Both total delay and delay due only to non-recurrent congestion decrease with decreasing incident probability. The relationship is essentially linear and directly related to the probability of an incident occurring. Obviously, policies that reduce the probability of an incident blocking capacity will result in a decrease in average travel times. Figure 7-9 shows the percent of total delay that is due to non-recurrent delay. As the incident probability increases so does the percent of total delay which is due to non-recurrent delay, but at a diminishing rate. That is, one gets less effect from reducing incident probabilities from 25% to 20% as one does from reducing it from 20% to 15%.

Figure 7-10 shows the effect on average travel delay for a doubling of highway capacity from 1200 vehicles per hour to 2400 vehicles per hour. This is obviously very effective at reducing travel delay. Figure 7-8 showed that for a capacity of 1200 vehicles per hour, eliminating incident probabilities results in a reduction in average delay to about 2.5 minutes per vehicle. This is comparable to increasing the capacity, as shown in Figure 7-10, to about 1400 vehicles per hour for an incident probability level of 20%. While we don't know what the costs of reducing the an incident probability would be, we do know that freeway capacity expansions are generally very costly. Therefore, if reducing travel delay is the only objective, this shows the relative trade-offs of two possible alternative strategies for reducing delay.

Scheduling costs involved in commuting decisions may be as important as travel time costs. Figure 7-l 1 shows that reducing the probability of an incident results in significant shifts in schedules: many commuters who previously planned to arrive early or late now choose to instead arrive at their desired work start time. Figure 7-12 shows the overall shift, with about 400 (out of 5000) more commuters choosing to arrive with schedule delay of zero when incident probabilities are zero, compared to an incident probability level of 25%.

Such shifts do not occur as a result of increasing capacity as is shown in Figure 7- 13. Figure 7- 14 shows the difference in schedule delay choices between capacity level 1200 and 2400 for each incident probability level. The greatest shift occurs with an incident probability of 25% with a very small increase of about 50 (out of 5000) commuters choosing to arrive with no schedule delay (compared to about 400 in the above case with incident probability reductions).

Despite the scheduling benefits of incident reductions, the overall congestion profile does not really change. Figure 7- 15 shows this profile for incident probability equal to 25% and 0%. There is a slight increase in peak travel when there are no incidents, but it is essentially negligible and will have only a minor impact on increasing average travel delays; therefore, the scheduling cost reductions do not seem to be off-set by significantly more congestion at the peak.

7.4 Components of Total Travel Costs

The expected travel costs can be calculated using the demand model (Table 6-3, column 1) and the equilibrium travel conditions generated by the simulations. These are calculated for different incident probability levels and different capacity levels.

Figure 7-16 displays the average total cost (omitting free-flow travel time costs) by incident probability level and the percentage of each cost component is shown in Table 7- 1. The costs are disaggregated into components related to travel time, schedule delay early and late, lateness probability, and the coefficient of variation. Schedule delay early costs make up the largest segment of the total costs, but this proportion decreases with increasing incident probability When incident probability is high, travel time costs account for the largest proportion of total costs because of the high level of non-recurrent congestion. The “planning cost” as indicated by the coefficient of variation is relatively minor, but does increase with increasing incident probability. The costs associated with the probability of arriving late also increase. The major reduction in total costs with decreasing probability of an incident can be attributed to decreases in costs of schedule delay early and lateness probability.

Figure 7-17 and Table 7-2 show a similar brakedown for simulations with increasing levels of capacity. Total costs decrease by about the same amount when capacity is doubled from 1200 to 2400 as in the case when incident probabilities are reduced from 25% to 0%. The source of the decrease in costs is, however, different. When capacity is increased the main reduction comes from reductions in the travel time costs associated with both recurrent and non-recurrent congestion. Scheduling costs and lateness probability remain essentially the same. The “planning cost” is again negligible, as is its relative decrease with increasing capacity.

The cost calculations shown above are averages over all the clock intervals of the simulations. This averages peak and off-peak travellers together. Those choosing to travel at peak periods, due perhaps to job or other constraints, will face higher total costs, than those travelling at off-peak hours. The relative contribution of the various components will also differ.

Figure 7-18 and Table 7-3 show the cost components for an off-peak period (between the clock interval 6:35 am to 6:45 am). Travel time costs due to non-recurrent capacity reductions are negligible. There is also very little variation in total costs as the incident probability increases. Most of the increase is due to the costs of the probability of arriving late increasing.

During the peak period, travel time costs are a significant fraction of the total costs, which increase significantly as the incident probability increases (see Figure 7-19 and Table 7-4). Lateness probability costs also show an increase while scheduling costs do not change much and their total percent contribution decreases.

TABLE 7-l

Components of Total Cost by Incident Probability (capacity = 1200)

Incident Probability	Average cost ($/trip)	Travel Time	E(SDE)	E(SDL)	Coef. of Variation	Lateness probability
0	$1.51	**27.92%**	43.88%	10.91%	0.00%	17.29%
0.1	$1.89	30.83%	36.86%	9.51%	1.13%	21.67%
0.15	$2.07	32.00%	34.54%	9.08%	1.41%	22.97%
0.2	$2.24	33.04%	32.68%	8.75%	1.57%	23.96%
0.25	$2.39	33.99%	31.17%	8.50%	1.65%	24.69%
Difference between highest & lowest incident mobabilities	$0.88	44.33%	9.52%	4.39%	4.46%	37.30%

TABLE 7-2

Components of Total Cost by Capacity (Incident Probability = 0.2)

Capacity (vehicle&r)	Average cost ($/trip)	Travel Time	E(SDE)	E(SDL)	Coef. of Variation	Lateness probability
1200	$2.24	33.04%	32.68%	8.75%	1.57%	23.96%
1500	$1.76	18.08%	41.67%	10.75%	1.02%	28.49%
1800	$1.56	10.10%	47.20%	11.90%	0.61%	30.18%
2100	$1.46	5.90%	50.37%	12.55%	0.37%	30.81%
2400	$1.41	3.60%	52.03%	12.91%	0.23%	31.23%
Difference between highest & lowest capacity	($0.83)	83.68%	-0.61%	1.61%	3.88%	11.44%

TABLE 7-3

Components of Total Cost During Off-peak Intervals, by Incident Probability (capacity = 1200)

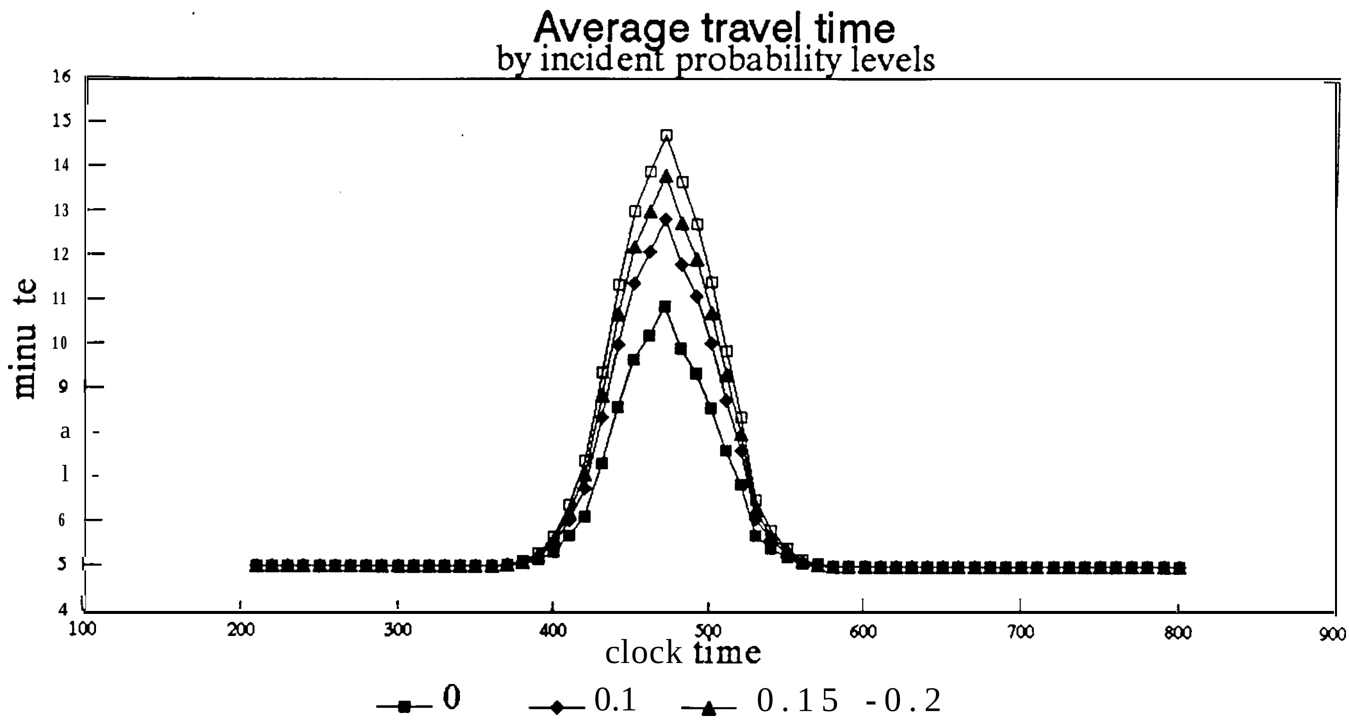
Incident Probability	Average cost ($/trip)	Travel Time	E(SDE)	E(SDL)	Coef. of Variation	Lateness probability
0	$1.11	2.86%	60.09%	14.19%	0.00%	22.86%
0.1	$1.27	3.65%	55.77%	12.85%	0.17%	27.56%
0.15	$1.34	4.03%	54.44%	12.39%	0.23%	28.91%
0.2	$1.40	4.42%	53.48%	12.01%	0.27%	29.82%
0.25	$1.46	4.81%	52.79%	11.70%	0.31%	30.38%
Difference between highest & lowest incident probabilities	$0.3 5	11.05%	29.42%	3.73%	1.30%	54.49%

TABLE 7-4

Components of Total Cost During Peak Intervals, by Incident Probability (capacity = 1200)

