

## POISSON ANALYSIS OF COMMUTER FLEXIBILITY IN CHANGING ROUTES AND DEPARTURE TIMES

FRED L. MANNERING

Department of Civil Engineering, University of Washington, Seattle, WA 98105, U.S.A.

(Received 12 March 1987; in revised form 2 February 1988)

**Abstract**—This paper investigates the determinants of commuter flexibility in changing routes and departure times for the morning trip to work. A sample of commuters in a congested metropolitan area is used to estimate Poisson regressions of how often commuters change routes and departure times per month. The estimation results provide valuable insight into the effects of traffic system and socioeconomic conditions on the frequency of route and departure time changes. The results also have significant implications for real-time traffic information systems and future research on the route and departure time choice decision-making process.

### INTRODUCTION

Traffic congestion has long been recognized as a major problem in large metropolitan areas. Attempts to seek a solution to this problem have resulted in the implementation of a diverse assortment of strategies ranging from supply oriented approaches, such as new road construction and improved signal timings, to strategies designed to redirect travel demand, including car and van pool incentives and improved public transportation. Unfortunately, the numerous attempts to relieve the traffic congestion problem have been, at best, only marginally successful, and, as a consequence, traffic congestion continues to be a major source of frustration for a large percentage of commuters.

The focus of this paper is not to suggest or evaluate another possible solution to the traffic congestion problem, but instead to simply analyze commuters' responses to a persistently congested highway network. To undertake this analysis, attention will be given to the morning commute to work that, due to its nondiscretionary nature, will limit a commuter's response to congestion to: (1) mode changes (i.e. switching from drive alone to car pools, van pools, or transit), (2) route changes, and (3) departure time changes. Since mode changes often involve longer-term and more elaborate decisions (i.e. acquiring transit schedules, organizing car and van pools, and so on), this paper will concentrate exclusively on commuters' route and departure time options.

Over the past few years there has been a very active research effort in the area of route and departure time choice in response to congestion. Mahmassani and Chang (1985, 1986), Chang and Mahmassani (1988), and Mahmassani and Tong (1986) have undertaken extensive investigations on the dynamics of the process by which commuters arrive at a satisfactory choice of route and departure time. In other work, Ben-Akiva, de Palma, and Kanaroglou (1986a, 1986b) and Abu-Eisheh and Mannering (1988a, 1988b) have used econometric-based methods to arrive at equilibrium route and departure times in response to projected congestion. While past work has clearly provided valuable insight, commuters' actual route and departure time responses in a congested, real-world highway network have not been adequately investigated. The objective of this paper is to undertake such a study and add an additional chapter to our expanding knowledge of the route and departure time choice process.

The paper begins with a discussion of the background and empirical setting of the study. Next, the methodological approach is described and this is followed by the presentation of model estimation results. A discussion of the implications of the findings then follows and the paper concludes with a summary and directions for future research.

### BACKGROUND AND EMPIRICAL SETTING

At the beginning of every work trip the commuter is faced with the decision of when to leave home and which route to take. This decision is not made blindly since

the commuter has the potential to accumulate a substantial amount of information relating to likely traffic conditions before making his choice. Such information can be classified into two broad categories: (1) experience-based information and (2) real-time information. The experience-based information is collected through the actual driving experiences of the commuter and/or information gathered on the experiences of other commuters. Overall this information would include knowledge of the existence of alternate routes and some expectations of approximate congestion on feasible routes by time of day and day of week. However, experience-based data has an inherent limitation in that unforeseen occurrences such as vehicle breakdowns and accidents remain unknown. In contrast, real-time information provides reports on actual existing traffic congestion from sources such as helicopter-based radio broadcasts.

With information from these sources available, the question becomes, how much of this information will the commuter process and, more importantly, to what extent will he/she use it to actually influence route and departure time choices? Conceptually, the answer to this question will involve traffic system constraints as well as individual characteristics. Traffic system constraints relate to the physical location of home and work places, proximity of alternate routes, and overall traffic conditions. Thus, a commuter with only one feasible route is not likely to process any information that would be needed for a route choice decision. Similarly, if a commuter's normal route to work is uncongested, it is unlikely that any traffic information will be gathered. Starting from these extremes there is a range of level-of-information and processing needs.

