On the Measurement and Valuation of Travel Time Variability Due to Incidents on Freeways

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ABSTRACT

Incidents on freeways frequently cause long, unanticipated delays, increasing the economic cost of travel to motorists. This paper provides a simple model for estimating the mean and variance of time lost due to incidents on freeways. It also reviews methods for assigning a monetary value to the variability that such incidents introduce into daily travel. The paper offers an easy-to-implement approach to measuring the performance of freeway incident reduction strategies, an approach that should be useful in early project selection exercises where a sketch planning process is used to identify promising actions.

INTRODUCTION

From the perspective of economic theory, avoidable time spent traveling is a nonproductive activity against which there is an opportunity cost. For example, work time may be lost due to delays in the daily commute. A common approach to placing a cost on this extra time spent in travel is to assess the value of such time in terms of the hours lost multiplied by some fraction of the gross hourly wage, including Worker's Compensation and other fringe benefits paid for by employers (Hensher

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1997). Alternatively, numerous travel behavior studies have used consumer choice models to derive the value of time spent in travel, for both work and nonwork purposes. The most popular approach has been to estimate logit models of mode or route choice. In these models, the choices made by a sample of travelers are related to the differences these individuals face in terms of in-vehicle and out-of-vehicle travel times and also in terms of the various monetary costs associated with each mode or route alternative. The ratio of the resulting parameter values assigned to the travel time versus travel cost variables in these models is then used to derive a monetary value of time savings (Hensher 1997).

Most of these time valuation studies have based their findings on estimated traveler responses to changes in averaged or, more usually, representative daily travel times. However, a number of empirical studies have demonstrated the importance of also considering travel time variability in the derivation of traveler cost functions (for example, Jackson and Jucker 1982, Polak 1987, Black and Towriss 1993, Senna 1994, Abdel-Aty et al. 1995, Noland and Small 1995, Small et al. 1995, 1997). These studies indicate that under the right circumstances, notably during congested peak period travel, reducing the variability, and hence the uncertainty, associated with trip times can offer significant traveler benefits. This is important because it is usual for travel time savings to dominate the benefits assigned to major transportation improvement projects (USDOT FHWA 1996).

Empirical evidence confirms that a major cause of day-to-day variability in trip times is the occurrence of traffic incidents, including major accidents that block traffic lanes for extended periods and many minor incidents, such as vehicle breakdowns (see Lindley 1987, Giuliano 1989, Schrank et al. 1993). In the following section, a model is described for estimating both the mean and variance in the time lost due to such traffic incidents along freeways. The model is fitted to data on a number of different incident types, for two-, three-, and four-lane freeways, and for a range of congestion levels.

In the third section of the paper, methods are reviewed for assigning a monetary value to the variability that such incidents introduce into daily travel. A high level of daily variability in the time it takes to complete a specific trip implies a less-than-reliable transportation system. Such variability is likely to result in one of two outcomes, either a) the traveler arrives late or b) the traveler makes an earlier departure than desired, with the possibility on any given day of arriving earlier than necessary. Either way, time is lost or at least used in a less than optimal fashion. If travelers attach a high value to on-time arrivals, then a high level of variability in daily travel times represents a significant disbenefit that needs to be accounted for in project assessments. Recent research, discussed below, indicates that this is the case. In particular, a number of studies were found to have used stated preference (SP) surveys to capture and quantify traveler perceptions about the day-to-day reliability of their travel options. While numerical results from these studies vary a good deal, they indicate that travelers involved in repetitive trip-making are likely to place a significant premium on consistency in day-to-day trip times. Based on this literature, two different valuation methods were selected and linked to the incident delay model described in the second section of the paper. The two methods are used to demonstrate the importance of incorporating the costs of either travel time variability or the congestion that produces it into project benefit-cost analyses.

The results of the modeling also suggest that real time incident management (IM) systems, based on rapid and accurate incident detection and clearance, are promising components of regional Intelligent Transportation System (ITS) strategies. In this context, freeway-based IM systems appear to be especially good candidates for further analysis since they deal with the redirection or control of potentially large traffic volumes. The following analysis offers an easy-to-implement approach to measuring the performance of freeway incident reduction strategies, an approach that should be useful in early project selection exercises where a sketch planning process is used to identify likely project candidates.