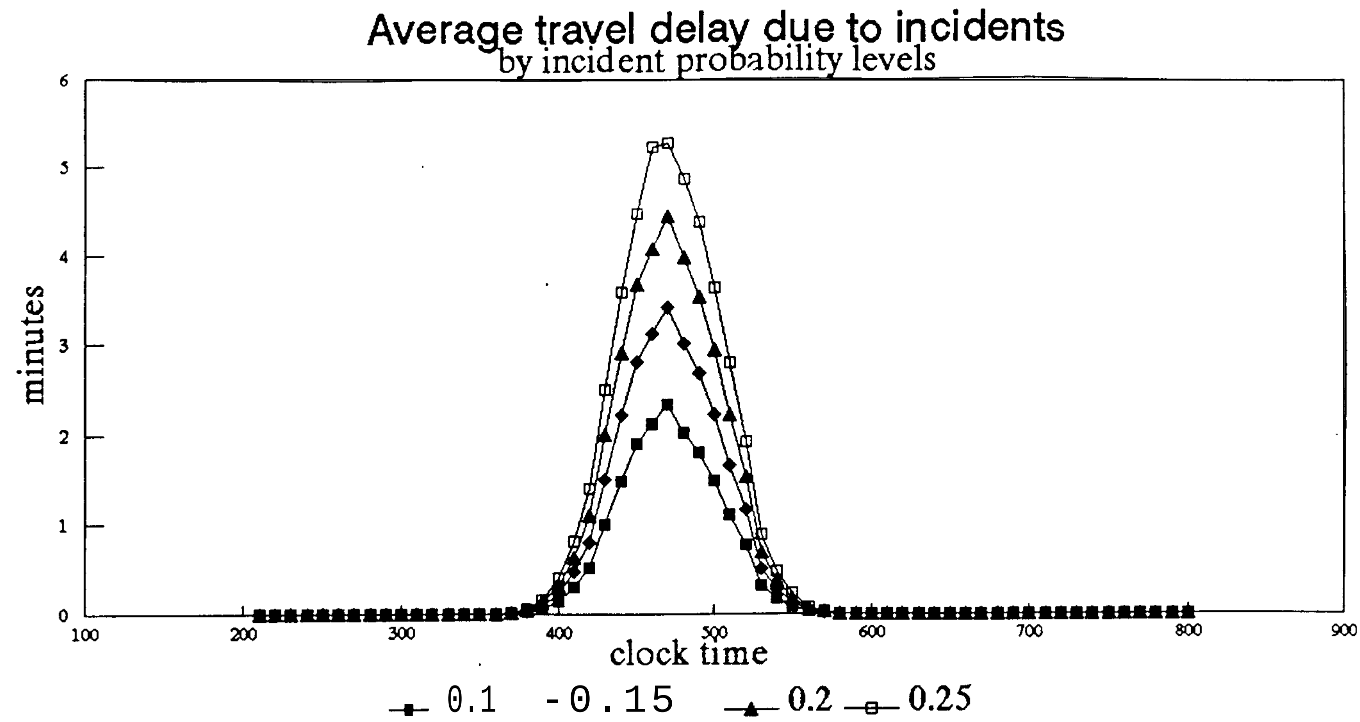
Incident Probability	Average cost ($/trip)	Travel Time	E(SDE)	E(SDL)	Coef of Variation	Lateness probability
0	$2.02	44.73%	32.82%	8.78%	0.00%	13.67%
0.1	$2.62	46.86%	26.40%	7.60%	1.61%	17.54%
0.15	$2.89	47.72%	24.34%	7.25%	1.96%	18.74%
0.2	$3.16	48.47%	22.72%	6.99%	2.13%	19.69%
0.25	$3.40	49.13%	21.37%	6.80%	2.20%	20.50%
Difference between highest & lowest incident Probabilities	$1.3 8	55.57%	4.61%	3.90%	5.42%	30.50%

FIGURE 7-l



Average travel time
by incident probability levels
minu te
16
15
14
13
12
11
10
9
a
l
6
5
4
100
200
300
400
500
600
700
800
900
clock time
0
0.1
0.15 -0.2

FIGURE 7-2



Average travel delay due to incidents
by incident probability levels
minutes
0
1
2
3
4
5
6
100
200
300
400
500
600
700
800
900
clock time
0.1
-0.15
0.2
0.25

FIGURE 7-3

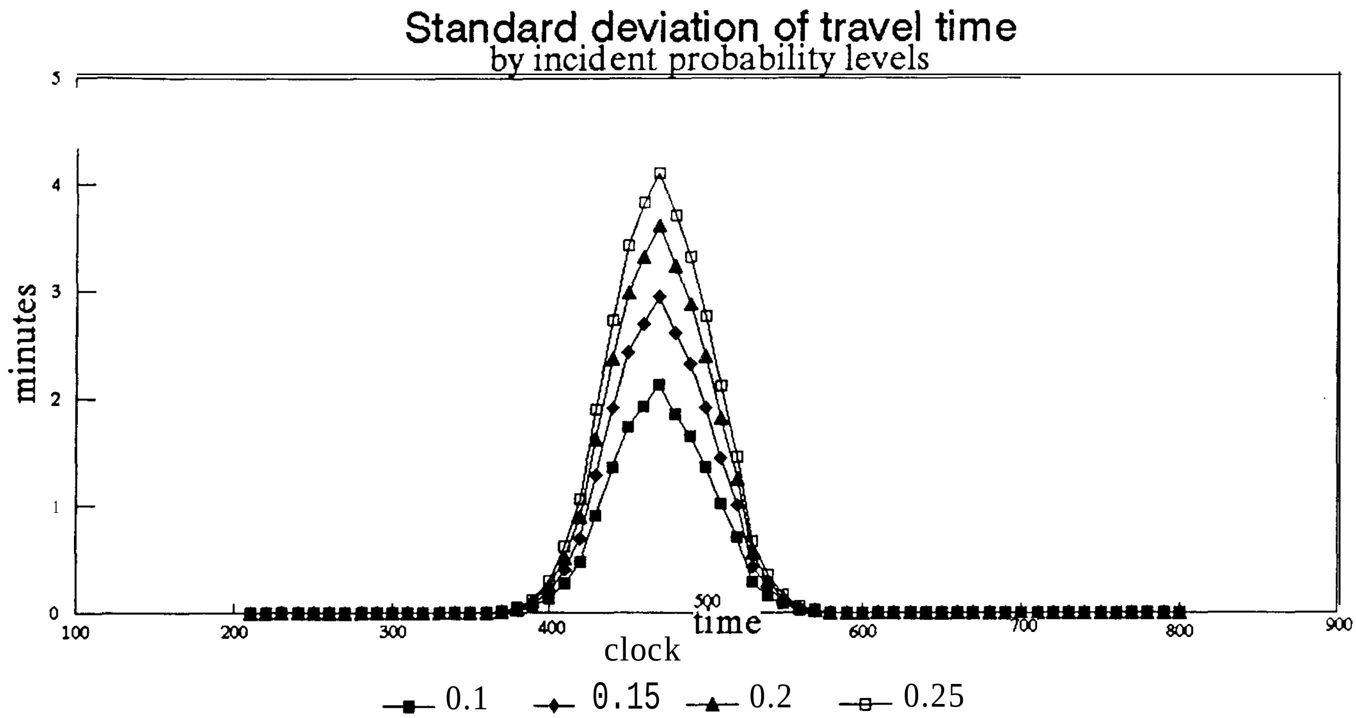

Standard deviation of travel time
by incident probability levels
minutes
5
4
3
2
1
0
100
200
300
400
500
600
700
800
900
time
clock
0.1
0.15
0.2
0.25