Individual characteristics will also influence traffic information acquisition and subsequent route and departure time decisions. For example, risk-averse commuters may seldom, if ever, change routes or departure times in response to traffic congestion, whereas risk seekers may make changes with great frequency. Also, family responsibilities may limit the freedom of route/departure time choices.

Direct empirical evaluation of commuters' collection and processing of traffic information would be an exceedingly difficult, if not impossible, task. However, an indirect approach, that focuses on the frequency of route and departure time changes and relates such changes to factors determining information needs, can readily be undertaken and still provide valuable insight into the route/departure time decision-making process. To undertake this approach, a survey of the morning worktrip commute was conducted in the Seattle, Washington area with the specific intent of gathering information on the frequency of commuters' route and departure time changes. The Seattle highway network is particularly well suited for route/departure time analysis since it is highly congested with geographic constraints often limiting the route choices available to commuters. In addition, there is extensive availability of helicopter-based traffic information from a number of local radio stations, thus permitting the study of real-time as well as experience-based commuter information acquisition and use.

The survey was conducted in May 1987 and focused primarily on commuters going from suburban communities to Seattle work locations. In terms of the frequency of route and departure time changes, information was gathered on the average number of times commuters change routes and departure times per month.<sup>†</sup> By structuring the survey in such a manner, attention is being given to a traffic system that is in some state of relative stability (i.e. there was no major reconstruction or other changes to the highway network during the months preceding the May interview period) with natural commuter experimentation and random events such as weather and incidents (vehicle breakdowns and accidents) factored in. Thus, such a sample affords the opportunity to evaluate patterns of route and departure time flexibility and change within a relatively stable traffic environment.

In all, 117 commuters were surveyed by telephone and summary statistics for the sample are presented in Table 1. The table indicates that the socioeconomic character-

<sup>†</sup>A departure time change was defined as any change from the most frequent or normal departure time with the intent of avoiding traffic congestion and/or decreasing trip travel time. Similarly, a route change was defined as any deviation from the normal route with the intent of avoiding congestion and/or decreasing travel time.

Travel time on most frequently used route (minutes)	30.49
Most frequently used route congested at level of service D or worse (percent)	89.70
Estimated additional trip travel time on the shortest time alternate route (minutes)	7.84
Number of departure time changes per month	2.32
Percent never changing departure time	54.70
Number of route changes per month	2.81
Percent never changing route	51.30
Think traffic congestion is a serious problem in the Seattle area (percent)	85.60
Listen to radio for traffic advisories (percent)	61.58
Percent of commuters with flexible work starting times	68.38
Age (years)	37.81
Percent married/single	65/35
Percent male/female	60/40
Number of household members	2.71
Number of household cars	2.22
Household income (dollars)	36,200

istics of the sample are fairly typical for suburban commuters. Furthermore, the high level of traffic congestion in the Seattle area is reflected by the fact that nearly 90% of the most frequently used routes, as reported by respondents, operate at an average level of service D [as defined by the Highway Capacity Manual (1985)] or worse† and almost 86% of the respondents think traffic congestion is a serious problem in the area. It was also found that quite a few respondents change departure time (45.3%) and/or route (48.7%) one or more times per month. Finally, to capture some notion of the feasibility of alternate routes facing commuters, Table 1 reports the expected additional travel time on the shortest time alternate route, which was calculated with highway network data based on average peak-hour volumes.

#### METHODOLOGICAL APPROACH

To assess commuter flexibility in changing routes and departure times, an appropriate statistical modeling technique is needed. Two models will be developed, one modeling the number of route changes per month and the other modeling the number of departure time changes per month.‡ Central to the modeling analysis is the behavioral assertion that, due to factors such as commuters' continual experimentation and search

†Average level of service D or worse is defined herein as having more than 50% of the physical route length functioning at a level of service D, E, or F.