MEASURING TRAVEL TIME VARIABILITY: AN INCIDENT ANALYSIS PROCEDURE

In this section, a model is presented for estimating the mean and variance of delays due to freeway incidents as a function of volume-to-capacity (V/C) ratio. Results of fitting the model to data on the magnitude, frequency, and duration of incidents are also presented.

The model provides estimates of delays due to accidents, debris, and vehicle breakdowns. It does not include the effects of delays due to day-to-day variations in traffic volume, weather conditions, or roadwork. Taking these effects into account could significantly increase our estimates of day-to-day variations in travel times. However, delays due to variations in traffic volume, weather conditions, and roadwork are more easily anticipated by motorists than delays due to accidents and vehicle breakdowns. Issues regarding the valuation of different types of delays are discussed further in the third section.

The following variables are used in the model description:

- V = average volume on the freeway (in vehicles per hour). This is the rate at which vehicles arrive at the back of the queue after an incident occurs and a queue forms.
- C = the capacity (Level of Service E) of the freeway prior to the occurrence of the incident (in vehicles per hour).
- r = capacity reduction factor due to the incident. The quantity rC is the rate at which vehicles pass the incident before it is cleared. If $r = 0$, the freeway is completely blocked by the incident.
- g = average "getaway" volume from the queue after the incident is cleared, expressed as a fraction of C.
- T_i = incident duration (in hours).
- T_g = duration of the getaway period during which the queue is dissipating (in hours).
- Q = maximum queue length (in vehicles).
- D_i = total delay incurred by all vehicles during the incident (in vehicle-hours).
- D_g = total delay incurred by all vehicles during the getaway period (in vehicle-hours).
- D = total delay incurred as a result of the incident (in vehicle-hours).

The model calculates D as a function of V, C, r, g, and T_i.

An incident will cause a queue if the freeway volume V is greater than the available freeway capacity during the incident (i.e., if $V>rC$). The queue will grow in length until the incident is cleared (T_i hours after the incident occurred). The queue growth rate during the incident (in vehicles per hour) is equal to the rate at which vehicles arrive at the end of the queue (V) minus the rate at which they get past the incident (rC). The maximum queue length, which occurs at that point in time when the queue is cleared, is calculated as follows

$$Q = (V - rC)\ T_i \tag{1.1}$$

Because the queue grows from a length of zero (when the incident occurs) to a length of Q (when the incident is cleared), the average length of the queue during the incident is $Q/2$. Hence, the delay incurred by vehicles during the incident is calculated as follows:

$$D_i = (1/2)\ Q\ T_i = (1/2)(V - r\,C)\ T_i^2 \tag{1.2}$$

After the incident is cleared, the queue will gradually dissipate, at a rate dependent on the getaway capacity and the volume:

$$T_g = Q/(gC - V) \tag{1.3}$$

Hence, the delay incurred by vehicles while the queue is dissipating is calculated as follows:

$$D_g = (1/2)\ Q\ T_g = (1/2)\ Q^2/(gC - V) = (1/2)\ (V - r\,C)^2\ T_i^2\ /(gC - V) \tag{1.4}$$

Total delay due to the incident is then calculated as follows:

$$D = Di + D_g = (1/2)\ C\ T_i^2\ (V/C - r)\ (g - r)/(g - V/C) \tag{1.5}$$

An important implication of this simple model is that the total delay due to an incident varies with the *square* of incident duration. For example, if the duration of incidents is reduced by 10%, then the total delay caused by the incident is reduced by 19% ($1-0.9^2$). This is because reducing incident duration by 10% means that 10% fewer vehicles will be caught in the queue caused by the incident, and each vehicle caught in the queue will spend 10% less time in the queue.

Equation (1.5) provides an estimate of total delay to all vehicles due to an incident. To estimate the mean and variance of incident-related delays experienced by individual motorists, we make the following assumptions for each class of incident (k) to be examined:

- The occurrence of incidents on a highway section is governed by a Poisson process such that the expected number of incidents is equal to $\lambda_k VL$, where λ_k is the incident rate, V is volume, and L is section length.
- Incident durations follow a Gamma distribution[1] with mean m_k and variance s_k^2.
- Not all motorists affected by an incident experience the same amount of delay. In particular, we assumed that delays experienced by motorists during a given incident would follow a uniform distribution ranging from zero to twice the expected delay for the incident.