FIGURE 7-4

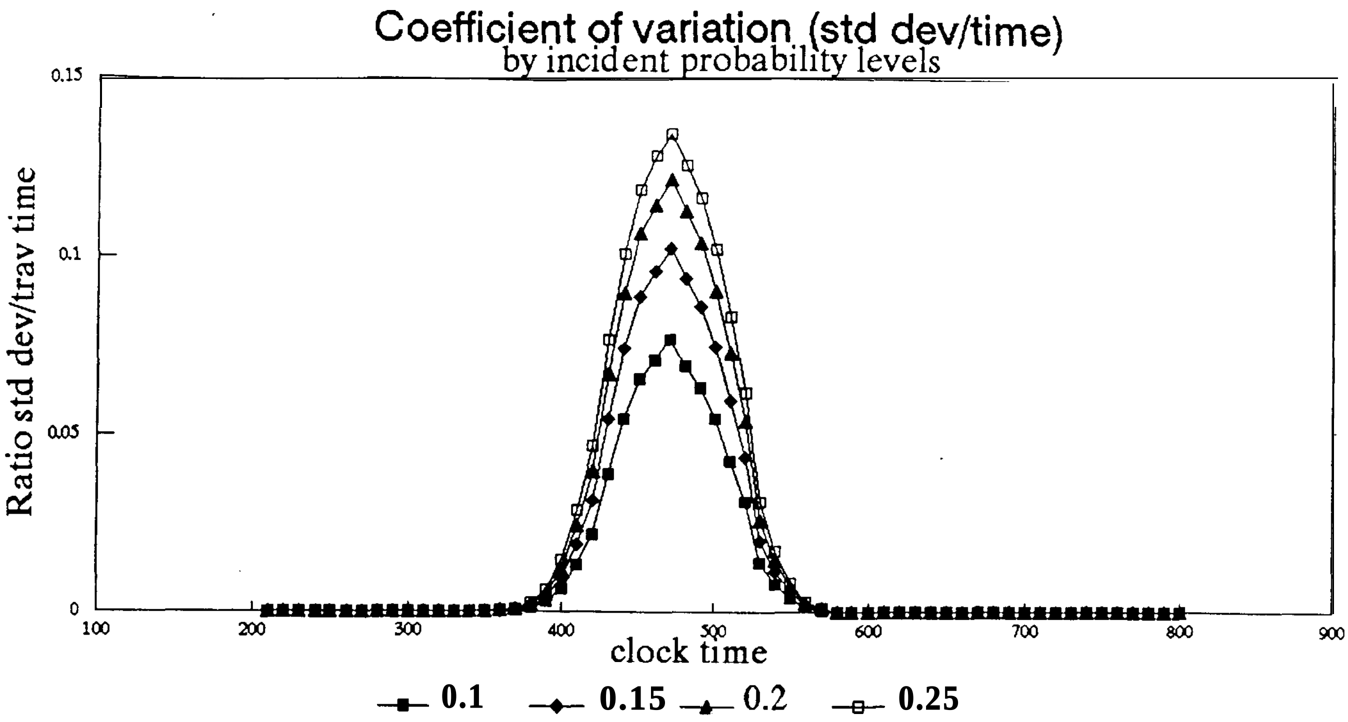
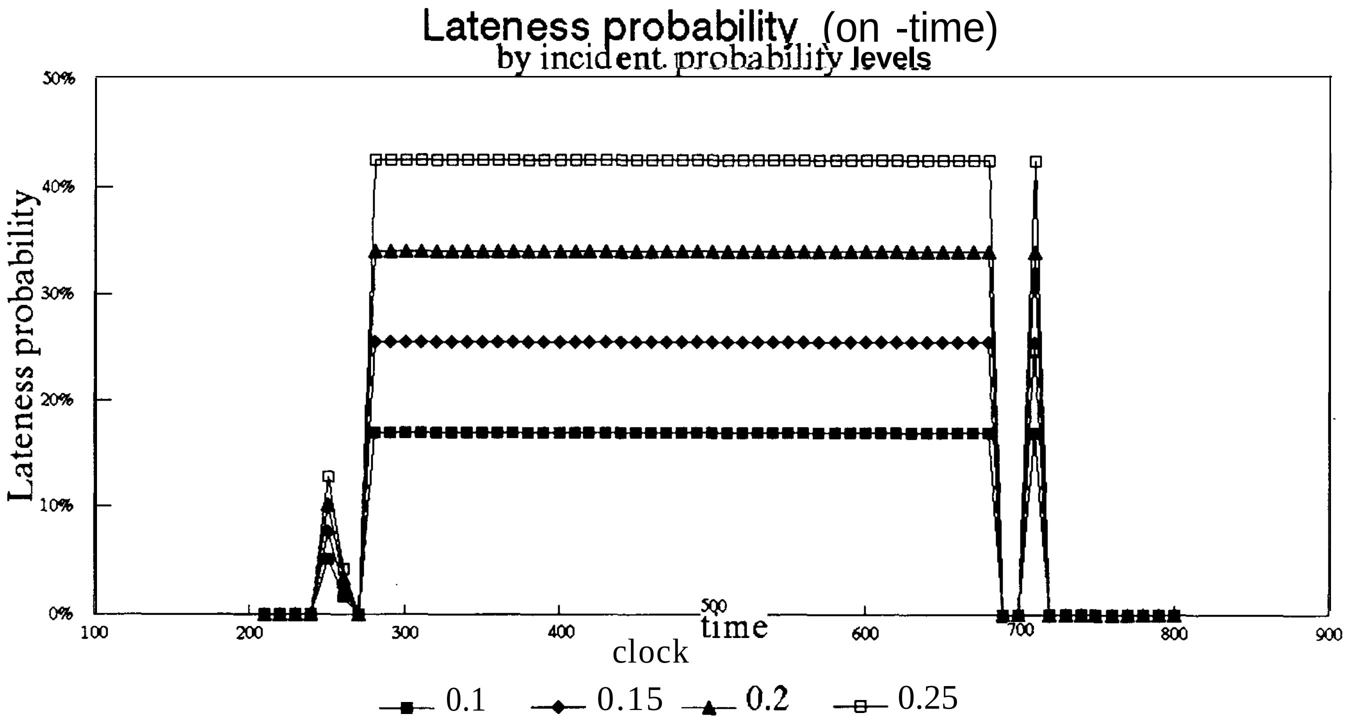
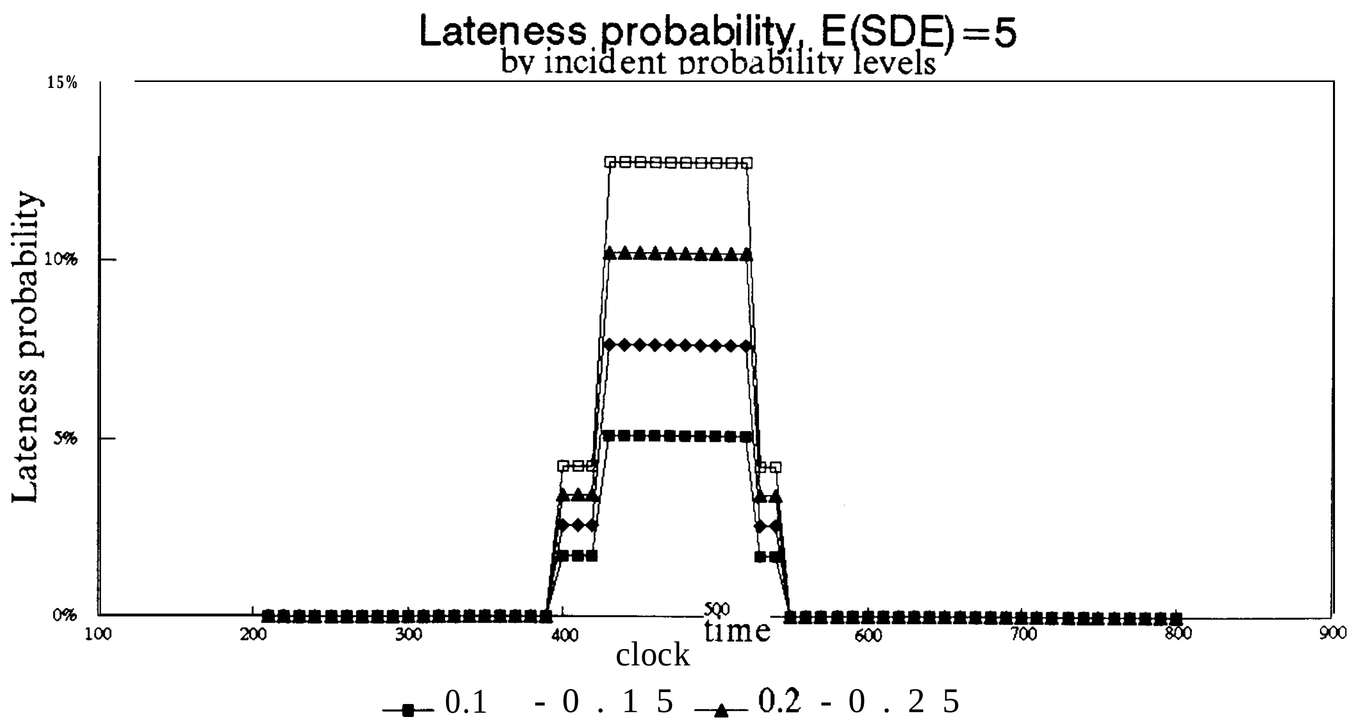

Coefficient of variation (std dev/time)
by incident probability levels
Ratio std dev/trav time
0.15
0.1
0.05
0
100
200
300
400
500
600
700
800
900
clock time
0.1
0.15
0.2
0.25

FIGURE 7-5



Lateness probability (on -time)
by incident probability levels
Lateness probability
50%
40%
30%
20%
10%
0%
100
200
300
400
500
600
700
800
900
clock time
0.1
0.15
0.2
0.25

FIGURE 7-6



Lateness probability, E(SDE)=5
by incident probability levels
Lateness probability
15%
10%
5%
0%
100
200
300
400
500
600
700
800
900
clock time
0.1 - 0.15
0.2 - 0.25

FIGURE 7-7

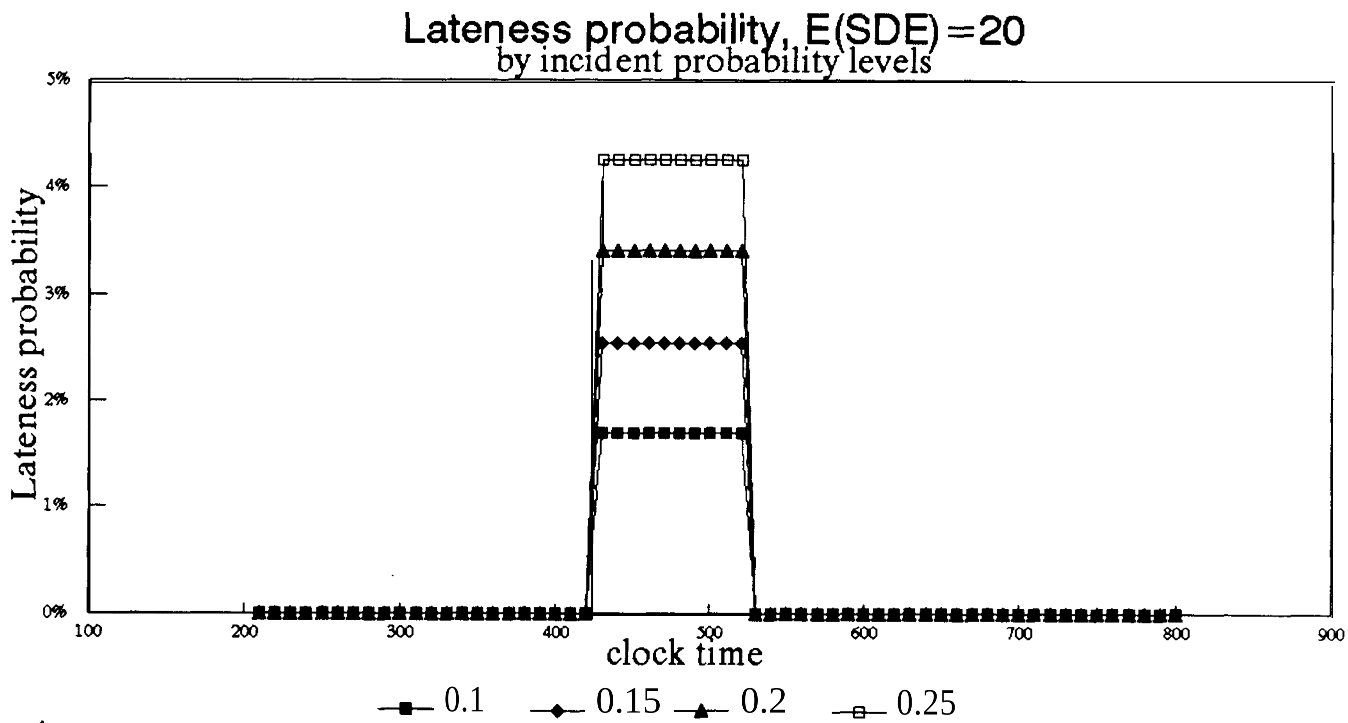
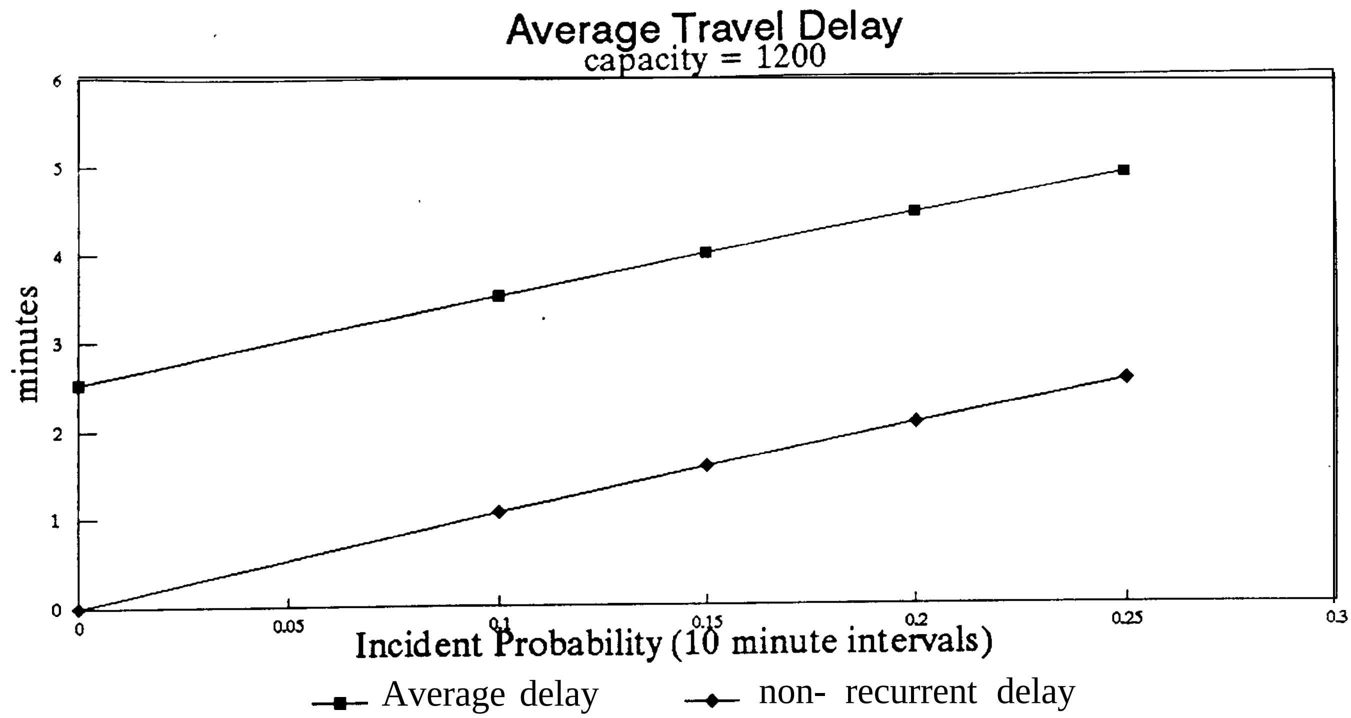
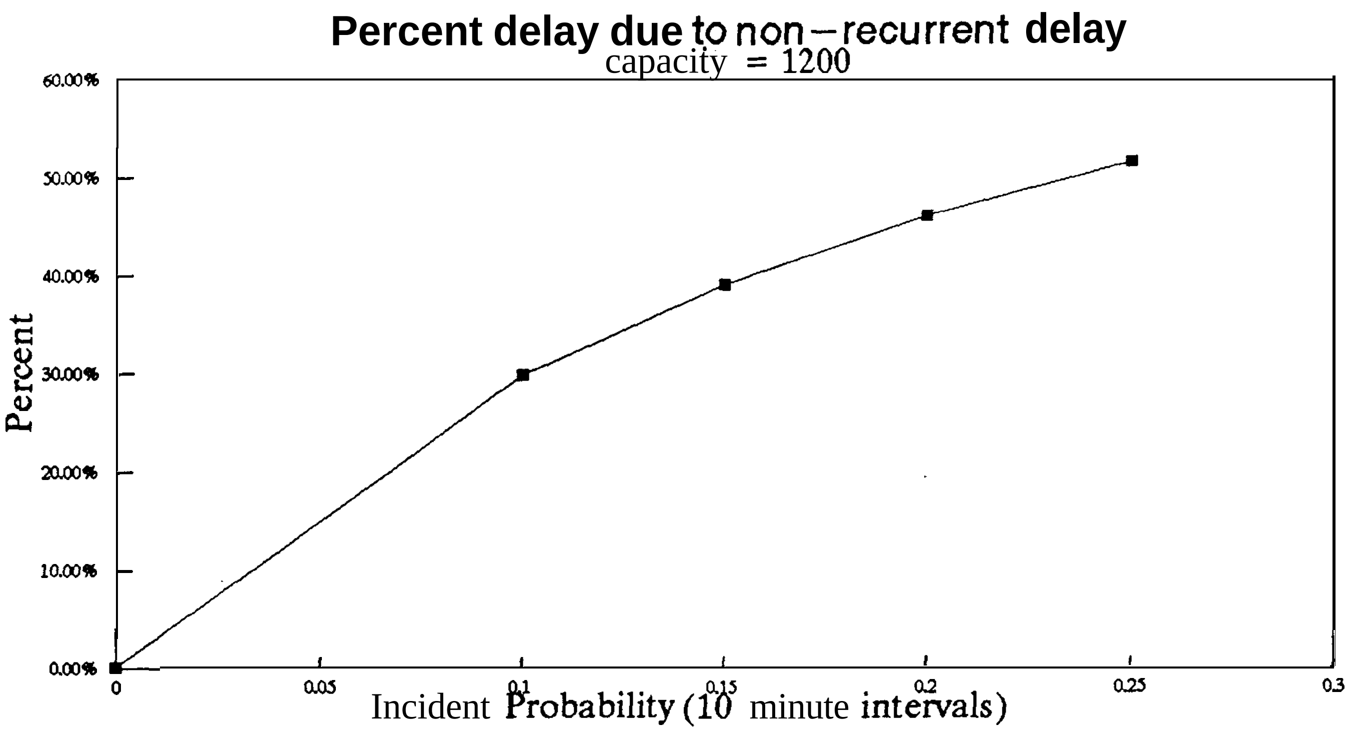