‡While legitimate arguments could clearly be made for a joint, simultaneous model, data limitations force consideration of separate models only. Such data limitations resulted from the telephone interview process that, due to time and attention span constraints, did not allow the interviewer to provide an adequate articulation of possible route/departure time interrelations. Thus, respondents tended to report these in isolation. If respondents were to complete an actual trip diary, such limitations could be readily overcome and a joint model could be realistically considered.

for traffic-related information as well as random effects including vehicle breakdowns, accidents, and weather conditions, commuters will never completely settle with a fixed route and departure time.† Within this context, a Poisson distribution is a reasonable description of the number of route and departure time changes occurring during a one month period. That is,

$$P(n_i) = \frac{\exp(-\lambda_i)\lambda_i^{n_i}}{n_i!}, \quad (1)$$

where  $P(n_i)$  is the probability of commuter  $i$  making  $n$  changes per month and  $\lambda_i$  is the Poisson parameter for commuter  $i$  [also the mean of the Poisson distribution  $\lambda_i = E(n_i)$ ] which will be some estimable function of the independent variables.

Such a methodological approach is commonly referred to as a Poisson regression [see Lerman and Gonzalez (1980) and Hausman, Hall, and Griliches (1984)] and is particularly well suited to the route/departure time application since it not only accounts for continual commuter experimentation and response to congestion-generating incidents, but also accounts for the no-change option ( $n_i = 0$ ) as well as all other possible non-negative integer outcomes.

Poisson models, as illustrated in eqn (1), can be readily estimated by standard maximum likelihood methods. Herein, the Poisson parameter is defined as

$$\log \lambda_i = \beta \mathbf{X}_i, \quad (2)$$

where  $\beta$  is a vector of estimable parameters and  $\mathbf{X}_i$  is a vector of commuting and socioeconomic characteristics for individual  $i$ . It follows that the likelihood function is [from eqns (1) and (2)]

$$L(\beta) = \prod_i \frac{\exp[-\exp(\beta \mathbf{X}_i)] [\exp(\beta \mathbf{X}_i)]^{n_i}}{n_i!} \quad (3)$$

which gives the log-likelihood of

$$\log L(\beta) = \sum_i [-\log n_i! - \exp(\beta \mathbf{X}_i) + n_i \beta \mathbf{X}_i] \quad (4)$$

with gradient and Hessian

$$\frac{\partial \log L}{\partial \beta'} = \sum_i [n_i \mathbf{X}_i - \mathbf{X}_i \exp(\beta \mathbf{X}_i)] \quad (5)$$

$$\frac{\partial \log L}{\partial \beta' \partial \beta} = \sum_i [-(\mathbf{X}_i \mathbf{X}_i') \exp(\beta \mathbf{X}_i)]. \quad (6)$$

The objective of the Poisson analysis is to estimate the vector  $\beta$ , thereby providing an estimate of the natural log of the mean number of route or departure time changes per month [see eqn (2)]. Finally, it should be noted that, unlike standard least squares regression,  $\lambda_i$  is a deterministic function of  $\mathbf{X}_i$  with the randomness coming from the probability specification for  $n_i$ .

†In fact, there is experimental evidence to support this assertion. The work of Mahmassani and Chang (1986) and Mahmassani and Tong (1986) has found that commuters settle on fixed routes and departure times, in a hypothetical traffic system (without random events such as accidents, breakdowns, and adverse weather), after about 20 or 30 days of experimentation. With such a long experimentation period, under relatively stable conditions, it is easy to imagine that the influence of random events may effectively prevent commuters from ever attaining truly fixed route and departure times.

## ESTIMATION RESULTS

A Poisson regression of route changes per month was first estimated and the results are presented in Table 2. The table indicates that all variables are of plausible sign and reasonably high statistical significance. In addition, the log-likelihood movement from zero to convergence is quite satisfactory.

Turning to specific estimation results, it was found that the travel time of the most frequently used route has a positive impact on the average number of route changes per month indicating that longer commutes (timewise) make travelers more likely to change routes. Two possible explanations for this finding are worthy of note. First, this variable is likely capturing some distance effects suggesting that commuters living farther away from their work place may simply have more route options available. The second explanation can be that time-consuming commutes increase frustration and/or lead to a greater awareness and use of alternate routes.

The variable of average level of service of the most frequently used route indicates that travelers normally commuting on congested routes tended to make more route changes per month. This finding is consistent with the notion that commuters are "sensitized" to route change possibilities when faced with congested traffic conditions.

The estimated additional trip travel time on the shortest time alternate route proved to be a particularly strong variable. The coefficient indicates that as the additional travel time associated with the nearest alternate route increases, fewer route changes will be made per month. As mentioned earlier, this variable is a strong measure of the feasibility of alternate routes.

