

OCCURENCE, FREQUENCY, AND DURATION OF COMMUTERS' WORK-TO-HOME DEPARTURE DELAY

FRED L. MANNERING and MOHAMMAD M. HAMED

Department of Civil Engineering, University of Washington, Seattle, WA 98195, U.S.A.

(Received 12 August 1988; in revised form 19 June 1989)

Abstract—This paper investigates commuters' decision to delay their departure from work to home, in an effort to avoid traffic congestion. A sample of commuters, from the congested Seattle metropolitan area, is used to estimate a model of the decision to delay homeward departure as well as models of the frequency and duration of this delay. The estimation results suggest, as expected, that traffic system characteristics dominate the delay choice, with socioeconomic characteristics and the characteristics of the area near the work location (which provides activity opportunities that can be undertaken during the departure delay) playing a lesser role. The estimated magnitude of influence that these determinants have, on the delay choice, has important implications for future departure-time-choice research.

INTRODUCTION

Historically, transportation and traffic planning has, for the most part, focused extensively on the study of commuters' mode and route changes in response to traffic congestion. However, more recently, another very important dimension of commuters' response to congestion has begun to receive increasing attention. This dimension, the choice of departure time, has become an increasingly significant concern as levels of traffic congestion continue to rise dramatically in urban areas. It is now generally recognized, by researchers and practitioners alike, that commuters' choice of departure time is a critical concern in the study of traffic congestion.

Unfortunately, from a modeling perspective, the choice of departure time necessitates that explicit consideration be given to the rather complex issue of the time-varying dynamic nature of commuter travel decisions. Operationalizing a traffic forecasting model to predict urban congestion, while explicitly accounting for departure time decisions, is a monumental undertaking due to these time-varying concerns, and one that is well beyond the level of currently used traffic forecasting methods. Due to the complexity of the problem, research in the area of commuter departure time choice has concentrated on small, often isolated components of the problem in an effort to gain a further understanding of the factors involved the departure time decision. For example, Mahmassani and Chang (1985, 1986), Chang and Mahmassani (1988), and Mahmassani and Tong (1986), have investigated the process by which commuters arrive at a satisfactory departure time and route choice in a small, isolated traffic network. Their work provided valuable insight into time involved for a traffic system to reach a state of dynamic equilibrium. In other work, Abu-Eisheh and Mannering (1988), and Mannering, Abu-Eisheh, and Arnadottir (in press) have used econometric-based methods to arrive at equilibrium route and departure times, in response to projected congestion, but again their work was confined to the analysis of a small, isolated traffic network. Finally, Mannering (1989) investigated the frequency with which commuters make route and departure time changes in a real traffic network, but his work did not provide for a theoretical or empirical link to a traffic equilibrium process. However, despite some rather obvious limitations, past research has made measurable strides toward a truly operational urban forecasting model that explicitly accounts for changes in commuter departure time. Such strides have been accomplished by concentrating on specific components of the departure time choice problem. The intent of this paper is to continue with the component-concentration approach used in the past and to add still more to our growing understanding of the departure time choice process.

One key element of commuters' departure time choice, that has not been adequately dealt with in past research, is the choice of departure time from work to home or, more

specifically, the choice to delay homeward departure, from work, to avoid traffic congestion.† Previous work (as listed above) has, for the most part, focused on the choice of departure time from home to work. Although the departure time decision-making process for the work-to-home and home-to-work trips share many commonalities, there are some significant differences. Three important differences come to mind; (1) the work-to-home trip often does not have fixed, or even preferred, times for arrival at home, (2) the penalties associated with late arrival at home are substantially different than those associated with late arrival at work and, (3) delays in departure from work to home give the commuter the option of participating in activities, near the work place, from which some utility or satisfaction can be derived. This paper will present an analysis of the work-to-home departure time choice process using data from a highly congested real-world traffic network. As will be shown, the analysis results provide interesting insights into this important problem.

The paper begins with an intuitive discussion of the factors affecting the work-to-home departure time delay choice decision. Next, the empirical setting is described and a summary of the conducted survey is given. This is followed by a presentation of the specification and estimation of the work-to-home departure-time delay choice model as well as models of the frequency and duration of departure delay.