Lateness probability, E(SDE)=20
by incident probability levels
Lateness probability
5%
4%
3%
2%
1%
0%
100
200
300
400
500
600
700
800
900
clock time
0.1
0.15
0.2
0.25

FIGURE 7-8



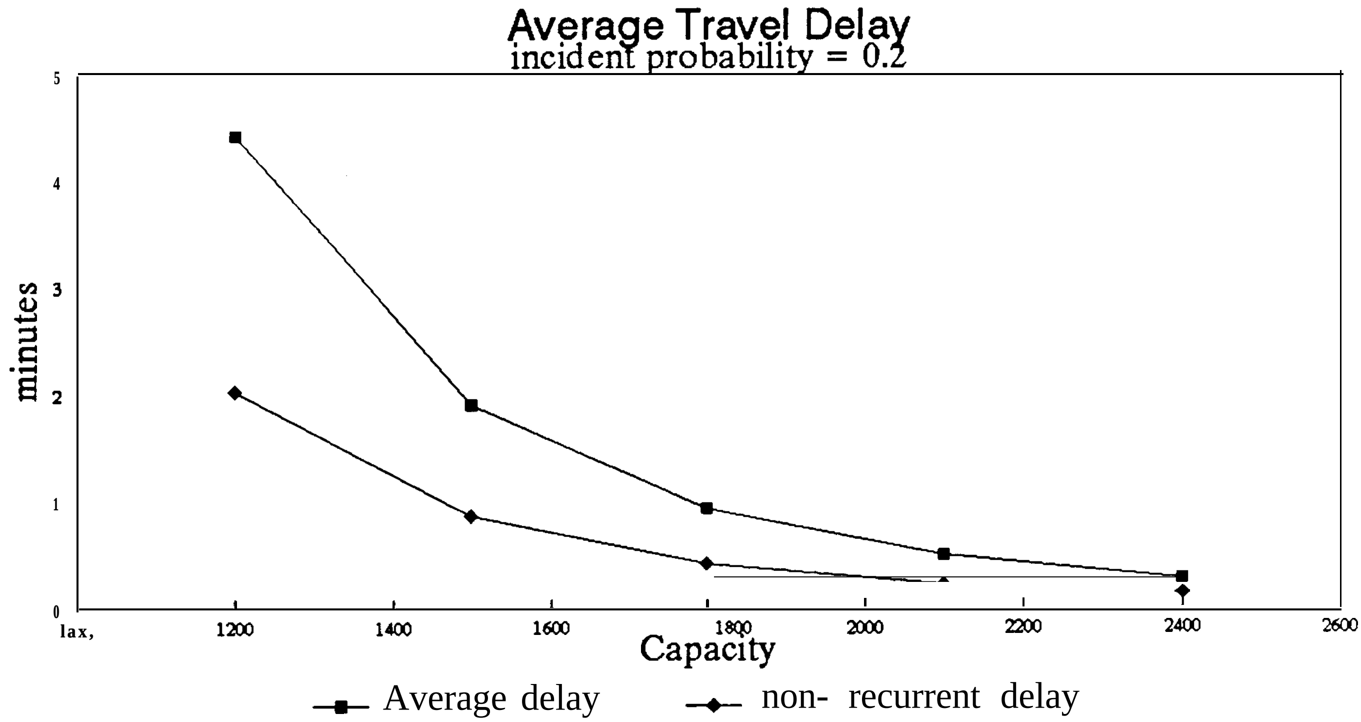
Average Travel Delay
capacity = 1200
minutes
6
5
4
3
2
1
0
0
0.05
0.1
0.15
0.2
0.25
0.3
Incident Probability (10 minute intervals)
Average delay
non- recurrent delay

FIGURE 7-9



Percent delay due to non-recurrent delay
capacity = 1200
60.00%
50.00%
40.00%
30.00%
20.00%
10.00%
0.00%
Percent
0
0.05
0.1
0.15
0.2
0.25
0.3
Incident Probability (10 minute intervals)

FIGURE 7-10


Average Travel Delay
incident probability = 0.2
minutes
5
4
3
2
1
0
1200
1400
1600
1800
2000
2200
2400
2600
Capacity
Average delay
non- recurrent delay