Using these assumptions, we can calculate the mean and variance of a motorist's delay per vehicle-mile for each class of incidents as follows:

$$\mu_{dk} = \lambda_k (1/2)\, C\, (m_k^2+s_k^2)\, (V/C-r_k)(g-r_k)/(g-V/C) \quad (1.6)$$

$$\sigma_{dk}^2 = (4/3)\mu_{dk}\, m_k\, (1-r_k/(V/C))(s_k^2 + m_k^2/2)/(s_k^2 + m_k^2)-\mu_{dk}^2 \quad (1.7)$$

where

- μ_{dk} is the mean delay (in hours per vehicle-mile) due to the class of incidents.
- σ_{dk}^2 is the variance of delay due to the class of incidents.
- Other variables are as defined above.

In deriving equations (1.6) and (1.7), we used the fact that the expected value of the square of any random variable is equal to the sum of its variance and the square of its mean. We also used the fact that if the probability density function of a random variable t is uniform between 0 and $2T$, then the expected value of t^2 is equal to $4T^2/3$.

A spreadsheet was developed to apply these equations to estimate the mean and variance of delays due to incidents as a function of volume-to-capacity ratio. In the spreadsheet, incidents were classified by type (abandoned vehicle, accident, debris, mechanical/electrical, stalled vehicle, flat tire, and other) and severity (shoulder, one, two, three, or four lanes blocked). For each class of incident, data from Sullivan et al. (1995) were used to estimate m_k, s_k^2, λ_k, and r_k, and runs of the traffic microsimulation model FRESIM[2] performed by Margiotta et al. (1997) were used to estimate g.

With the above equations for μ_{dk} and σ_{dk}^2, estimates of the mean and variance of delays due to each class of incident were developed for volume-to-capacity ratios ranging from 0.05 to 1.0 for freeways with 2, 3, and 4 lanes in each direction.[3] The means and variances for individual incident classes were then summed to produce the mean and variance of all delays due to incidents as a function of number of lanes and volume-to-capacity ratio.[4] The results, shown in figures 1 and 2, were a set of smooth curves to which the following equations[5] were fit.

- Freeways with two lanes in each direction:

$$\mu_d = 0.0154(V/C)^{18.7} + 0.00446(V/C)^{3.93} \quad (1.8)$$

$$\sigma_d^2 = 0.00408(V/C)^{21.2} + 0.00199(V/C)^{4.07} \quad (1.9)$$

- Freeways with three lanes in each direction:

$$\mu_d = 0.0127(V/C)^{22.3} + 0.00474(V/C)^{5.01} \quad (1.10)$$

$$\sigma_d^2 = 0.00288(V/C)^{23.2} + 0.00166(V/C)^{5.06} \quad (1.11)$$

[1] Golob et al. (1987) and Giuliano (1989) found incident durations to fit a log-normal distribution. However, this distribution presents some analytically intractable problems. The Gamma distribution offers an approximation that is easier to work with.

[2] FRESIM is a traffic microsimulation model. Simulation runs were required to estimate the value of the parameter g. The other variables are derived directly from the data provided by Sullivan et al. (1995).

[3] In estimating the mean and variance of incident delays for a given V/C ratio, we assume that the volume of traffic does not vary over time, since our focus is on developing simple relationships for sketch planning. For more detailed applications, Sullivan et al. (1995) developed a computer program named IMPACT for estimating incident delays with time-varying traffic.

[4] Under the assumptions presented earlier in this section, delays for the different incident classes constitute a set of independent random variables. For independent random variables, the mean of their sum is equal to the sum of their means, and the variance of their sum is equal to the sum of their variances (see Drake 1967, 107–108).

[5] Equations are not applicable when $V/C > 1.0$, i.e., when demand volume exceeds capacity so that queuing occurs even if there are no incidents.

- Freeways with four or more lanes in each direction:

$$\mu_d = 0.00715(V/C)^{32.2} + 0.00653(V/C)^{7.05} \quad (1.12)$$

$$\sigma_d^2 = 0.00229(V/C)^{22.2} + 0.00124(V/C)^{5.27} \quad (1.13)$$

where

- μ_d is the average delay experienced by a motorist due to all incidents in hours per vehicle-mile.
- σ_d^2 is the variance of delay experienced by a motorist due to all incidents in hours squared per vehicle-mile.
- V is volume in vehicles per hour.
- C is capacity in vehicles per hour.

The equations presented above closely fit the results presented in figures 1 and 2. In all cases, the adjusted R-squared values exceeded 0.99.