DETERMINANTS OF WORK-TO-HOME DEPARTURE DELAY

The decision to delay departure from work to home, in an effort to avoid traffic congestion, is influenced by factors that can be broadly classified into four areas; (1) socioeconomic, (2) traffic system, (3) activity opportunities, and (4) related travel choices.‡ Socioeconomic factors can play a potentially important role, since one might expect individuals with different socioeconomic characteristics to respond differently to traffic congestion. For example, regardless of traffic conditions and radio traffic reports indicating traffic delay, risk-seeking individuals and/or those with a high tolerance for traffic congestion can be expected to depart from work without delay whereas risk-averse individuals and/or those with a low tolerance for traffic congestion may very well delay their homeward trip in an effort to avoid congestion. In as much as socioeconomics are correlated with risk characteristics, traffic tolerance, and the tendency to listen for, and use, radio traffic reports, they can be expected to be important factors in the delay decision. Moreover, socioeconomics are likely to have a more direct effect on the decision to delay, with certain socioeconomic characteristics influencing the utility derived from activities that the commuter may undertake if the decision to delay homeward departure is made. Such activities include additional work, shopping, recreational activities, and social activities.

The traffic system also plays an important role in determining whether or not commuters delay. Traffic system factors that likely influence this decision include: (1) the level of congestion, with more congested traffic networks making delay more likely, (2) the duration of congestion, with traffic congestion over extended periods of time reducing the benefits from delaying and, (3) the availability of alternate homeward routes, with a high availability making options other than departure delay possible as a means of avoiding traffic congestion.

Activity opportunities at or near the commuter's work location clearly influence the choice to delay, with the possibility of working additional hours, shopping in nearby stores, visiting friends and undertaking recreational activities (jogging, aerobics, music lessons, and so on) all increasing the attractiveness of the delay alternative.

Finally related travel choices, such as mode choice, impact delay decisions with, for

†This paper considers only the possibility of delaying work-to-home departure. As such, the possibility of departing earlier than scheduled from work, to avoid congestion, is not addressed.

‡In this paper, departure delay is defined as a delay from a departure time that would normally be taken if traffic congestion was not sufficiently high to induce a delay. This definition of delay applies to commuters with and without flexible work hours.

example, modes such as carpools and vanpools offering much less departure-time delay opportunity than the single-occupancy automobile mode, due to scheduling problems among pool participants. To be truly correct, the choice of mode should be considered jointly with the choice of work-to-home departure delay. However in this study, we will focus exclusively on departure delay with the assumption that mode choice decisions are fundamentally longer-term in nature and, in contrast to departure time decisions, are not likely to be made in response to short-term fluctuations in traffic congestion. †

EMPIRICAL SETTING AND SURVEY RESULTS

To study the delay of departure from work to home, a traveler survey was conducted in the Seattle area. The Seattle area is particularly well suited to the study of work-to-home departure delay due to its heavily congested traffic network. In all, 204 Seattle commuters were surveyed, in May 1988, and a summary of their socioeconomic and commuting characteristics is presented in Table 1.

Referring to Table 1, it is noted that, although the sample contains a slightly higher than expected percentage of male respondents, most of the socioeconomic characteristics, such as age, number of household automobiles, number of children, income, percent with flexible work hours, and mode split percentages are fairly reasonable for west-coast urban commuters. Turning to work-to-home departure delay, we find that nearly half (47.06%) of the respondents delay their homeward departure, from work, to avoid traffic congestion and that the average of this delay is slightly less than one hour (51.29 minutes). In terms of activities undertaken by respondents during this departure delay, there is roughly a 50/50 split between working and not working (i.e. shopping, social, and recreational). The

†The fact that only work-to-home departure delay is being considered, further diminishes the possibility of a mode change being made to avoid traffic congestion. This is because commuters are limited in their modal options due to their having already chosen a mode for their home-to-work trip.

Table 1. Sample summary statistics (Averages unless otherwise noted)

Number of household automobiles	1.8
Number of children in the household	0.7
Annual household income (dollars)	32,456
Age of respondent (years)	32.45
Sex of respondent (percent male/female)	63.7/37.3
Percent of respondents with flexible work hours	62.3
Percent of respondents commuting in single-occupant autos/buses/carpool-vanpool	59.31/15.69/25.00
Percent of respondents indicating that they sometimes delay work-to-home trip departure in an attempt to avoid traffic congestion	47.06
Average duration of delay, for those respondents indicating that they sometimes delay (minutes)	51.29
Activity undertaken during work-to-home delay, for those respondents indicating that they sometimes delay, percent working/shopping-social-recreational	48.96/51.04
Frequency of work-to-home delay, for those respondents indicating that they sometimes delay (number of times in past week)	1.83
Distance from work to home (miles)	7.35
For average weekday, the ratio of expected work-to-home travel time, during the afternoon peak, to the free-flow travel time	1.61
Population of the work zone	25,367
Retail employment in the work zone	4,605
Service employment in the work zone	9,733
Size of the work zone (acres)	3,088

frequency of departure delay, which is presumably a function of recurring traffic congestion and commuters' activity plans, was found to be 1.83 times per week.