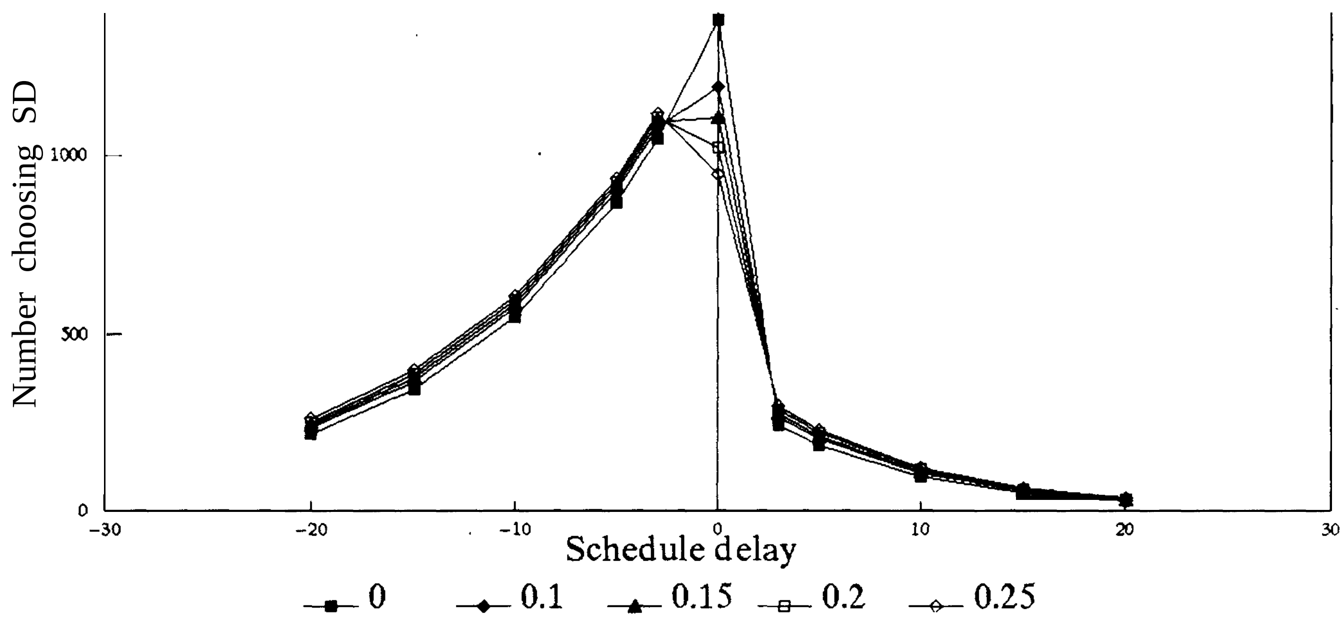
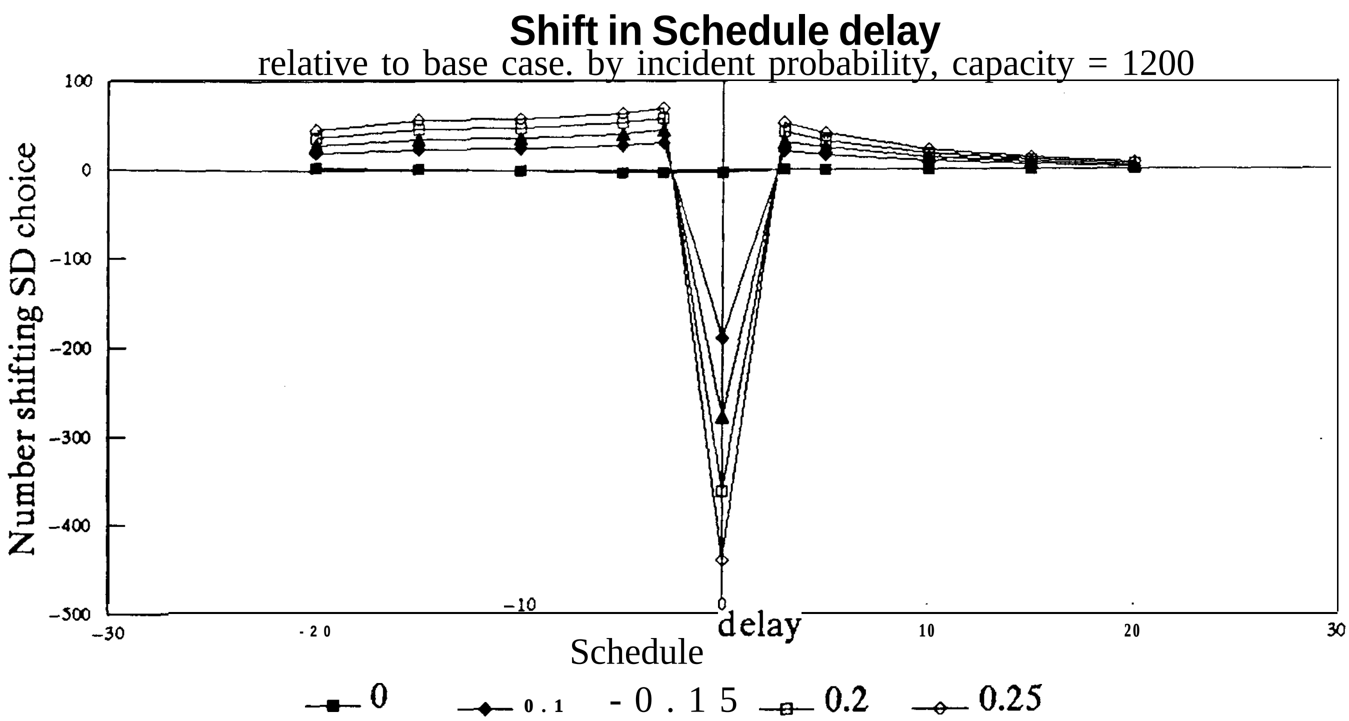
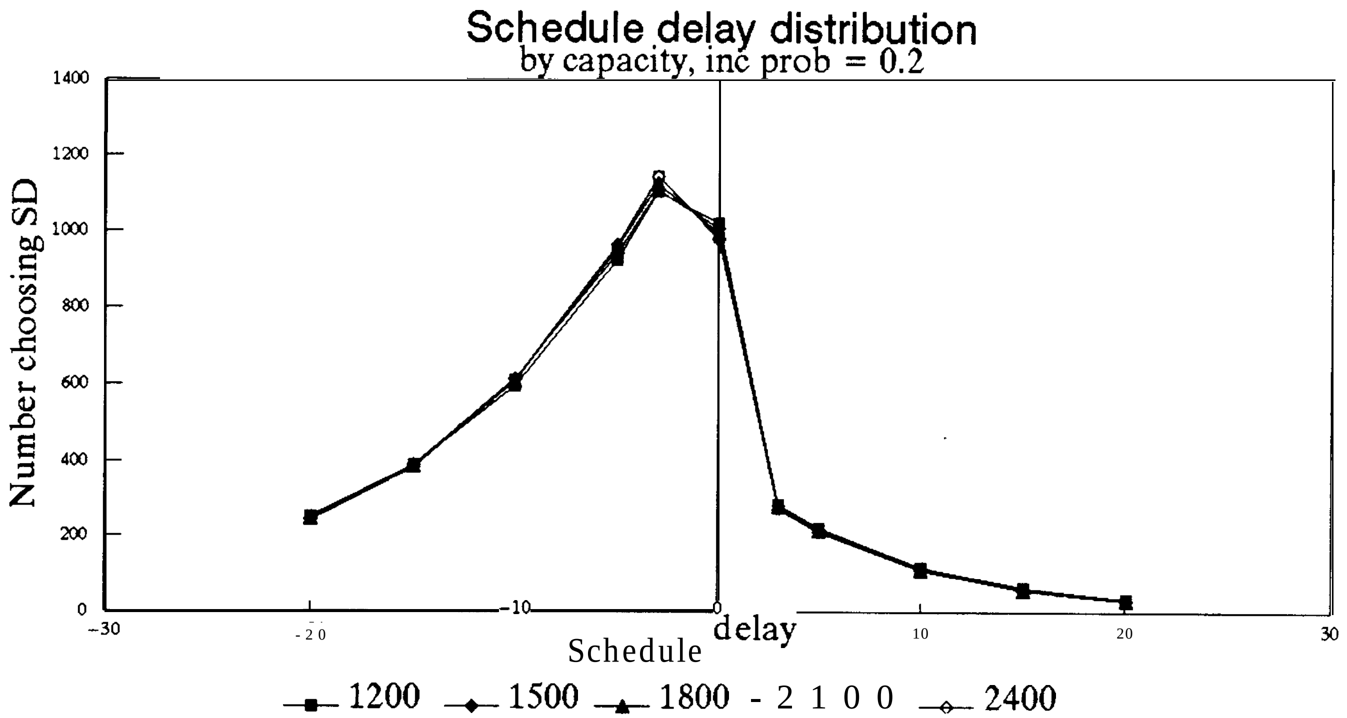

Number choosing SD
1000
500
0
-30
-20
-10
0
10
20
30
Schedule delay
0
0.1
0.15
0.2
0.25

FIGURE 7-12



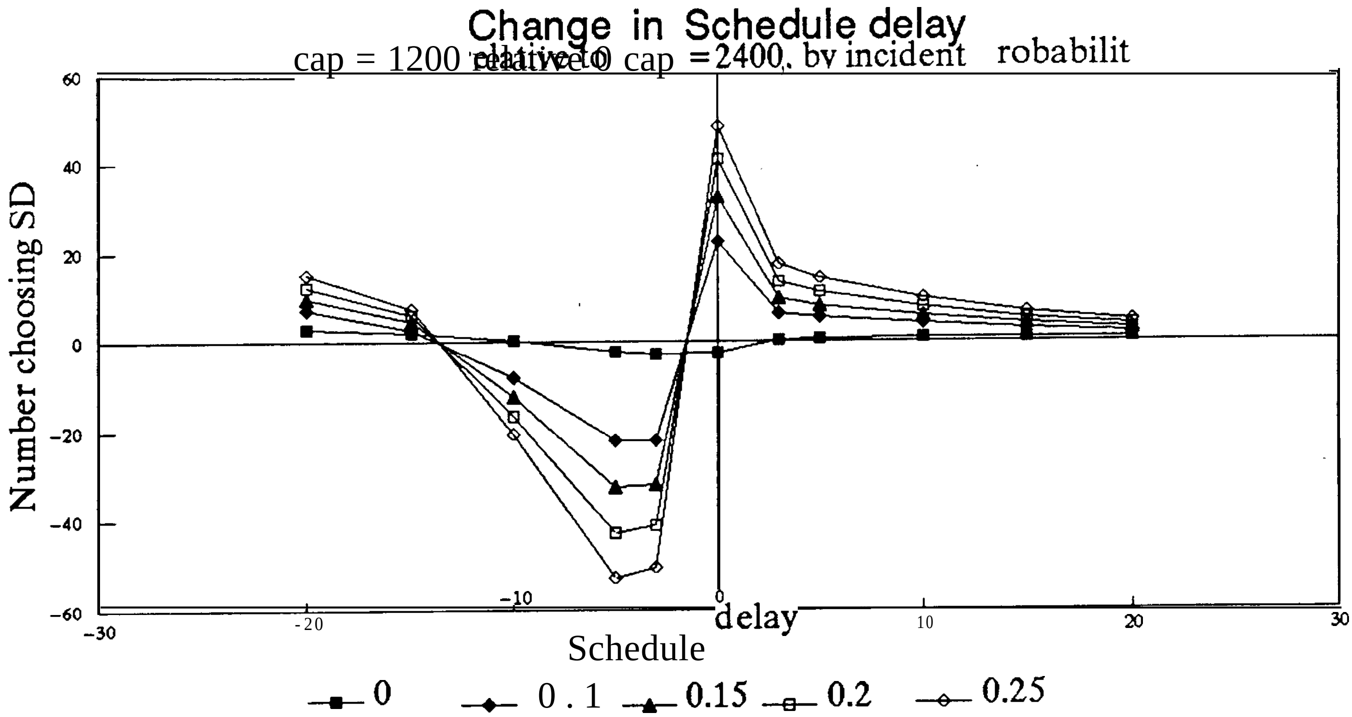
Shift in Schedule delay
relative to base case. by incident probability, capacity = 1200
Number shifting SD choice
100
0
-100
-200
-300
-400
-500
-30
-20
-10
0
10
20
30
Schedule delay
0
0.1
0.15
0.2
0.25

FIGURE 7-13



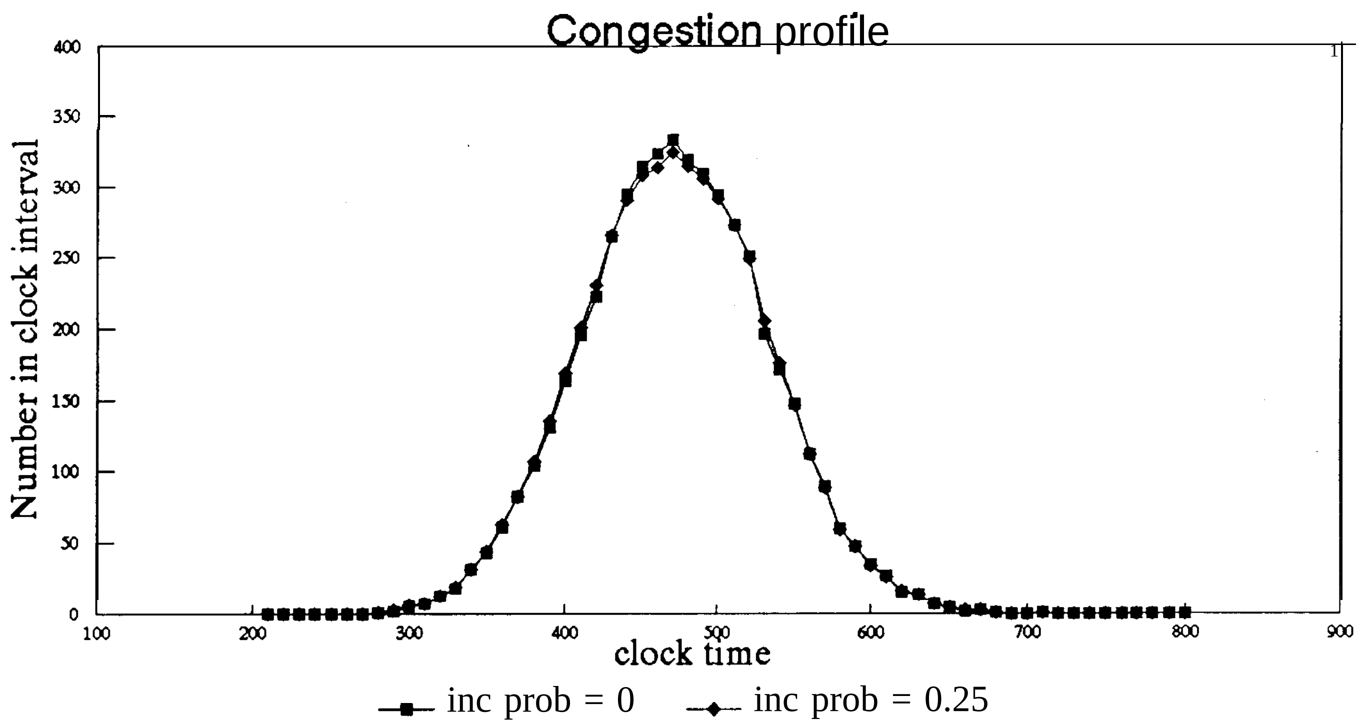
Schedule delay distribution
by capacity, inc prob = 0.2
Number choosing SD
1400
1200
1000
800
600
400
200
0
-30
-20
-10
0
10
20
30
Schedule delay
1200
1500
1800
2100
2400

