Journal of Bangladesh Institute of Planners ISSN 2075-9363
Vol. 5, December 2012, pp. 107-118, © Bangladesh Institute of Planners

Departure Time Choice Analysis Using Ordered Response Probit Model: Journey to Work Trip in Dhaka City

A.H.M. Mehbub Anwar*

Abstract

With growing concern about travel time increase and energy consumption, transportation planners and decision makers are becoming gradually more conscious of the necessary reallocation of the departure time at the peak period travel in an effort to reduce traffic congestion, environmental emission and peak load. The paper addresses this particular problem through the development and estimation of a journey to work (JTW) departure time choice model. The model has been developed by considering five characteristics, such as individual socio-demographics, household socio-demographic characteristic, employment related attributes, trip related attributes and arrival related aspects. By identifying departure time choice, one can observe the level of earlier start as an ordinal variable that expresses extremity of earlier start behavior which is increased with larger values of departure time. To represent this ordinal variable, an ordered response probit (ORP) model has been employed to investigate the JTW trips in Dhaka city.

Introduction

The departure time decisions of trip makers are of fundamental importance to the study of peak-period traffic congestion and to the analysis of traffic control as well as broader demand-side congestion relief measures, such as pricing and ride sharing incentives (Rosenbloom, 1978). Over the past decades, there have been very active research efforts in the departure time problem, both in econometric modeling and dynamic user equilibrium.

Because of traffic congestion and extreme travel demand in developing countries, urban planners as well as transportation planners and operators alike have become increasingly aware of developing strategies to balance or distribute the trip over the morning and afternoon peak period at a reasonable cost and time. The problem of departure time choice is particularly acute for traveling periods. Therefore, a set of suitable strategies to reduce the peak period problem should be based on dispersion of concentration of peak period demand. The implementation of flexible work time policies could be a one option. On the other hand, imposing additional tools/road pricing might also be other appropriate options to reduce traffic congestion during the peak period. The intended effect of these strategies is to encourage commuters to alter the time at which they travel to work. If some commuters amend their decision to depart other than the peak, commuter travel can be more uniformly distributed across the commute period which can reduce the peak effect.

This study provides valuable insights into dynamic commuter decision making and also addresses this issue through the development and parameter estimation of a disaggregate model of commuter departure time choice. Changes in the dependent variable, the time at which a traveler decides to depart for work, can be forecast based on the extent to which policy alternatives being considered impact the factors which affect the commuter departure time decision.

* Associate Professor, Urban and Rural Planning Discipline, Khulna University, Khulna
E-mail: ahmma324@uowmail.edu.au, mehbub30@yahoo.com

There are a limited number of literatures pertaining to departure time choice model for journey to work and non-work trips. Nevertheless the interest in modeling the departure time choice of individuals has been growing over the years. This increasing interest is a result of the need to model the temporal nature of trip making. As congestion during the peak period grows, trip makers try to defer their time of travel to avoid delays. As a result there has been evidence of spreading of peak periods in many urban areas. This shift in departure times away from peak period continues to grow with the increase in congestion levels. Modeling such behavioral change is necessary as it affects the times and costs of trip making. This information brief reviews studies that have attempted to model the departure time choice of trip makers. Therefore, such kind of departure time choice model research for journey to work is becoming important nowadays.

Previous Studies

Trips occur at different times of day; however the traditional travel demand models did not include the time of day factor. The traditional models have not lost their validity and they still work for long range planning purposes. Although increasing congestion levels on roads together with economic and environmental concerns have emphasized the need to forecast traffic throughout the day. Departure time choice models try to encapsulate this need and research in this field is making headway.

Cosslett (McFadden *et al.,* 1977a) estimated a multinomial logit model of departure time choice for auto drive-alone and carpool commuters based on data collected in the San Francisco Bay Area for the Urban Travel Demand Forecasting Project (UTDFP), representing one of the first attempts to understand work departure time behavior. Cosslett's contributions to understanding work departure time behavior included explicit consideration of commuter sensitivities to arrival time, noting the difference in early and late arrival sensitivities. He also identified the importance of the uncertainty of late arrival associated with commuter departure decisions. Following Cosslett's efforts, Small (1978) estimated departure time models for auto, motorcycle, and bus travelers using data collected in Singapore by the World Bank.

Small (1982) studied the scheduling of trips at the individual level and estimated the coefficients by assuming a discrete choice between 12 possible arrival times. The results indicated that people were willing to shift their schedules by one or two minutes earlier to if they saved some travel time.