Additional characteristics of respondents' commutes were computed based on information provided in the survey. Specifically, zip codes of the work place and home were used to compute work-to-home trip length, based on the shortest available route by distance, and, for the average weekday, the ratio of expected afternoon-peak work-to-home travel time to the free flow travel time. The expected peak-period travel time was computed using a user equilibrium traffic assignment model of the Seattle area.[†] The average commuting trip distance of 7.35 miles and the average ratio of expected to free flow travel time of 1.61 are viewed as reasonable values. Finally, to capture the attractiveness of the area near work for engaging in nonwork activities during the departure delay, information on work zone population, retail and service employment, and work zone size, were imputed, using zip code information, for each respondent.

DEPARTURE TIME DELAY CHOICE

To begin the empirical analysis of commuters' decision to delay departure from work to home, we first focus on whether or not they ever delay their departure, in response to traffic congestion, and later will shift our attention to the frequency and duration of departure delay. The commuter can be assumed to face three choices with respect to possible work-to-home departure time delays, (1) never delay departure time, (2) delay departure time and undertake a work activity and, (3) delay departure time and undertake a nonwork activity such as shopping, social, or recreational activities[‡]. These choices are shown schematically in Fig. 1. With the choice alternatives in mind, consider a function (referring back to the earlier discussion of the determinants of work-to-home departure delay) that defines the utility that each commuter, k , derives from the departure time delay choice as,

$$U_k = F_k(i, z_k, y_k, v_k, c_k, \epsilon_i) \quad (1)$$

where U_k is the total utility derived from the choice, i denotes the departure delay alternative, z_k is a vector of commuter socioeconomic characteristics, y_k is a vector of traffic characteristics faced by the commuter, v_k is a vector of activity opportunities at or near the work-place location, c_k is a vector of related travel choices (e.g. mode choice), and ϵ_i is the random, unobservable portion of utility. It can be readily shown that if the ϵ_i 's are assumed

[†]It is assumed, in standard user equilibrium, that travel time is constant over the peak period (defined herein as covering the hours from 4:00 p.m. to 7:00 p.m.). Therefore, this variable does not account for the fluctuations in travel time within the peak period. Instead, average peak-period travel times are used as a proxy for the actual departure-time dependent travel time faced by commuters. This averaging is necessary due to data limitations.

[‡]Respondents were only asked which activity they generally undertook during departure delay. This precludes analysis of the potentially interesting phenomenon of commuters undertaking different activities on different days. A more extensive trip-diary type survey is needed to study such activity variation.

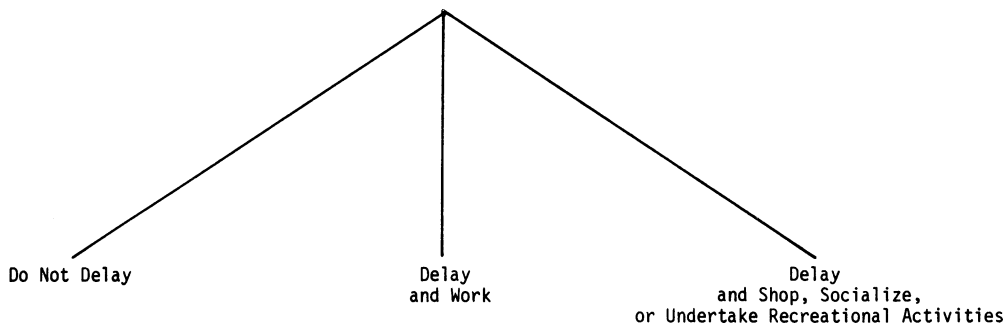


Fig. 1. Structure of commuters' departure-time delay choice.

to be generalized extreme value distributed, the standard multinomial logit probabilistic choice model can be obtained such that,

$$P_{ki} = \exp[V_{ki}] / \sum_J \exp[V_{kj}] \quad (2)$$

where P_{ki} is the probability of the commuter selecting departure delay alternative i , V_{ki} is the mean utility of alternative i to commuter k , and J is the set of available alternatives.