FIGURE 7-14



Change in Schedule delay
cap = 1200 relative to cap = 2400, by incident robabilit
Number choosing SD
60
40
20
0
-20
-40
-60
-30
-20
-10
0
10
20
30
Schedule delay
0
0.1
0.15
0.2
0.25

FIGURE 7-15



Congestion profile
Number in clock interval
0
50
100
150
200
250
300
350
400
100
200
300
400
500
600
700
800
900
clock time
inc prob = 0
inc prob = 0.25

FIGURE 7-16

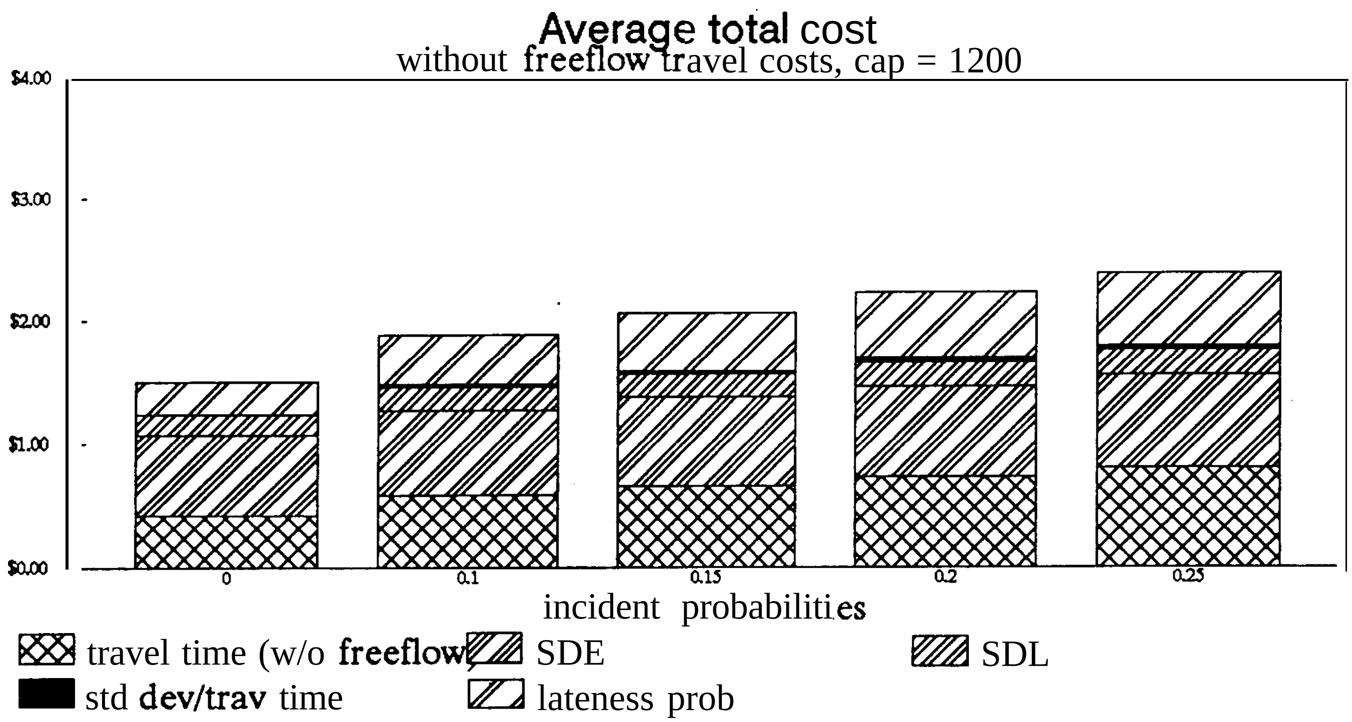

Average total cost
without freeflow travel costs, cap = 1200
$4.00
$3.00
$2.00
$1.00
$0.00
0
0.1
0.15
0.2
0.25
incident probabilities
travel time (w/o freeflow)
SDE
SDL
std dev/trav time
lateness prob

FIGURE 7-17

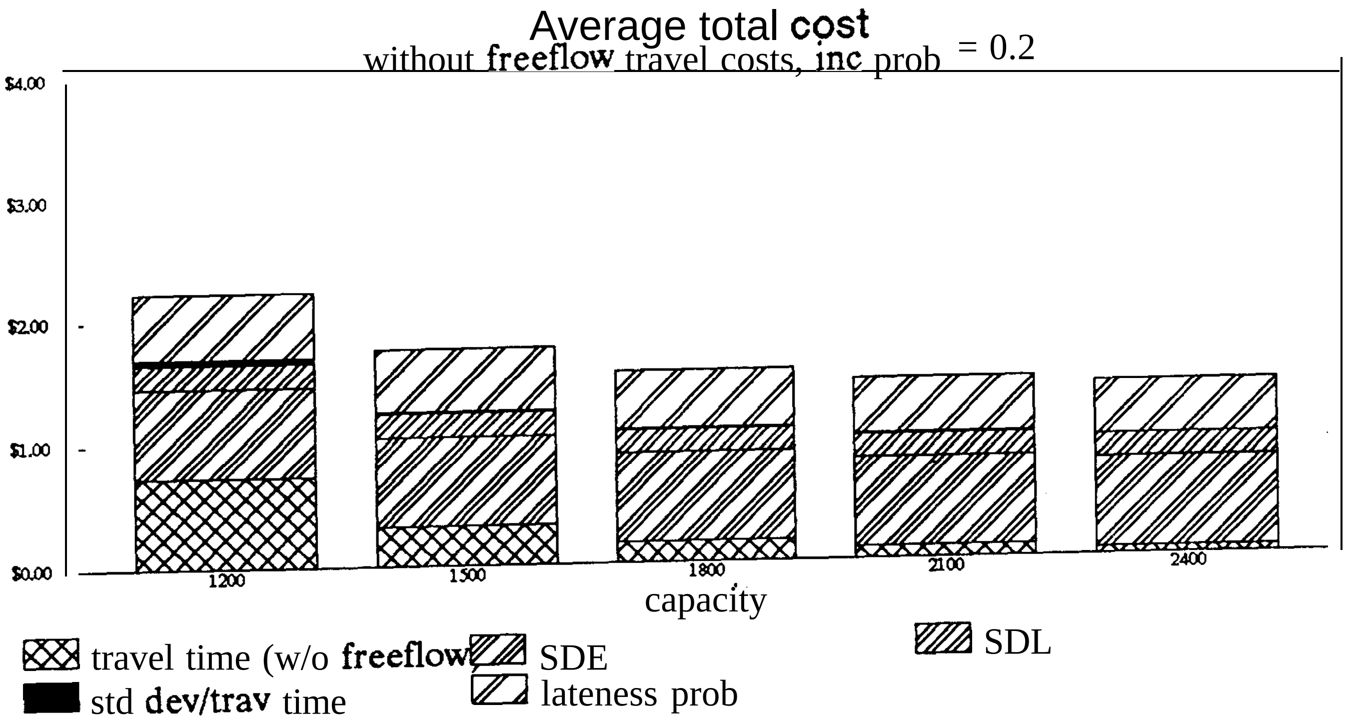

Average total cost
without freeflow travel costs, inc prob = 0.2
$4.00
$3.00
$2.00
$1.00
$0.00
1200
1500
1800
2100
2400
capacity
travel time (w/o freeflow
SDE
SDL
std dev/trav time
lateness prob