VALUATION METHODS: BENEFITS OF MORE RELIABLE TRAVEL TIMES

In this section, two different approaches to assigning a user benefit (cost) to more (less) reliable travel times are linked to the above model of delays due to incidents. In each case the method is based on recently reported empirical analyses in which traveler cost models have been fitted to data from SP surveys designed to explore traveler responses to variability in day-to-day travel times. In the first approach, an additional cost of travel is assigned directly to a measure of trip time variability. In the second approach, an additional cost of travel is assigned instead to that part of a trip in which delays caused by congestion occur. The objective in both instances is to provide a method for quantifying the benefits associated with improved system reliability that can also make use of data that can be routinely collected with the deployment of real time regional traffic monitoring systems.

The first of these trip cost models (model 1) has the form:

$$U_c = a_1{*}T + a_2{*}V(T) + a_3{*}M \quad (2.1)$$

where U_c equals the expected cost of the daily trip (e.g., the commute), and a_1, a_2, and a_3 are parameters that reflect travelers' relative dislike of, respectively, trip time T, a measure of trip time variability $V(T)$, and a monetary travel cost, M. In recent years, a number of researchers have attempted to derive the parameters for this and more elaborate travel cost models by using SP surveys. In such surveys, a sample of travelers is asked to choose between a number of hypothetical trip-making options that offer different trade-offs between trip time, trip time variability, and trip costs (see Jackson and Jucker 1982, Black and Towriss 1993, Small et al. 1997). The resulting ratio of a_2/a_1 in equation (2.1) provides a useful

FIGURE 1 Expected Delay Due to Incidents on Two-, Three-, and Four-Lane Freeways

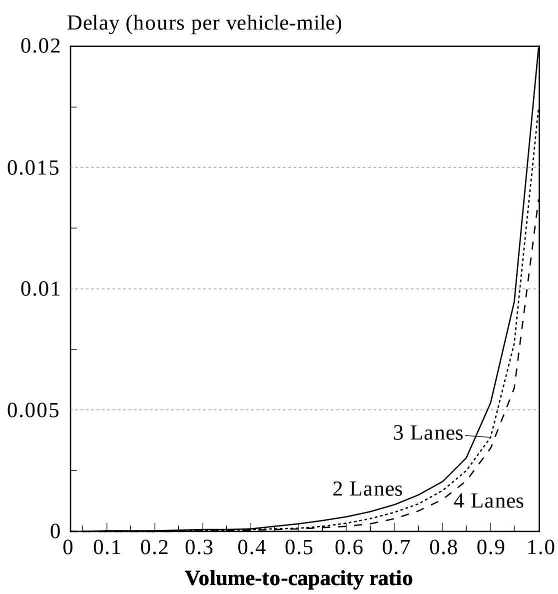
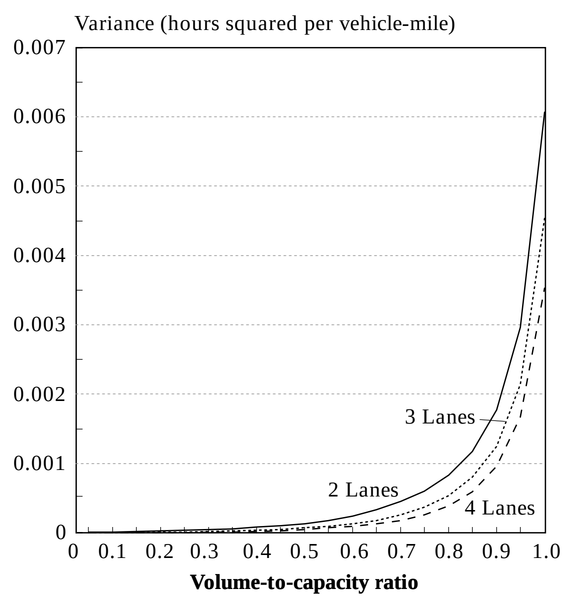


FIGURE 2 Variance of Delay Due to Incidents on Two-, Three-, and Four-Lane Freeways



measure of the relative importance of changes in travel time variability versus changes in total trip time. The ratio of a_2/a_3 also allows a monetary cost to be assigned to the importance of such variability.