With the model formulation defined in eqn 2, the mean utility for each alternative, i , can be estimated as the linear function,

$$V_{ki} = \beta_0 + \beta_1 z_k + \beta_2 y_k + \beta_3 v_k + \beta_4 c_k \quad (3)$$

where β 's are coefficient vectors estimable by standard maximum likelihood methods (see Train (1986) for additional details).

In estimating the multinomial logit model (eqn 2), we define alternative 1 as the never delay choice, alternative 2 as the delay and work choice, and alternative 3 as the choice to delay and to shop socialize or participate in recreational activities. Without loss of generality, the utility of alternative one, the never delay choice, is implicitly scaled to zero. The resulting coefficient estimates are given in Table 2.

Table 2 indicates that all coefficients are of plausible sign, and most are highly significant, statistically. The ratio of expected afternoon-peak work-to-home travel time to free flow travel time, has a strong positive effect on the likelihood of a commuter delaying homeward departure.† Thus, this variable reflects the reasonable finding that an increase in travel time of 10 minutes, on a trip that would take 8 minutes under free flow conditions, is much more onerous than an increase of 10 minutes, on a trip that would take 45 minutes under free flow conditions. The use of a single-occupancy auto also was found to have a strong positive effect on the likelihood of delaying, due to the fact that this modal alternative provides much more departure time flexibility than carpools, vanpools or even

†It is interesting to note that this variable was found to be much more significant than the arithmetic difference between the increase in travel time, resulting from congestion, and the free flow travel time.

Table 2. Multinomial logit estimation results, t -statistics in parentheses

Variable	Estimated Coefficient
Constant (Alt2, Alt3)	-14.088 (-8.056)
Ratio of the expected work-to-home travel time, during the afternoon peak, to the free-flow travel time (Alt2, Alt3)	7.480 (7.213)
Single-occupancy auto indicator (Alt2, Alt3) (1 if single-occupancy auto used, 0 otherwise)	1.081 (2.109)
State route 520 indicator (Alt2, Alt3) (1 if state route 520 used, 0 otherwise)	-1.147 (-1.791)
Distance from work to home, in miles (Alt2)	0.01 (2.745)
Population of the work zone (Alt3)	0.000036 (2.686)
Female indicator (Alt3) (1 if female, 0 if male)	0.330 (0.825)
Income indicator (Alt3) (1 if annual income greater than \$60,000, 0 otherwise)	0.966 (1.327)

Note: Alt=alternative, Alt1=no delay choice (implicitly normalized to zero), Alt2=delay and work, Alt3=delay and shop, socialize, or participate in recreational activities. A variable's coefficient value is defined only for those alternatives listed in parentheses and is zero for non-listed alternatives. Number of observations=204; log-likelihood at zero = -224.12 and at convergence = -120.14.

bus. One network specific variable, commuters' use of State Route 520, was found to have a negative effect on the delay alternatives. State Route 520 is the major bridge-crossing connecting Seattle with her extensive eastern suburbs and is characterized by it exceptional long periods of congestion. It is speculated that the length of congestion on this facility implies that little is to be gained by commuters by delaying.

Four model variables were defined for only one of the two delay alternatives. The distance from work to home was found to have a positive effect the choice of delaying departure and engaging in additional work, supporting the reasonable assertion that longer commute distances are generally more prone to have major traffic disruptions. Since the work activity choice tends to be somewhat less spontaneous than nonwork activity choice, the distance variable seems to be capturing some longer-term departure-delaying response. The population of the work zone had a positive effect on the choice of delaying and undertaking nonwork activities, with population being used as an indicator of opportunities for nonwork activities in the work zone. Finally, there was a slight tendency for female respondents and wealthier respondents to be more likely to delay and shop, socialize, or participate in recreational activities.

To more accurately assess the implications of the coefficient estimates, it is useful to compute point elasticities. For the logit model, average elasticities can be readily computed by sample enumeration (see Train, 1986). The computed values are shown in Table 3. Indicator variables are excluded from the table since, by definition, their point elasticities are not particularly meaningful. Note that the table indicates that only the number of times longer that the expected travel time is, relative to free flow travel time, has an elasticity greater than unity. This underscores the dominant effect that traffic congestion conditions have on the decision to delay. To a much lesser extent, distance and work zone activity opportunities (as captured by zonal population) influence the delay decision.