FIGURE 7-18

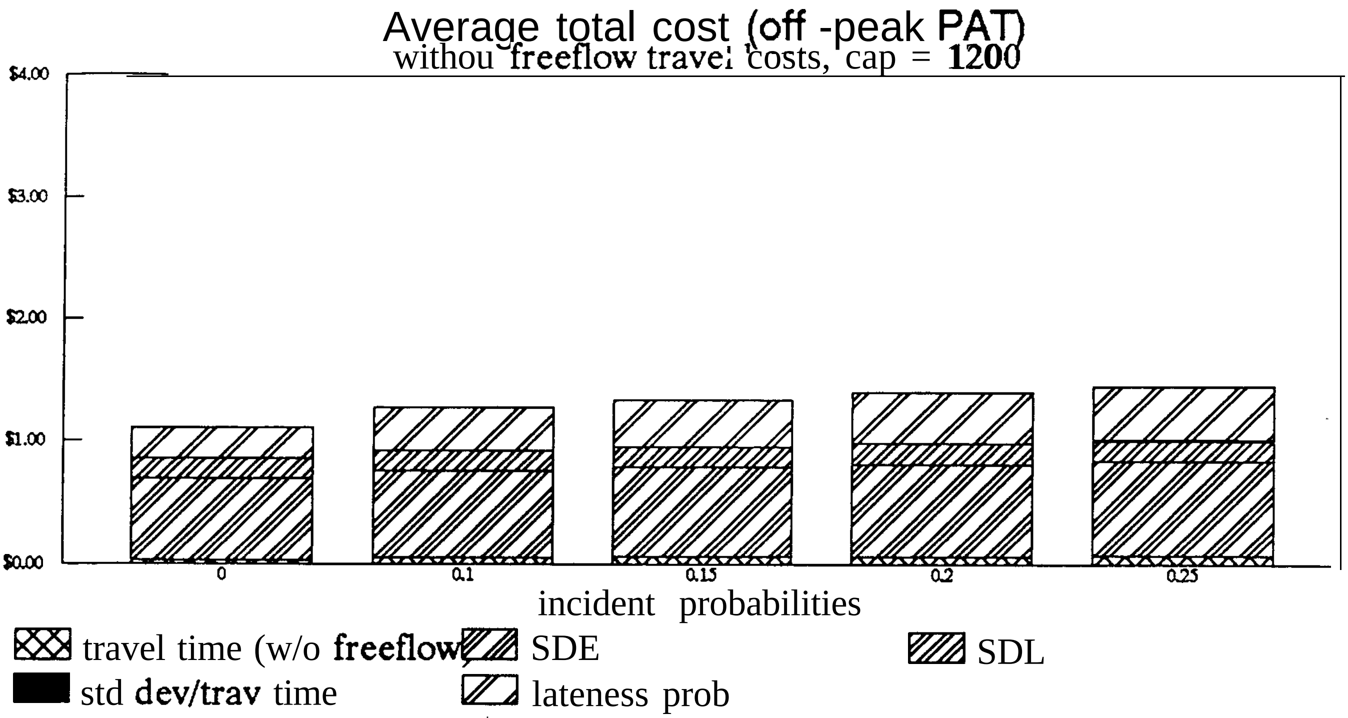
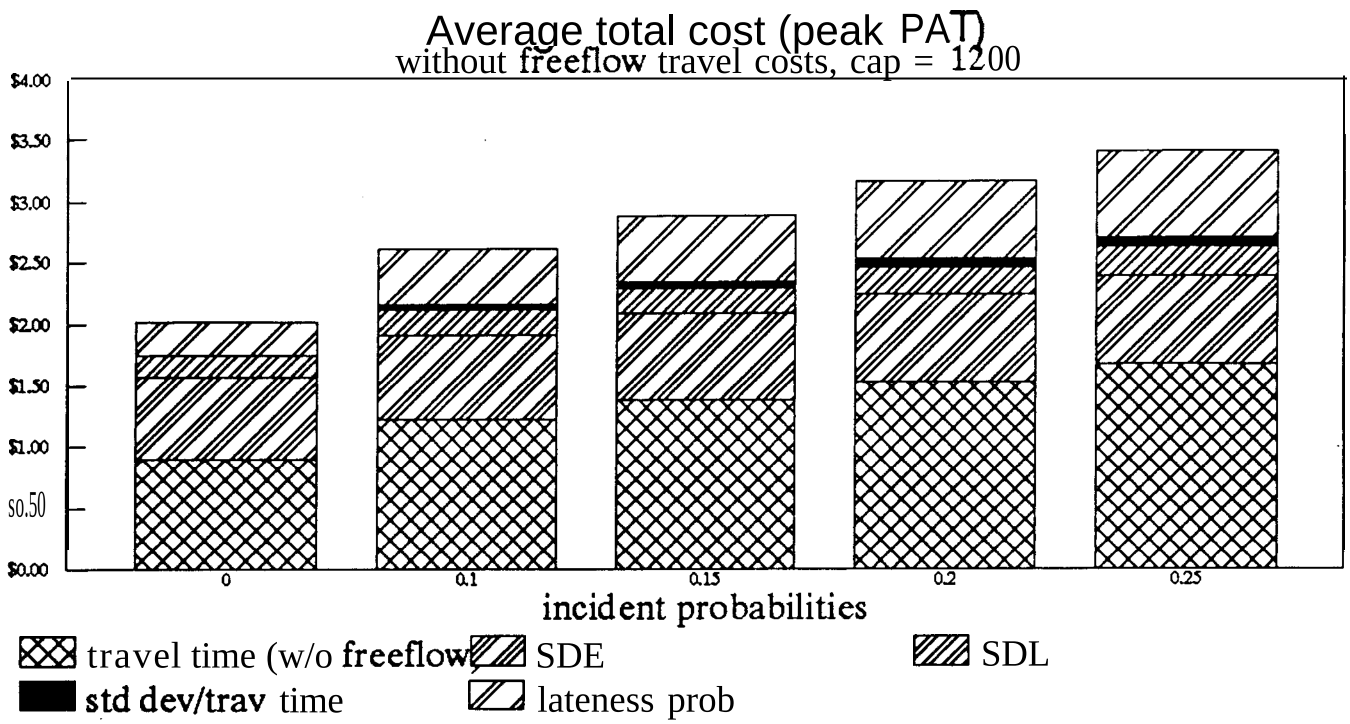

Average total cost (off -peak PAT)
withou freeflow travel costs, cap = 1200
$4.00
$3.00
$2.00
$1.00
$0.00
0
0.1
0.15
0.2
0.25
incident probabilities
travel time (w/o freeflow)
SDE
SDL
std dev/trav time
lateness prob

FIGURE 7-19



Average total cost (peak PAT)
without freeflow travel costs, cap = 1200
$4.00
$3.50
$3.00
$2.50
$2.00
$1.50
$1.00
$0.50
$0.00
0
0.1
0.15
0.2
0.25
incident probabilities
travel time (w/o freeflow)
SDE
SDL
std dev/trav time
lateness prob

8. CONCLUSIONS AND POLICY IMPLICATIONS

The research reported here leads to a number of conclusions about the factors that determine commuters' behavior and the resulting congestion patterns in situations of uncertain travel times. We also discuss some implications for policy and future research directions.

Our primary research conclusions are summarized as follows:

1. **Scheduling decisions interact substantially with reliability.** Improvements in the reliability of the system cause people to reschedule their trips so as to arrive closer to their more preferred arrival times. This rescheduling seems to have only minimal effect on congestion and reliability patterns, probably because people's desired arrival times are dispersed so rescheduling does not make much difference to the amount of bunching of trips.

2. **Scheduling accounts for an important part of the costs of congestion and of unreliability.** As the probability of a capacity-reducing incident is increased in our model, commuters' total travel costs increases. Nearly half the increase (44 percent) is due to the extra travel time due to incidents, and almost as much (37 percent) is due to the extra probability of late arrival at work; the remaining 15 percent is due to other scheduling considerations such as spending more time at work before work begins. This implies that greater flexibility at the workplace would substantially reduce the costs of unreliability to commuters.

3. **Once the costs of non-optimal schedules are taken into account, uncertainty in travel time has only a very small additional cost.** As just noted, costs rise as incident probability is increased, and slightly under

half of this is due to increased average travel time. Of the rest, 92 percent is explained by costs of early or late arrival at work; the "planning cost" or residual pure cost of uncertainty accounts for only 9 percent. Therefore we are able to explain most of people's aversion to uncertainty in terms of their being unable to avoid the costs of early or late arrival. This is an important finding because earlier studies measuring people's aversion to uncertainty have not distinguished among the causes.

4. **People's workplace environments differ widely in the degree of flexibility toward travel schedules and the ability to adjust work times.** These differences may or may not be susceptible to change through transportation policy; in part they reflect real differences in work requirements due to the nature of the work. Another important feature is that many people face significant constraints on some days but not others.

5. **People's behavior when facing uncertainty in travel time can be explained by a simple model with basic scheduling variables.** Socioeconomic and occupational variables do little to improve the fit of the model. The most important socioeconomic variable of those we measured is an indicator of whether the person is paid by an hourly wage or by salary; hourly workers are less averse to travel time and to time spent at the workplace before work begins, but they are equally or more averse to being at risk for arriving late.

6. **Some systematic differences are also observed among occupational groups as defined by the Holland occupational codings.** People in occupations classified as "conventional" or "realistic," who deal in a routinized way with objects or data, tend to place lower values on time spent traveling or waiting for work to begin. Members of these

occupational groups also report having relatively strict arrival time requirements and relatively little flexibility toward working late or taking work home; as a result they budget more slack time at the workplace before work begins.

7. **Occupational groups differ in their reported consequences of arriving late.** The most common consequence, reported by nearly half the sample, is loss of reputation. This is especially common among the more professionally or business oriented occupations ("investigative" and "enterprising"). People in "conventional" and "realistic" occupations, on the other hand, are more likely to suffer a deduction from their pay. One consequence of late arrival seems to be consistent across all occupational groups: about one-fourth of respondents say that arriving late increases stress and makes them feel rushed.

Our results suggest that one of the more effective courses of government policy to reduce the costs associated with unreliability is to encourage more flexible work schedules. Late arrival and adherence to strict schedules seems to be the greatest source of both stress and the costs of unreliability. Many occupational categories and professions may require employees to have coordinated schedules; this is obviously dependent on the nature of the specific business or professional activity. It is therefore difficult for policy interventions to mandate the removal of strict work schedules. Probably the best that can be done is to encourage flexible work schedules. Future research efforts could seek to determine how worker productivity could be affected by allowing more flexibility.

We have shown how reducing the probability of incidents and non-recurrent congestion can affect the costs of schedule delay. Policies aimed at reducing incident probability may be more effective than policies increasing capacity at reducing costs to society. There is an assumption that capacity increases can also reduce the probability of incidents and their severity (i.e., the number of lanes blocked); however, our review of the literature did not show any clear indication that this is the case. There is a clear need for research to analyze the incidence, severity, and duration of non-recurrent events in both congested and uncongested conditions, and the effect on travel time variance. Methodologies for determining the cost of specific policies and how they reduce travel time variance are needed to perform cost/benefit analysis of alternative methods for decreasing non-recurrent congestion. For example, what would be the effects on travel time variance, travel costs, and traveler benefits of a capacity expansion relative to a freeway service patrol?

We found that our hypothesized "planning cost" did not seem to account for a large fraction of the total costs of unreliable travel. However, if advanced traveller information systems become widely available, it could effect these costs; that is, people will need to plan to use them. Future research could determine whether the benefits of these systems will exceed both the monetary costs and planning costs of using them.

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APPENDIX

COPY OF SURVEY INSTRUMENT

FIRST SOME QUESTIONS ABOUT YOU AND YOUR WORK

1. Are you the same person who filled out the last transportation survey?

☐$_1$ Yes
☐$_2$ No

2. Have you changed jobs since February 1994?

☐
☐$_2$

3. Which industry do you work in? (Please, check only one)

EXAMPLE: If you drive a delivery car for a bank, you are working in Finance industry, not in Transportation.

☐$_1$ Agriculture, Forestry, and Fisheries
☐$_2$ Mining
☐$_3$ Construction
☐$_4$ Manufacturing, nondurable goods
☐$_5$ Manufacturing, durable goods
☐$_6$ Transportation
☐$_7$ Public utilities, Post, and Telecommunications
☐$_8$ Wholesale trade
☐$_9$ Retail trade
☐$_{10}$ Finance, Insurance, and Real estate
☐$_{11}$ Business and Repair services
Cl,, Personal services
☐$_{13}$ Entertainment and Recreation services

Professional and related services:

☐$_{14}$ Health services
☐$_{15}$ Educational services
Cl,, Other professional and related services

Cl,, Public administration

4. People have different arrangements for getting paid. Are you:

Cl, An employee with benefits
☐$_2$ An employee without benefits
☐$_3$ An independent contractor within a company
☐$_4$ Self-employed / An entrepreneur
☐$_5$ Other______________________________

5. Is your earned income based on

Cl, A fixed monthly salary
☐2 An hourly wage

6. What is your title in your work organization? ________________________________

7. What is your occupation? ____

8. How long have you been in your current occupation? _____ years _____ months

9. In any occupation we need to deal with recurring situations by undertaking certain activities as part of our work. Please read the list of activities below. Choose one activity that best describes your work, and write 1 in front of it. Similarly, choose a second activity that is the next best description and write 2 in front of it.