In their London study of travel time reliability, Black and Towriss (1993) used such a model to obtain a value of 0.55 for the ratio of a_2/a_1 (quoted in Small et al. 1995, 54). They define *V(T)* in their model as the standard deviation of travel time. This indicates that changes in the standard deviation of trip time is significant, at a little more than half the value of an equivalent increase in trip duration itself. A similar ratio of 0.35 was obtained by the SP-based study of morning commuters route choice in Los Angeles, carried out by Abdel-Aty et al. (1995). In this case, their model leaves out the monetary costs of commuting. A more recent study by Small et al. (1997) also used a stated preference survey of morning peak period commuters in southern California. They estimated a number of different binary logit choice models, including a version of equation (2.1) above, with *V(T)* also set equal to the standard deviation of travel time. They obtained much higher values on this variability term than previous studies. In their case, an additional increase of 1 minute in the standard deviation of travel time was valued at 1.31 times that of an additional minute of total time savings per se, where this latter was taken to be 50% of the median wage rate in their sample. A similar result, with a_2/a_1 producing a ratio of 1.27, was also obtained by Small et al. (1995), using a different SP survey of Los Angeles commuters and a model that left out the monetary cost variable M in equation (2.1) above.

The significant differences in the values associated with variability (reliability) across these and related studies appear to result to a large degree from differences in study intent as well as survey design. However, the empirical work discussed by Senna (1994), Small et al. (1995, 1997), Noland et al. (1997), and Bates (1997) also demonstrates that we should expect some significant differences in value of time use parameters based on trip purpose (notably work-related versus commuting versus noncommuting activities), socioeconomic status (such as income and family structure), and based on differences in traveler attitudes towards schedule compliance (e.g., risk-prone versus risk-averse types). Scheduling constraints imposed by the inflexibility and importance of fixed working hours are also likely to differentially influence travelers' responses to uncertain trip times. It is also possible, though currently unclear, that the underlying level of recurrent congestion may affect such valuations. Small et al. (1995, 54) quotes a British study (MVA Consultancy 1992) as suggesting a plausible value for the ratio of a_2/a_1 between 1.1 and 2.2, but this is based on very limited empirical evidence. More work is obviously warranted on this topic, with the probable conclusion that the effects of travel time reliability ought to be evaluated on a market-sector and context-sensitive basis.

Model 1 is one of the simplest traveler cost models to incorporate travel time variability impacts. Polak (1987), Senna (1994), and Noland et al. (1997) offer others. In particular, the recent work by Small et al. (1997) provides a more direct empirical link between commuting costs, travel time variability, and travelers' valuation of early as well as late arrivals. An important finding of their work is that model 1, with *V(T)* defined as the standard deviation of travel time, appears to be a useful surrogate for their more elaborate travel (commuting) cost equations, in which the effects of scheduling delays are captured by the use of explicit early and late arrival penalties. This suggests that we can use equation (2.1) to capture most of the time-use benefits resulting for incident-induced delays, without having to go into more elaborate schedule-impact modeling, at least for the purposes of sketch planning studies.

A second approach (model 2) to assigning a valuation to system reliability is to assign a cost directly to congestion. This has the practical advantage of linking directly computable measures of the location and duration of congestion (using in-vehicle and along-the-highway sensor systems) to a suitable valuation of travelers' dissatisfaction with unexpected en route delays. There is a limited body of empirical evidence to indicate that congested travel time is assigned a comparatively high cost by travelers, although once again the values reported cover quite a wide range. The most recent empirical work on this topic is reported by Small et al. (1997), who

TABLE 1

	Model 1	Model 2
Value of travel time under uncongested conditions	V	V
Value of incident-related delay	V	2V to 6V
Value of standard deviation of trip time	0.3V to 1.3 V	—

TABLE 2

Cost components	Model 1	Model 2
Travel time under uncongested conditions	3.64	3.64
Incident-related delay	0.80	1.60 to 4.81
Standard deviation of trip time	0.47 to 2.03	—
Total	4.91 to 6.47	5.24 to 8.45

estimated binary logit travel choice models using travel cost functions of the following general form, again using data from their SP survey of southern California morning commuters in 1995:

$$U_c = a_1{*}T + a_2{*}f[T_c] + a_3{*}M \qquad (2.2)$$

where T=total expected travel time, $f(T_c)$ = a function of the time spent in traffic congestion, M=monetary cost of travel, and a_1, a_2, a_3 are again the estimated model parameters. They use two specifications for $f(T_c)$. The first of these sets $f(T_c)$ equal to the percentage of the trip time spent in congestion, while the second model uses the number of minutes spent in congestion directly. The authors also introduce income effects into their more elaborate model formulations. As a set, their results indicate a considerable aversion to congestion among their respondents. Their results imply that, for the study's median trip length of 26 minutes, a shift from 1 minute of uncongested to congested travel time was valued at almost 3 times the value of the time itself, which in turn implies that the value of congested time is about 4 times the value of uncongested time. Their results also suggest that this ratio may vary a good deal by trip length, with values ranging from about 2 times higher for 60-minute trips to six times higher for 15-minute trips. Past literature suggests that their results are on the high side. This is probably due to the congestion focus of the study and to the high levels of congestion their respondents are used to. Again, results to date are likely to be model-formulation as well as context and market-sector sensitive.

Table 1 summarizes high and low values suggested by the literature for models 1 and 2 in relation to the value of travel time under uncongested conditions.

LINKING INCIDENT DELAY MODELS AND VALUATION METHODS

In this section, we demonstrate the implications of linking the valuation methods in the third section with the incident delay models in the second.

Our first hypothetical case for this demonstration is a 20-mile commuter trip on a 3-lane freeway with a typical volume to capacity ratio of 0.90. These circumstances are typical of those experienced by the California commuters surveyed by Small et al. We also assume that when traffic is not affected by incidents, the average speed is 55 miles per hour and the cost of travel time under uncongested conditions for commuters is $10 per vehicle-hour.

For this hypothetical case, the average delay due to incidents is:

$$(20 \text{ miles})(0.0127(0.90)^{22.3} + 0.00474 (0.90)^{5.01}) = 0.080 \text{ hours}$$

and the standard deviation of trip time is:

$$((20 \text{ miles})(0.00288(0.90)^{23.2} + 0.00166 (0.90)^{5.06}))^{0.5} = 0.156 \text{ hours}$$

Table 2 shows the results of applying models 1 and 2 with high and low values.

Our second hypothetical case for this demonstration is a 5-mile commuter trip on a 2-lane freeway with a typical volume to capacity ratio of 0.80. We also assume that when traffic is not affected by incidents, the average speed is 60 miles per hour and the cost of travel time under uncongested conditions is $10 per hour.

For this hypothetical case, the average delay due to incidents is:

$$(5 \text{ miles})(0.0154(0.80)^{18.7} + 0.00446 (0.80)^{3.93}) = 0.010 \text{ hours}$$

TABLE 3

Cost components	Model 1	Model 2
Travel time under uncongested conditions	0.83	0.83
Incident-related delay	0.10	0.21 to 0.63
Standard deviation of trip time	0.19 to 0.84	—
Total	1.12 to 1.77	1.04 to 1.46

and the standard deviation of trip time is

$$((5 \text{ miles})(0.00408(0.80)^{21.2} + 0.00199 (0.80)^{4.07}))^{0.5} = 0.065 \text{ hours}$$

Table 3 shows the results of applying models 1 and 2 with high and low values.

Model 2 produces somewhat higher costs for our hypothetical case with a 20-mile trip, and model 1 produces somewhat higher costs for our hypothetical case with a 5-mile trip. The principal reason for this difference is that model 2 is based on incident delay only, whereas model 1 is based on both incident delay and the standard deviation of trip time. Expected incident delay increases in direct proportion to trip distance. The standard deviation of trip time increases in proportion to the square root of trip distance. Hence, model 1 will produce higher costs for short trips, and model 2 will produce higher costs for long trips, other things being equal. The difference between these two models highlights the need for more research to determine the most appropriate model form for valuation of delays due to incidents.

SUMMARY

In summary, a model of traffic incident-based delays was formulated and estimated for freeways of different capacities, for a range of traffic congestion levels up to ideal roadway capacities. This yielded equations for both the mean and variance of such delays, on a per vehicle-mile basis. These results were used to demonstrate the potentially significant time-use benefits that could occur from reducing such variances. To do this, the literature on valuing travel time reliability was surveyed for appropriate models and parameter values. Two simple models were chosen to demonstrate the size of the potential time-use benefits involved. The results mirror similar conclusions reached by Wilson (1989) and by Noland and Small (1995). If the results implied by the above approach are reflective of actual traffic conditions, then policies to reduce variability in commuting times, such as rapid response incident clearance systems, may prove cost-effective, even if *average* trip times change little or not at all. Such systems may perhaps offer a cost effective alternative to relatively expensive capacity expansion projects that focus on reducing average commuting times per se. Given the limited amount of empirical work on both the valuation and nature of traveler responses to highly variable travel conditions, more work in this area is warranted in support of more accurate benefit-cost analyses.