From a model specification perspective, the issue of possible Independence of Irrelevant Alternatives (IIA) violations in the multinomial logit (MNL) structure must be considered. One might expect such violations since the delay alternatives (delay and undertake a work activity and delay and undertake a nonwork activity) might be viewed as grouped since both involve the decision to delay. This would in turn imply shared unobservables which would violate the logit modeling structure. To investigate the possibility of IIA violations, the specification test developed by Small and Hsiao (1985) was conducted. Numerous combinations of subsamples of the population and reductions in available alternatives were used in the tests. The findings indicate that in the worst case, the validity of the MNL structure could only be rejected with 58% confidence (as indicated by the chi-squared statistic). Thus, it appears that commuters view the delay choices of work and nonwork, as qualitatively distinct, making the MNL formulation appropriate as used.

FREQUENCY OF DEPARTURE TIME DELAYS

In addition to modeling the choice of whether or not commuters ever delay their work-to-home trip in response to traffic congestion, it would also be useful to develop, for those commuters indicating that they sometimes delay, a model of the frequency with which they delay. One would expect this conditional frequency of delay to be some function of the utility that the individual commuter derives from delaying as well as random fluctuations in traffic congestion resulting from the occurrence of accidents and other disruptive incidents. In accounting for the randomness of traffic disruptions, a Poisson

Table 3. Multinomial logit elasticity estimates

Elasticity with respect to:	Elasticity
Ratio of expected travel time to free flow travel time (Alt2)	8.67
Ratio of expected travel time to free flow travel time (Alt3)	8.44
Distance from work to home (Alt2)	0.513
Population of work zone (Alt3)	0.669

Note: All variables, Alt2 and Alt3 as defined in Table 2.

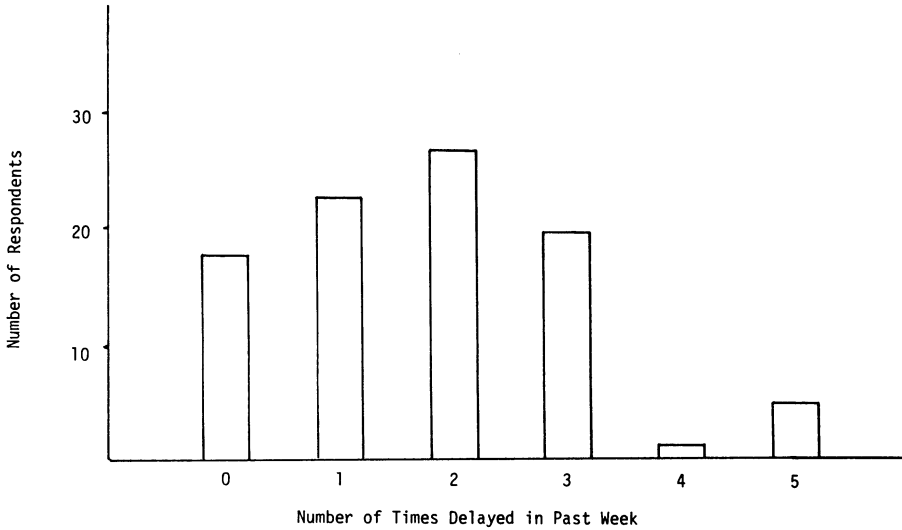


Fig. 2. Frequency of departure delay, in the past week, for those commuters indicating that they sometime delay.

distribution is a reasonable descriptive making a Poisson regression an obvious frequency-of-delay modeling approach (see Lerman and Gonzalez, 1980; Hausman, Hall, and Griliches, 1984; and Mannering, 1989).

One of the questions asked in the survey was, the number of times, in the past week, that a delay in work-to-home departure was actually made. For those respondents indicating that they sometimes delay (47.06% of the sample), the distribution of the frequency of their delaying, in the past week, is shown in Fig. 2.† Since there is a maximum of five delays per week, it is necessary to specify a right-truncated Poisson distribution for the delay-frequency model (see Johnson and Kotz, 1969). The right-truncated Poisson model is,

$$P(n_k) = [\lambda_k^{n_k} / n_k!] \left[\sum_{m_k=0}^r (\lambda_k^{m_k} / m_k!) \right]^{-1} \quad (4)$$

where $P(n_k)$ is the probability of commuter k delaying work-to-home departure n times per week and λ_k is the Poisson parameter for commuter k which will be some estimable function of the utility that the commuter derives from delaying, m_k is the number of departure delays per week, and r is the right truncation (in our case, 5 times per week).‡