Before concluding the discussion on the traffic system-oriented variables in the model, it is important to mention one other variable that was seriously considered: the ratio of the additional trip travel time on the shortest time alternate route to the travel time on the most frequently used route. This variable attempted to account for the fact that the value of an alternate route is proportional to the total commute time. Thus, an alternate route taking an average of 5 minutes longer than the most frequently used route would be valued less on a 10-minute commute than it would be on a 40-minute commute. Unfortunately, although this variable's coefficient was properly signed and

Table 2. Route change Poisson regression estimates

Variable	Estimated Coefficient	t-Statistic
Constant	2.681	6.99
Travel time of most frequently used route (minutes)	0.019	3.99
Most frequently used route congestion indicator (1 if level of service D or worse, 0 otherwise)	0.520	1.67
Additional trip travel time on shortest time alternate route (minutes)	-0.458	-15.14
Commuter's age (years)	-0.011	-1.70
Marital status indicator (1 if single, 0 otherwise)	0.250	1.81
Male indicator (1 if male, 0 otherwise)	0.694	5.43
Number of observations	117	
Log likelihood at zero	-537.85	
Log likelihood at convergence	-213.44	

statistically significant, the degree of overall model likelihood convergence suffered considerably when compared to the selected model specification presented in Table 2.

Turning to the socioeconomic factors affecting the number of route changes per month, it was found that as a commuter's age increases fewer changes were made. This finding supports the belief that older people tend to be more risk-averse. Next, unmarried people were found to be more likely to change routes than their married counterparts. This may be reflecting more risk-seeking or impatient behavior among single commuters, or simply capturing the fact that married commuters may be constrained by the need to take a spouse to work or by some other family responsibilities. Finally, male commuters were found to be more likely to change routes than were females. This suggests that men may have a higher degree of risk-seeking behavior or a greater degree of frustration with traffic conditions.

The estimation results of the Poisson regression of departure changes per month are presented in Table 3. As was the case with the route change model, the higher the travel time on the most frequently used route, the more likely the commuter is to change departure times. This could be explained by the possibility that longer trips make commuters more sensitive to departure time change options. As an alternate explanation, the variable could be acting as a surrogate for variance in travel time (i.e. a longer trip will likely have a higher travel time variance) indicating that commuters are compensating for travel time variance by making more frequent departure time changes.

The variable indicating whether or not the commuter has a flexible work starting time is properly signed (indicating flex-time workers make more frequent departure time changes) but is statistically disappointing. It is speculated that the relatively low significance of this variable arises from the fact that traffic congestion occurs over such a long time period in the Seattle area that the flexibility provided in work start hours is not sufficient to avoid traffic delays.

The socioeconomic variables of age and marital status produced results similar to those of the route change Poisson model. Again, increasing age suggests a more risk-averse approach to traffic congestion and the marital status coefficient suggests more risk-averse behavior and/or more factors that limit departure time freedom among married commuters. Examples of such factors could include joint trips with the spouse or children, prearranged breakfast times, or even bathroom priorities as family members prepare for daily activities.

#### IMPLICATIONS OF FINDINGS

To assess the implications of the model estimation results, it is useful to compute the elasticity of the average number of changes per month with respect to the models'

Table 3. Departure time change Poisson regression estimates

Variable	Estimated Coefficient	t-Statistic
Constant	1.094	7.43
Travel time of most frequently used route (minutes)	0.022	3.95
Flexible work start time indicator (1 if flexible, 0 otherwise)	0.096	1.07
Commuter's age (years)	-0.031	-4.87
Marital status indicator (1 if single, 0 otherwise)	0.177	1.33
Number of observations	117	
Log likelihood at zero	-434.24	
Log likelihood at convergence	-336.89	

Table 4. Average number of route changes (per month): Elasticity estimates

Elasticity with Respect to	Value
Travel time of most frequently used route (minutes)	0.579
Additional trip travel time on shortest time alternate route (minutes)	-3.590
Commuter's age (years)	-0.397

independent variables. In this case, the elasticity for commuter  $i$  is

$$E_{x_{ik}}^{\lambda_i} = \frac{\partial \lambda_i}{\partial x_{ik}} \cdot \frac{x_{ik}}{\lambda_i} \quad (7)$$

or [by differentiating eqn (2) and substituting]

$$E_{x_{ik}}^{\lambda_i} = \beta_k x_{ik}, \quad (8)$$

where  $\beta_k$  is the coefficient estimate of independent variable  $k$  (as presented in Tables 2 and 3) and  $x_{ik}$  is the value of independent variable  $k$  for commuter  $i$ .