Abkowitz (1981) used the same data as Small, including additional socio-demographic variables (income and age) and transit mode use as determinants of commute departure time choice behavior and found considerable effects of income, age, occupation, and travel mode on desired arrival time to work. McFadden and Talvitie (1977_b) analyzed the trip timing decisions for travel to work using the utility maximization principles and multinomial logit model.

McCafferty and Hall (1982) modeled different temporal partitioning schemes to represent discrete periods of departure time choice. These categories included peak and off-peak time periods, division of off-peak period into pre-peak and post-peak and another categorization based on identification of periods of relatively homogeneous traffic volumes and travel times. They found that departure time is not affected significantly by travel time or socio-economic variables.

Hendrickson and Plank (1984) developed a more complex formulation whereby they widened the model to deal with simultaneous mode and departure time choice. Mannering (1989) studied the variables that affected an individual’s likelihood to shift departure times using a poisson regression and he observed that most often-used route’s travel time and variable work time influenced the frequency of departure time changes. It was also found that as a commuter’s age increases fewer changes in departure times were made.

Chin (1990) also modeled the choices among eleven 15-minutes time periods. He concluded that travel time choices were influenced by journey time, and also occupation and income affected propensity for switching departure times. Palma *et al.* (2000) concluded that each user chooses the train that minimizes his schedule delay cost. A non-parametric method and binary logit model is used in this study.

All the previous mentioned studies used discrete methods to model departure time choice; however there has been some exploration into using continuous methods for the same purpose. Mannering and Hamed (1990) used a joint discrete/continuous method to model the decision to delay departure to home from work in order to avoid congestion. A discrete model was used for the decision of whether or not to delay departure, and then the duration of the delay was modeled using a continuous Weibull survival function. The duration of the delay was based on the utility derived from the activity undertaken during the delay (which could be either work, or some non-work activity near the job site).

Hunt and Patterson (1996) analyzed recreational trip departure time choice at the individual choice level. The study considers a hypothetical recreational trip to movies. Since the choice of the movie start time is pre-determined, the emphasis of the study is to find out the effect of factors such as travel time, desired "cushion" time at the theatre before the movie begins, the probability of being late, parking cost, and whether the movie is a new or old release on departure time choice. "Since the movie start time is considered fixed in the study, there is limited temporal flexibility in departure time (as in the case of the work departure time studies reviewed earlier)".

Bhat and Steed (2000) conducted a study on modeling departure time choice for home based non-work trips. They observed that departure times for non-work trips are determined for the most part by individual/household socio demographics and employment characteristics, and to a lesser extent by trip level of service characteristics.

Past research has been restricted primarily to a study of auto commuters, and transit users have been neglected from consideration. Some potentially important socio-demographic factors affecting departure time choice have also not been examined. Finally, although the significance of the tradeoff between mean travel time and flexibility of arrival time has been demonstrated to some degree, the effect of travel time variability and modal choice preference for work trip have not been properly represented. Most of the departure time choice researches were analyzed by the multinomial logit model. But this present study has categorized the departure time choice into a ordinal class and ordered response probit (ORP) model has been applied to make the ordinal categories statistical significant.

Model Specification

Ordered-response models recognize the indexed nature of various response variables; in this application, departure time choices are the ordered response. Underlying the indexing in such models is a latent but continuous descriptor of the response. In an ordered response probit model, the random error associated with this continuous descriptor is assumed to follow a normal distribution.

In contrast to ordered-response models, multinomial logit and probit models neglect the data's ordinarily, require estimation of more parameters (in the case of three or more alternatives, thus reducing the degrees of freedom available for estimation), and are associated with undesirable properties, such as the independence of irrelevant alternatives (IIA, in the case of a multinomial logit [Ben-Akiva and Lerman, 1985]) or lack of a closed-form likelihood (in the case of a multinomial probit [Greene, 2000]).