Given this specification, it is now necessary to develop an expression that captures the utility that a commuter derives from delaying departure. The multinomial logit model previously estimated can be used (see McFadden, 1981) to arrive at the expected maximum utility, X_k , that a commuter will derive from delaying work-to-home departure. That is,

$$X_k = \ln[\exp(V_{kdw}) + \exp(V_{kdnw})] \quad (5)$$

where V_{kdw} is the mean utility, for commuter k , of the delay and work alternative and V_{kdnw} is the mean utility, for commuter k , of the delay and nonwork alternative (both as shown in eqn 3 with coefficients estimated in Table 2). Note that since the MNL structure was shown to be valid, this maximum utility is the same as that that would have been obtained

†The mean of this distribution is 1.83 departure changes per week, with a variance of 1.88, and, since the Poisson distribution has the restrictive property that the mean and variance are equal, it would appear that this data is particularly well suited to Poisson regression analysis (see Lee, 1986).

‡Note that the traditional Poisson factor, $\exp(-\lambda_k)$, is omitted from both numerator and denominator.

had a nested logit structure been adopted with the delay choice of either work or shop/social/recreational activities occupying the lower-level nest.

With this definition of maximum expected utility, the Poisson parameter of eqn 4 can be defined as,

$$\ln \lambda_k = \alpha X_k \quad (6)$$

where α is coefficient that can be readily estimated, by maximum likelihood, from the Poisson regression likelihood function (using eqns 4 and 6),

$$L(\alpha) = \prod_k [\exp[\exp(\alpha X_k)]^{n_k/n_k!} [\sum_{m_k=0}^r \exp[\exp(\alpha X_k)]^{m_k/m_k!}]^{-1}. \quad (7)$$

Table 4 presents the estimation results of the Poisson regression. As can be seen, the coefficient is of plausible sign, with increasing utility from the delay choice increasing the average number of departure delays per week. To assess the importance of the variables comprising the utility, on the frequency of departure delays (which enter the Poisson regression as indicated by eqn 5), elasticity estimates are again made. The elasticity estimates are presented in Table 5 (again, for reasons previously discussed, point elasticities for indicator variables are not computed). The table indicates that, as was the case for the delay choice model, only the ratio of expected travel time to free flow travel time has an elasticity greater than unity. Thus, even more so than the decision to ever delay or not, the frequency of delay is dominated by the level of congestion.

DURATION OF DEPARTURE DELAYS

The final area of concern is to develop a model of the average duration of departure delay, using commuters' reported average delay duration (in minutes). In modeling departure delay duration, the hazard function approach is an obvious choice. The premise of the approach is to focus on the probability of ending a departure-delay duration conditioned on having delayed up to a specified time. Formally, if the probability distribution is defined as,

$$F(t) = Pr(T < t) \quad (8)$$

where T is a random variable and t is some specified value, with corresponding density function,

$$f(t) = dF(t)/dt \quad (9)$$

the hazard function is,

$$\mu(t) = f(t)/[1 - F(t)] \quad (10)$$

Table 4. Frequency of delay Poisson regression results, t -statistics in parentheses

Variable	Coefficient Estimate
Expected maximum utility of delaying work-to-home departure time (eqn. 5)	0.1512 (7.464)
Number of observations	96
log-likelihood at zero	-194.21
log-likelihood at convergence	-146.06

Table 5. Poisson regression elasticities (estimated by sample enumeration)

Elasticity with respect to:	Elasticity
Ratio of expected travel time to free flow travel time	1.790
Distance from work to home	0.061
Population of work zone	0.072

Note: All variables defined as in Table 2.

where $\mu(t)$ is roughly the rate at which delay durations are ending at time t , given that they have lasted until time t .

An interesting assessment of hazard functions can be made by evaluating the first derivative with respect to time, $d\mu(t)/dt$. If the value of this derivative is greater than zero, at some time t' , the hazard is increasing in duration, indicating that the probability that a departure-delay duration will end soon increases with increasing departure-delay duration. If $d\mu(t)/dt < 0$, a decreasing hazard exists and the probability that a departure delay will end soon decreases with increasing departure-delay duration, and if $d\mu(t)/dt = 0$, a constant hazard exists and the probability of ending a departure delay is independent of departure-delay duration. For commuters' departure delay as defined herein, an increasing hazard is expected since the longer the duration the more likely it is to end soon.