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REFERENCES

Abdel-Aty, M., R. Kitamura, and P.P. Jovanis. 1995. Investigating Effect of Travel Time Variability on Route Choice Using Repeated-Measurement Stated Preference Data. *Transportation Research Record* 1493:39–45.

Bates, J.J. 1997. Departure Time Choice—Theory and Practice, paper presented at the 8th Meeting of the International Association for Travel Behaviour Research, September 21–25, 1997. Austin, Texas.

Black, I.G. and J.G. Towriss. 1993. *Demand Effects of Travel Time Reliability.* London, England: United Kingdom Department of Transport.

Drake, A.W. 1967. *Fundamentals of Applied Probability Theory.* New York, NY: McGraw-Hill Book Company.

Giuliano, G. 1989. Incident Characteristics, Frequency, and Duration on a High Volume Urban Freeway. *Transportation Research* 23A:387–396.

Golob, T.F., W.W. Recker, and J.D. Leonard. 1987. An Analysis of the Severity and Incident Duration of Truck-Involved Freeway Accidents. *Accident Analysis and Prevention* 19:375–395.

Hensher, D.A. 1997. Behavioral Value of Time Savings in Personal and Commercial Automobile Travel. *The Full Costs and Benefits of Transportation*. Berlin, Germany: Springer-Verlag, 245–280.

Jackson, W.B. and J.V. Jucker. 1982. An Empirical Study of Travel Time Variability and Travel Choice Behavior. *Transportation Science* 16.4:460–475.

Lindley, J.A. 1987. Urban Freeway Congestion: Quantification of the Problem and Effectiveness of Potential Solutions. *Journal of the Institute of Traffic Engineers* 57.1:27–32.

Margiotta, R.A., A.K. Rathi, M. Penic, and A. Dixson. 1997. Examination of Freeway Bottleneck Traffic Parameters Using FRESIM, unpublished manuscript.

MVA Consultancy. 1992. Quality of a Journey: Final Report, prepared for the United Kingdom Department of Transport, contract no. 02/c/5274.

Noland, R. B. and K.A. Small. 1995. Travel-Time Uncertainty, Departure Time Choice, and the Cost of Morning Commutes. *Transportation Research Record* 1493:150–158.

Noland R.B., K.A. Small, P.M. Kostenoja, and X. Chu. 1997. Simulating Travel Reliability. *Regional Science and Urban Economics* (Forthcoming).

Polak, J. 1987. Travel Time Variability and Travel Departure Time Choice: A Utility Theoretic Approach, discussion paper no. 15. Polytechnic of Central London.

Schrank, D.L., S.M. Turner, and T.J. Lomax. 1993. Estimates of Urban Roadway Congestion–1990, report no. FHWA/TX-90/1131-5. Washington, DC: U.S. Department of Transportation, Federal Highway Administration.

Senna, L.A.D.S. 1994. The Influence of Travel Time Variability on the Value of Time. *Transportation* 21:203–229.

Small, K., X. Chu, and R. Noland. 1997. Valuation of Travel-Time Savings and Predictability in Congested Conditions for Highway User-Cost Estimation, NCHRP 2-18(2), draft. Washington, DC: Hickling Lewis Brod Inc.

Small, K.A., R.B. Noland, and P. Koskenoja. 1995. Socio-Economic Attributes and Impacts of Travel Reliability: A Stated Preference Approach, California PATH research report UCB-ITS-PRR-95-36. University of California, Irvine, CA.

Sullivan, E., S. Taff, and J. Daly. 1995. A Methodology for Measurement and Reporting of Incidents and Prediction of Incident Impacts on Freeways, report prepared for the U.S. Department of Transportation, Federal Highway Administration. San Diego, CA: Ball Systems Engineering Division.

U.S. Department of Transportation, Federal Highway Administration (USDOT FHWA). 1996. Exploring the Application of Benefit-Cost Methodologies to Transportation Infrastructure Decision Making, report no. 16, Policy Discussion Series. Washington, DC.

Wilson, P.W. 1989. Scheduling Cost and the Value of Travel Time. *Urban Studies* 26:356–366.