By identifying departure time choice, one can observe the level of earlier start as a ordinal variable that expresses extremity of earlier start behavior which can be increased with larger values of y_i . To represent this ordinal variable, an ordered response probit (ORP) model is more suitable. On the other hand, ORP model is able to distinguish the effect of various factors contributing to the classification among the data. Four departure time alternatives were ordered as follows for Ordered Response Probit (ORP) model:

8:30am – 8:50am = 0 (Lower Earlier Start, abbreviated as LES)

8:10am – 8:30am = 1 (Medium Earlier Start, abbreviated as MES)

7:50am – 8:10am = 2 (Higher Earlier Start, abbreviated as HES)

7:30am – 7:50am = 3 (Extremely Higher Earlier Start, abbreviated as EHES)

The ordered response probit can be estimated via several commercially available software packages such as TSP, LIMDEP etc. and is theoretically superior to most other models for the data analyzed in this work. For this particular study, LIMDEP software was used to analyze the data. The following specification was used here:

$$y_i^* = \beta' z_i + \varepsilon_i \qquad (1)$$

where, y_i^* = latent and continuous measure of departure time by commuter i in a work day;

z_i = a vector of explanatory variables describing the individual socio-demographics, household socio-demographics, employment related attributes, trip-related attributes and arrival related attributes;

β' = a vector of parameters to be estimated; and

ε_i = a random error term (assumed to follow a standard normal distribution).

The observed and coded discrete departure time choice variable, y_i , is determined from the model as follows:

$$y_i = \begin{cases} 0 \text{ if } -\infty \le y_i^* \le \mu_1 \text{ (lower earlier start)} \\ 1 \text{ if } \mu_1 < y_i^* \le \mu_2 \text{ (medium earlier start)} \\ 2 \text{ if } \mu_2 < y_i^* \le \mu_3 \text{ (higher earlier Start)} \\ 3 \text{ if } \mu_i < y_i^* \le \infty \text{ (extremely higher earlier Start)} \end{cases} \qquad (2)$$

where, the μ_i*'s* represent thresholds to be estimated (along with the parameter vector β).

Figure 1 shows the correspondence between the latent and continuous underlying departure time choice variable y_i^*, and the observed departure time choice class, y_i.

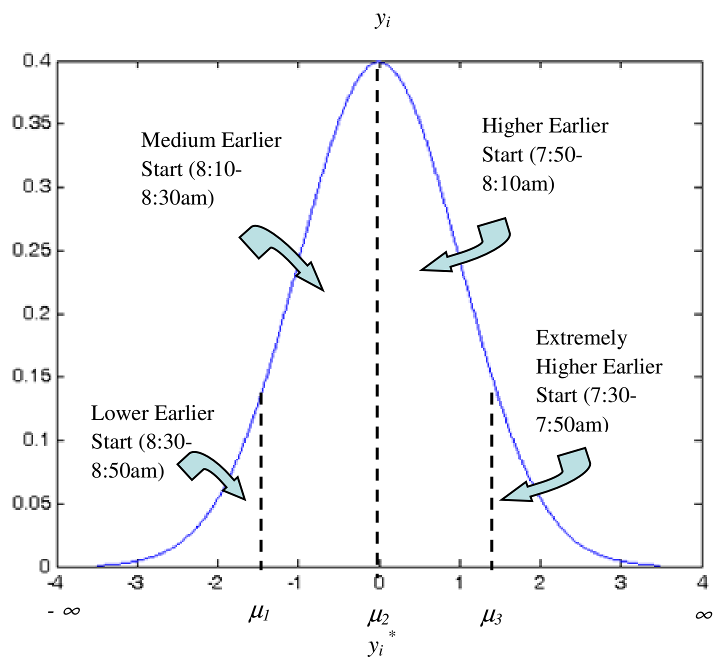
The probabilities associated with the coded responses of an ordered response probit model are as follows:

$$P_i(0) = Pr(y_i = 0) = Pr(y_i^* \le \mu_1) = Pr(\beta' z_i + \varepsilon_i \le \mu_1) = Pr(\varepsilon_i \le \mu_1 - \beta' z_i) = \Phi(\mu_1 - \beta' z_i)$$

$$P_i(1) = Pr(y_i = 1) = Pr(\mu_1 \le y_i^* \le \mu_2) = Pr(\varepsilon_n \le \mu_2 - \beta' z_i) - Pr(\varepsilon_n \le \mu_1 - \beta' z_i) = \Phi(\mu_2 - \beta' z_i) - \Phi(\mu - \beta' z_i)$$

$$P_i(k) = Pr(y_i = k) = Pr(\mu_k \le y_i^* \le \mu_{k+1}) = \Phi(\mu_{k+1} - \beta' z_i) - \Phi(\mu_k - \beta' z_i)$$

$$P_i(K) = Pr(y_i = K) = Pr(\mu_K < y_i) = 1 - \Phi(\mu_K - \beta' z_i) \qquad (3)$$



Source: Author, 2012

Fig. 1: Relationship between latent and coded departure time choice variables

where, i is an individual;

k is a response alternative;

$P(y_i=k)$ is the probability that individual i responds in manner k

$\Phi()$ is the standard normal cumulative distribution function

It is noted that $\mu_1 = 0$ is assumed for ease of interpretation without loss of generality in this study.