Given the hazard function of eqn 10, the question becomes one of selecting an appropriate duration probability distribution. A convenient and reasonable distribution is the Weibull,[†] with its relatively simple hazard and its provision for the special case of a constant hazard, in which case it reduces to the exponential distribution's hazard. The two parameter Weibull ($\gamma > 0$ and $\rho > 0$) has,

$$F(t) = 1 - \exp[-(\gamma t)^\rho] \quad (11)$$

$$f(t) = \gamma\rho(\gamma t)^{\rho-1} \exp[-(\gamma t)^\rho] \quad (12)$$

with hazard,

$$\mu(t) = \gamma\rho(\gamma t)^{\rho-1}. \quad (13)$$

Note that with this specification, the hazard function is increasing in duration if $\rho > 1$, decreasing in duration if $\rho < 1$, and constant in duration if $\rho = 1$ (i.e. the exponential hazard).[‡]

To estimate our model of duration delay, an accelerated lifetime model is specified (Kalbfleisch and Prentice, 1980). The accelerated lifetime approach assumes a baseline survivor function (see earlier footnote for definition) for all individuals and rescales time to account for individual characteristics that impact duration. For the departure-delay duration model, the rescaling of time in the accelerated lifetime framework should be a function of the expected maximum utility that a commuter will derive from delaying work-to-home departure (X_k as previously defined in eqn 5 and also used as a basis for the frequency of delay model). With this, an accelerated lifetime model can be formalized as,

$$S(t, X_k, \theta_0, \theta_1) = S_0[t\eta(\theta_0, \theta_1, X_k)] \quad (14)$$

[†]The end of a departure delay can be viewed as being induced by any one of a number of random factors such as a decrease in homeward traffic congestion, boredom with the activity undertaken, completion of the activity undertaken, and so on. Thus, since the end of departure delay depends on the shortest time to the occurrence of one of these random factors (i.e. a distribution of the smallest extreme), some theoretical support exists for the use of a Weibull distribution. This is roughly analogous to reliability theory with, for example, machine failure being induced by the random failure of the single most severely flawed component (see Mann, Schaefer and Singpurwalla, 1974).

[‡]The survivor function, $S(t)$, is commonly presented in duration studies and is equal to $Pr(T \geq t)$ (see eqn 8). It follows that for the Weibull distribution $S(t) = \exp[-(\gamma t)^\rho]$.

where θ_0 and θ_1 are estimable parameters, $\eta(\theta_0, \theta_1, X_k)$ is the scaling factor, and $S_0[\cdot]$ is the baseline survivor function. It follows that the hazard function associated with $S(\cdot)$ is,

$$\mu(t, \theta_0, \theta_1, X_k) = \mu_0 [t \eta(\theta_0, \theta_1, X_k)] \eta(\theta_0, \theta_1, X_k). \quad (15)$$

For estimation we set $\eta(\theta_0, \theta_1, X_k) = \exp(-\theta_0 - \theta_1 X_k)$.[†] The estimation results of an accelerated lifetime model of commuters' work-to-home departure delay duration (in minutes) are presented in Table 6. Note that since $\eta(\cdot)$ is specified with $-\theta_0$ and $-\theta_1$, a positive coefficient estimate reduces $S(\cdot)$ (see eqn 14) and thus increases the expected duration of the departure delay.

The table indicates, as expected, that increasing utility from the delay choice increases the duration of departure delay. The duration parameter estimate of 1.65 implies an increasing hazard (positive duration dependence) with the probability of departure delay ending soon, increasing in duration. The fact that the standard error of the duration parameter estimate is so small (0.148), suggests that the hypothesis of a constant hazard (as implied by the exponential distribution) can be readily rejected. As previously mentioned, the finding of an increasing hazard is intuitively reasonable for commuters' departure-delay durations.

As with the Poisson model of delay frequency, it is again interesting to compute implied duration elasticities as presented in Table 7 (with point elasticities for indicator variables excluded for reasons previously discussed). The table indicates that only the ratio of expected to free flow travel time is elastic with a 1% increase in this variable resulting in roughly a 2.05% increase in the duration of departure delay. The fact that only this variable is elastic, underscores the dominance of the overall level of traffic congestion in determining the length of commuters' work-to-home departure delay.