The average values (over all commuters) of variable elasticities are presented in Tables 4 and 5 for the route and departure time change models, respectively. Indicator variables are excluded from both tables since, by definition, their point elasticities are not particularly meaningful. For the route change model, all variables are inelastic (absolute values less than unity) with the exception of the additional trip travel time on the shortest time alternate route. In some respects the highly elastic nature of this variable is encouraging in that it suggests that being able to provide commuters with accurate real-time information on traffic congestion, as opposed to letting them rely on some perception of alternate route travel times, could prove to be highly effective in relieving traffic congestion. Thus, efforts focused on introducing traffic information systems in individual vehicles or providing more reliable and up-to-date congestion information with existing systems (e.g. helicopter-based reporting) would appear to be on target.

The departure time choice elasticities show that the commuter's age is elastic while travel time is not. Therefore, encouraging commuters to make more frequent changes in departure time in response to congestion would require some sort of informational campaign to convince them of the benefits of departure time changes (i.e. change existing commuter preferences).

In a more academic sense, this study should be of benefit to the ongoing research on commuters' route and departure time choices. Most existing research work assumes the existence of traffic equilibrium or, in the case of research on commuter dynamics, the existence of a steady state. The findings of this paper suggest that, due to random incidents (vehicle breakdowns, weather, and so on) and/or changing commuter tastes and perceptions of congestion, a "true" equilibrium is not realistically achievable and a steady state will be, at best, unstable, or, more likely, will not even exist. This finding has potentially serious implications for many recent departure time research efforts that either implicitly or explicitly assume the existence of a steady state. There is clearly a

Table 5. Average number of departure time changes (per month): Elasticity estimates

Elasticity with respect to	Value
Travel time of most frequently used route (minutes)	0.671
Commuter's age (years)	-1.146

need to further explore the instability induced by random traffic-related incidents. Finally, the results of the model estimations underscore the need to carefully consider socioeconomic concerns in predictive models. Unfortunately, this is a consideration that has often been given only passing concern in many research efforts.

#### SUMMARY AND CONCLUSIONS

In this paper, an investigation of the factors influencing commuters' route and departure time choices was undertaken. To do so, a survey of commuters in a highly congested metropolitan area was conducted and a Poisson regression model was estimated for both route and departure time changes. The results underscore the importance of socioeconomic factors as well as traffic system conditions in determining commuters' willingness to change routes and departure times. Also, the findings suggest a promising future for more accurate real-time traffic information systems.

In terms of future work, it is hoped that some of the empirical findings presented in this paper will be useful to future research on route and departure time choice. Moreover, it is felt that additional applications of the modeling methodology used in this paper on a more extensive and elaborate sample (perhaps collected through an actual trip diary) could prove to be quite fruitful.

#### REFERENCES

- Abu-Eisheh S. and Mannering F. (1988a) A discrete/continuous analysis of commuters' route and departure time choice. *Transpn. Res. Rec.* (in press).
- Abu-Eisheh S. and Mannering F. (1988b) Traffic equilibrium with discrete/continuous route and departure time choice models. Working Paper, University of Washington, Seattle, Washington.
- Ben-Akiva M., de Palma A. and Kanaroglou P. (1986a) Effects of capacity constraints on peak-period traffic congestion. *Transpn. Res. Rec.* **1085**, 16–26.
- Ben-Akiva M., de Palma A. and Kanaroglou P. (1986b) Dynamic model of peak-period congestion with elastic arrival rates. *Transpn. Sci.* **20**, 166–181.
- 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**, 909–938.
- Highway Capacity Manual (1985) Transportation Research Board, Special Report 209, National Research Council, Washington, D.C.
- Lerman S. and Gonzalez S. (1980) Poisson regression analysis under alternate sampling strategies. *Transpn. Sci.* **14**, 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. Rec.* **1037**, 88–101.
- Mahmassani H. and Chang G.-L. (1986) Experiments with departure time choice dynamics of urban commuters. *Transpn. Res.* **20B**, 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.