To estimate equation (3), the following log-likelihood function is adopted in order to apply the maximum likelihood estimation method.

$$L = \sum_{i=1}^{N}\sum_{k=1}^{4} \delta_i^k \ln(P_i(y_i = k)) \qquad (4)$$

Here, δ_i^k is a dummy variable with a value of 1, if y_i belongs to category k, otherwise 0; and N is the sample size. When interpreting the estimation results, β positive signs indicate *higher earlier start* departure time as the value of the associated variables increase, while negative signs suggest the converse. On the other hand, since the latent variable in the ORP model has a linear relationship with the explanatory variables, positive signs for the estimated parameters can be interpreted as an increase of *higher earlier start*. These interactions must be compared to the ranges between the various thresholds, μ_i in order to determine the most likely departure time class for a particular respondent.

Variable Description of Departure Time Choice Model

The model has been developed by considering five characteristics as explanatory variables; one is individual socio-demographics which have been determined by age and gender. Second are the household socio-demographic characteristics which have been observed by presence of children less than 5 years and children 5-10 years old. Third is employment related attributes which have been explained by employed in government sector or employed in non-government organization and monthly income. Fourth is trip related attributes those are described by travel time, travel cost, travel time variability, safety margin and modal choice just yesterday while he/she was going to work place. And fifth is arrival related aspects which are presented by flexibility about on time arrival (Table 1).

Table 1: Model specification – definition of variables

Independent variable	Descriptions
Individual socio-demographics	
Age	1 if over 40, 0 otherwise
Gender	1 if male, 0 otherwise
Household socio-demographics	
Chil5	1 if less than 5 years old children is available, 0 otherwise
Chil5_10	1 if 5-10 years old children is available, 0 otherwise
Employment related attributes	
Inc	1 if earning tk.15000 or less, 0 otherwise
Occu	1 if government job, 0 otherwise
Trip related attributes	
TTV	Travel time variability
Ttime	Travel time
Safe-merg	Safety margin to arrive on time
Tcost	Travel cost
Modal choice	1 if motorized vehicle (auto (car/taxi), transit (bus), CNG), 0 otherwise (non motorized vehicle i.e. rickshaw and walk)
Arrival related attributes	
Flex_on	1 if flexibility to arrive earlier, 0 otherwise
Flex_late	1 if flexibility to arrive late, 0 otherwise

Source: Author, 2012

Data Sources

The primary data source was used for this analysis which was conducted in Dhaka city of Bangladesh from August – September, 2009. This survey included a questionnaire to be filled out by the household heads who work. For the trip makers, the level of service (time, cost), travel time variability, safety margin, employment status, flexibility to arrive earlier or late at the work place, mode choice (motorized or non-motorized), and possibility of on time arrival were asked. In addition, the survey elicited individual and household socio-demographic information.

Sample Formation

The process of developing the sample for analysis involved several steps. First, only the work trip has been considered in this study. As “on time” arrival is most key variable in this departure choice model and only the work trip can be related to the “on time” arrival issue, therefore only work tip has been considered here. Second, the trips those are from home to work were made out and considered.

Third, the departure time of work trip with one of the following four time periods such as 8:30 am to 8:50 am which was considered as lower earlier start, 8:10 am to 8:30 which was regarded as medium earlier start, 7:50 am to 8:10 am which was taken into account as higher earlier start and 7:30 am to 7:50 am which was treated as extremely higher earlier start. These are the dependent variable in this analysis.

Finally, several screening and consistency checks were carried out on the resulting data set from the previous steps. As part of this screening process, the observations those have the missing data on departure times and other relevant data have been eliminated.

A sample is any subset of sampling units from a population. The size of the sample is properly estimated by deciding what level of accuracy is required and, how large a standard error is acceptable. It also depends on the objectives of the research. There are various common misconceptions about the necessary size of a sample. One is that the sample should be a regular proportion (often put at 5 percent) of the population. Another is that the sample should total about 2000; still another is that any increase the sample size will increase the precision of the sample results. No such rules-of-thumb are adequate (Machmias and Nachmias, 1976).