CONCLUDING OBSERVATIONS

This paper has examined commuters' option to delay the departure from work to home in response to congestion. The findings suggest, as expected, that the overall level of congestion facing commuters plays the dominant role in the delay decision, with socioeconomics and activity opportunities at commuters' work locations playing a significant but noticeably less dominant role. With nearly half the commuters surveyed indicating that they sometimes change their departure time, in response to traffic congestion, it is clear that work-to-home departure-time delay is already an important phenomenon in urban commuting. This fact, when combined with the high elasticities computed in our empirical analysis paper, with respect to congestion level, suggest that the phenomenon of home-to-work departure delay, in terms of frequency and delay duration, will increase rapidly as urban traffic congestion continues to grow. Thus, ongoing research in the area of depart-

[†]This form implies survival probabilities $Pr[T \geq t \exp(-\theta_0 - \theta_1 X_k)]$.

Table 6. Duration Model Coefficient Estimates
(*t*-statistics in parentheses)

Variable	Estimated Coefficient
Constant	3.754 (33.41)
Expected maximum utility of delaying work-to-home departure time (eqn. 5)	0.1058 (3.71)
Duration parameter, ρ	1.65 (11.15)
Log-Likelihood at Convergence	-99.35
Number of Observations	96

Table 7. Duration elasticities (estimated by sample enumeration)

Elasticity with respect to:	Elasticity
Distance from work to home (in miles)	0.31
Ratio of expected travel time to free-flow travel time	2.052
Population of the work zone	0.075

Note: All variables defined as in Table 2.

ture time choice has a potentially important contribution to make now and even more so in the future.

In terms of future research on work-to-home departure delay, the key element is better and more elaborate data. Specifically, the models presented in this paper could have benefited considerably by having information on the duration of the traffic congestion facing commuters, both actual and perceived. Similar data limitations have plagued virtually every departure time study to date. It seems a virtual certainty that, in the future, truly significant advances in the study of commuter departure time choice will evolve largely from the availability of an excellent data source as opposed to further conceptual development of modeling approaches.

REFERENCES

- Abu-Eisheh S. and Mannering F. (1988) A discrete/continuous analysis of commuters' route and departure time choice. *Transpn. Res. Record* **1138**, 27-34.
- Chang G.-L. and Mahmassani H. (1988) Travel time prediction and departure time adjustment behavior dynamics in a congested traffic system. *Transpn. Res.* **22B**, 275-290.
- Hausman J., Hall B. and Griliches Z. (1984) Econometric models for count data with an application to the patents-R&D relationship. *Econometrica* **52**(4), 909-938.
- Johnson N. and Kotz S. (1969) *Distributions in Statistics: Discrete Distributions*. John Wiley and Sons, NY.
- Kalbfleisch J. and Prentice L. (1980) *The Statistical Analysis of Failure Time Data*. John Wiley and Sons, NY.
- Lee L.-F. (1986) Specification test for poisson regression models. *Intl. Econ. Rev.*, **27**(3), 689-706.
- Lerman, S. and Gonzalez S. (1980) Poisson regression analysis under alternate sampling strategies. *Transpn. Sci.* **14**(4), 346-364.
- Mahmassani H. and Chang G.-L. (1985) Dynamic aspects of departure-time choice behavior in a commuting system: theoretical framework and conceptual analysis. *Transpn. Res. Record* **1037**, 88-101.
- Mahmassani H. and Chang G.-L. (1986) Experiments with departure time choice dynamics of urban commuters. *Transpn. Res.* **20B**(4), 297-320.
- Mahmassani H. and Tong C. (1986) Availability of information and dynamics of departure time choice: experimental investigation. *Transpn. Res. Rec.* **1085**, 33-49.
- Mann N., Schaefer R. and Singpurwalla N. (1974) *Methods for Statistical Analysis of Reliability and Life Data*. John Wiley and Sons, NY.
- Mannering F. (1989) Poisson analysis of commuter flexibility in changing route and departure times. *Transpn. Res.* **23B**(1), 53-60.
- Mannering F., Abu-Eisheh S. and Arnadottir A. (in press) Dynamic traffic equilibrium with discrete/continuous econometric models. Forthcoming in *Transpn. Sci.*
- McFadden D. (1981) Econometric models of probabilistic choice. In: C. Manski and D. McFadden, eds., *Structural Analysis of Discrete Data with Econometric Applications*, MIT Press, Cambridge, MA.
- Small K. and Hsiao C. (1985) Multinomial logit specification tests. *Intl. Econ. Rev.* **26**(3), 619-627.
- Train K. (1986) *Qualitative Choice Analysis: Theory, Econometrics, and an Application to Automobile Demand*. M.I.T. Press, Cambridge, MA.