__1 Interpretation of feelings, ideas, or facts in terms of personal viewpoint.

__2 Precise attainment of set limits. tolerances. or standards.

__3 A variety of duties often characterized by frequent change.

__4 Repetitive operations carried out according to set procedures or sequences.

__5 Dealing with people beyond giving and receiving instructions.

__6 Performing under stress when confronted with the critical or unexpected, or when taking risks. .

__7 Evaluation of information.

__8 Influencing people in their opinions, attitudes, or judgements about ideas or things.

__9 Direction, control, and planning of an entire activity or the activities of others.

NOW WE WOULD LIKE TO KNOW ABOUT THE CONSTRAINTS ON YOUR DAILY WORK SCHEDULE

10. Does your employer allow you to arrive and start work before your normal working hours?

☐ No
☐ Yes ☞ 11. If yes, could you do that on any day without prior arrangements?

☐ Yes, I could arrive and start working before my normal hours.

☐ No ☞ Please, check all reasons that apply:

- ☐ The work requires the presence of co-workers. customers. or clients.
- ☐ I have another job.
- ☐ I car-pool with family members and could not change the timetable.
- ☐ I carpool with other working people.
- ☐ I have to stay at home until a relative/nurse/maid/day help arrives or until children leave for school.
- ☐ I am too tired to arrive and start working earlier.
- ☐ Other ____________________

12. Does your employer allow you to stav and continue working after your normal working hours'?

☐ No
☐ Yes ☞ 13. If yes, could you continue working after your normal hours on any day without prior arrangements?

☐ Yes, I could continue working after my normal hours.

☐ No ☞ Please. check all reasons that apply:

- ☐ The work requires the presence of co-workers, customers, or clients.
- ☐ I have another job.
- ☐ I carp001 and can't change the timetable the same day.
- ☐ I need to be at home to take care of my family.
- ☐ I have hobbies/ social gatherings arranged after work.
- ☐ I am too tired or hungry to continue working.
- ☐ Other ____________________

14. Does your employer allow you to take work home after your normal hours or work at home instead of at your work site?

- ☐2 No
- ☐1 Yes ☞

15. If ves. could vou work at home on any day without prior arrangements'?

- ☐1 Yes, I could work at home.
- ☐2 No ☞ Please, check all reasons that apply:
  - ☐1 The work requires the presence of co-workers. customers, or clients.
  - ☐2 The work requires special equipment not avaiiabie at home.
  - ☐3 I do not have avaiiabie the space or isolation required for working at home.
  - ☐4 I have another job.
  - ☐5 titer my normal work hours I want to spend the time at home with my family and do househoid work.
  - ☐6 I have hobbies/ social gatherings arranged after work.
  - ☐7 I am too tired to work at home after my normal work day.
  - ☐8 Other________________________________

16. What is your <u>official work start time</u> ?(Please. check and fill out only one)

☐1 Regular _ : _ am / pm. (circle am or pm)

Cl, It varies: It is mostly _ : _ am / pm , sometimes _ : w am / pm.

or _ _ am / pm.

Cl, I have no official work start time. but I usually start

between _ : _ am / pm and _ : _ am / pm.

17. How often is it important that you arrive at work at ~~a precise ore-determined~~ time?

- ☐1 Practically never.
- ☐2 Once a month or less frequently.
- ☐3 Two to four times a month.
- ☐4 Two to four times a week.
- ☐5 Every day.

☞ 18. Why is it important to arrive at a pre-determined time'?

Please indicate with numbers , 1 being most frequent reason.

___1 Employer monitors arrival closely.
___2 Group work or appointments with co-workers.
___3 Appointments with clients.
___4 Dead -line for completing work.
___5 Other ______________________________
___6 Other ______________________________

19. Are there negative consequences if you arrive late? (check all that appiy)

- ☐1 Yes, I get paid less.
- ☐2 Yes. my reputation as an employee / employer suffers.
- ☐3 Yes. I have to rush things and it creates stress.
- ☐4 Yes. ______________________________
- ☐5 No negative consequences.

NEXT WE WOULD LIKE TO KNOW ABOUT YOUR COMMUTING EXPERIENCES AND OPINIONS

20. Was your morning commuting time around March 1, 1994 different because of the January 17, 1994 earthquake?

- ☐1 Yes, it was longer every morning by approximately ______ minutes.
- ☐2 Yes, it was sometimes longer.
- ☐3 There was no change in my commuting time due to the earthquake.

21. Consider the <u>last ten working davs</u>. On the average, how many minutes before you actually started to work did you arrive at your workplace?

Cl, I started to work immediately.
☐ I arrived ______ minutes before I started working.

☞ 22. If you arrived earlier than when the you actually started to work, how did you spend that time? (Please, check <u>all</u> that apply)

- ☐ 1 Got organized for work.
- Cl, Talked with co-workers.
- Cl, Had refreshments.
- ☐ 4 Read papers/magazines.
- ☐ 5 Waited/rested in the car.
- ☐ 6 Changed clothes / showered.
- Cl, Other ____

23. The <u>morning commuting time</u> varies from day to day. Think about your last 10 commuting days to work. Mark in the table how many days fall into different commuting time categories. Make sure that the total number of days equals 10. (If you have several job sites, consider the last ten times you commuted to the job site you most often commute to in the morning.)

5 or less minutes	6 to 10 minutes	11 to 15 minutes	16 to 25 minutes	26 or more minutes
davs	davs	days	days	days

24. How often are you delayed from your <u>usual work arrival time</u> by <u>15 minutes or more because of unusuallv bad traffic conditions</u> ? (check only one)

- Cl, Once a week.
- Cl, Twice a month.
- ☐ 3 Once in l-2 months.
- ☐ 4 1-5 times a year.
- ☐ 5 Less than once a year.

25. You just stated how often you are delayed from work 15 minutes or more because of unusual traffic conditions. Suppose that those traffic conditions wouid occur twice as often as they do now. Would you (check all that apply):

- ☐ 1 Start to carp001 if you now drive alone.
- ☐ 2 Start to drive alone if you now car-pool.
- ☐ 3 Change your work and commuting hours.
- ☐ 4 Change your residence.
- ☐ 5 Change your work piace.
- ☐ 6 Be willing to pay a road toil to guarantee timely arrivai.
- ☐ 7 Reserve more time for commuting.
- ☐ 8 Not change your commuting habits.
- ☐ 9 Other ____________________

26. If your morning commuting time were to permanently increase by 15 minutes because of traffic conditions. wouid you (check all that appiy):

- ☐ 1 Start to carp001 if you now drive aione.
- ☐ 2 Start to drive aione if you now carpooi.
- ☐ 3 Change work and commuting hours.
- ☐ 4 Change your residence.
- ☐ 5 Change your work piace.
- ☐ 6 Be willing to pay a road toll to decrease the commuting time.
- ☐ 7 Reduce or drop some of your free time activities.
- ☐ 8 Other ____________________

27. Suppose during your regular morning commute you found yourself in a traffic jam where you expected to stand in immobile traffic for ~~30 minutes or more.~~ If you could bypass the traffic jam and continue uninterrupted by paying a fee. would you be willing to pay a fee of

a) S 0.50 ☐ 1 Yes ☐ 2 No

b) S 1.00 ☐ 1 Yes ☐ 2 No

c) $ 2.00 ☐ 1 Yes ☐ 2 No

d) $ 3.00 ☐ 1 Yes ☐ 2 No

e) $ 5.00 ☐ 1 Yes ☐ 2 No

28. If your morning commuting time would ~~permanently decrease~~ by 15 ~~minutes~~ due to traffic improvements, how would you use the time? (check all that apply)

- ☐ 1 Sleep longer.
- ☐ 2 Have longer breakfast.
- ☐ 3 Read newspaper.
- ☐ 4 Watch TV / listen to the radio.
- ☐ 5 Spend time with family.
- ☐ 6 Do chores.
- ☐ 7 Arrive at work earlier.
- ☐ 8 Other ____________________

29. Consider <u>your usual morning commute to work</u> when answering the next set of questions.

Below are nine pairs of scenarios for your usual morning commute. In these scenarios you do not know what the exact travel time will be, but you know it will be one of the five listed travel times (each has an equal chance). The departure time is expressed in minutes before your usual arrival time at the work place. You can refer to question 21 for your usual arrival time.

EXAMPLE: Suppose that the five possible travel times are 18, 19, 20. 21. and 22 minutes. If you depart 20 minutes before your usual arrival time. it means that you will arrive 2, 1, or 0 minutes earlier or 1 or 2 minutes later than your usual arrival time.

Time : minutes				
18	19	20	21	22

departure 20 minutes before your usual arrival time.

Please consider how you feel about the time spent at home and in traffic, and how early or late you feel comfortable of arriving at your work place. Then look at each pair and circle either A or B as the alternative you would be most likely to choose. It is possible that neither one of the alternatives describes your commuting in real life. In such a case circle the alternative you would be most likely to choose if you had no other alternatives.

1st PAIR OF SCENARIOS

A	B
Time : minutes	Time : minutes
9 9 10 10 12	4 5 6 8 12
Departure 12 minutes before your usual arrival time.	Departure 13 minutes before your usual arrival time.

Please circle your choice: **A** **B**

2nd PAIR OF SCENARIOS

A	B
Time : minutes	Time : minutes
4 5 6 8 12	12 13 14 16 20
Departure 13 minutes before your usual arrival time	Departure 15 minutes before your usual arrival time

Please circle your choice: **A** **B**

3rd PAIR OF SCENARIOS

A	B
Time : minutes	Time : minutes
2 4 6 9 15	4 5 6 8 12
Departure 12 minutes before your usual arrival time.	Departure 13 minutes before your usual arrival time.

Please circle your choice: **A** **B**

4th PAIR OF SCENARIOS

A	B
Time : minutes	Time : minutes
12 13 14 16 20	5 7 9 12 18
Departure 15 minutes before your usual arrival time.	Departure 10 minutes before your usual arrival time.

Please circle your choice: A B

5th PAIR OF SCENARIOS

A	B
Time : minutes	Time : minutes
4 5 6 8 12	5 7 9 12 18
Departure 13 minutes before your usual arrival time.	Departure 10 minutes before your usual arrival time.

Please circle your choice: A B

6th PAIR OF SCENARIOS

A	B
Time : minutes	Time : minutes
4 5 6 8 12	12 13 14 16 20
Departure 13 minutes before your usual arrival time.	Departure 15 minutes before your usual arrival time.

Please circle your choice: A B

7th PAIR OF SCENARIOS

Time : minutes				
12	13	14	16	20

Departure 15 minutes before your usual arrival time.

Time : minutes				
7	8	9	11	15

Departure 16 minutes before your usual arrival time.

Please circle your choice: A B

8th PAIR OF SCENARIOS

Time : minutes				
7	8	9	11	15

Departure 16 minutes before your usual arrival time.

Time : minutes				
4	5	6	8	12

Departure 13 minutes before your usual arrival time.

Please circle your choice: A B

9th PAIR OF SCENARIOS

Time : minutes				
5	7	9	12	18

Departure 10 minutes before your usual arrival time.

Time : minutes				
14	14	15	15	17

Departure 16 minutes before your usual arrival time.

Please circle your choice: A B