If cost, time and other practical limitation do not enter into decision about the sample size, there is no difficulty in determining the desired size by using standard formulas (Machmias and Nachmias, 1976). In deciding the sample size for this study researcher had to consider some basic limitation like cost, time and some other practical problems. So it was decided to set sample size at 100. Instead of selecting a fixed percent of samples, a fixed number of samples were selected.

Sample Description

Table 3 shows the distribution of modes for work trip according to departure choice alternatives. The dominant mode for work trip trips is MV (motorized vehicle) which is needed to manage properly. An important note must be made here about travel mode choice. The mode choice has been considered exogenous variable to departure time choice. This decision is based on the observation that almost all work trips are pursued using the MV (Table 2).

Table 2: Distribution of modes for work trip according to departure choice alternatives

Departure time choice alternatives	Actual choice in percent		
	MV	NMV	Total
8:30am – 8:50am (Lower Earlier Start)	3	3	6
8:10am – 8:30am (Medium Earlier Start)	4	1	5
7:50am – 8:10am (Higher Earlier Start)	36	10	46
7:30am – 7:50am (Extremely Higher Earlier Start)	43	0	43
Total	86	14	100

Source: Author, 2012

Table 3 indicates the pattern of departure time choice. Highest percentage of people starts their journey to work at between 7:50 am to 8:10 am. That means that about 70 minute earlier they need to start their journey to work to cover the delay time made by traffic congestion.

Table 3: Pattern of departure time choice

Discrete choice	Percent
8:30am – 8:50am (Lower Earlier Start)	6.0
8:10am – 8:30am (Medium Earlier Start)	5.0
7:50am – 8:10am (Higher Earlier Start)	46.0
7:30am – 7:50am (Extremely Higher Earlier Start)	43.0
Total	100

Parameter Estimation and Discussions

The research conducted in this study was directed at extending the study of commuter departure time decisions to expand the market to include the consideration of a wider range of socio-demographic characteristics, account properly for the importance of travel time uncertainty in departure time choices, and improve the definition of arrival measures.

As it was mentioned earlier that departure time choice was modeled considering four departure time choice. Among these, 8:30 am to 8:50 am has been considered as reference alternative. It was also assumed that MV service and non-motorized service frequency was sufficient during the peak period such that commuters were faced with the full set of alternative choices.

Departure time model is consisted of selecting independent variables which, a priori, made intuitive sense as explanatory variables of departure time. The variables were generically specified and were introduced all at a time into the departure time specification. For all variables, an order response probit model was estimated, and the variable coefficients were examined for statistical significance (t-statistic), proper signs, and for the possibility of different independent variables explaining similar effects in the model (by comparing the magnitude and t-statistics of the coefficients for the suspected variables when both are included in the same specification). The overall statistical fit of the model (log likelihood) was also considered. The variables considered for inclusion in the departure time model consisted of age, gender, travel time, travel cost, travel time variability, safety margin, modal choice household characteristics such as children under 5 years old and children between 5 – 10 years old and also flexibility of on time or late arrival.

Ordered response probit model was estimated to evaluate the extremity of higher earlier start for journey to work. Note that no variables were removed from the model on the basis of low statistical significance; since all variables are of interest and expected to have some effect on departure time choice behavior, all were maintained in the final model. Since the dependent variable increases with extremity of higher earlier departure, positive coefficients suggest the likelihood of more extremity of higher earlier departure. Thus, increased age, children 5 to 10 years old, occupation pattern, income level, travel time, safety margin, modal choice and flexibility of on time arrival are associated with more extremity of higher earlier departure, while children under 5 years old, gender, travel cost, travel time variability and flexibility of late arrival are associated with decreased earlier departure.

Table 4: Parameter estimation results

Variables	Coefficient estimate	t-statistic
Constant	-3.976	- 2.865*
Individual socio-demographics		
Age	0.061	1.648***
Gender	-0.548	- 1.745***
Household socio-demographics		
Chil5	- 2.381	- 3.146*
Chil5 – 10	0.298	1.998**
Employment related attributes		
Occu	0.443	2.338**
Income	0.198	1.152
Trip related attributes		
Ttime	- 3.455	- 4.441*
Tcost	- 2.203	- 2.914*
TTV	- 0.013	- 1.589
Safe-margin	0.018	-0.948
Modal choice	1.584	2.948*
Arrival related attributes		
Flex_on	0.450	2.038**
Flex_late	- 0.395	- 1.265
Threshold parameters		
μ_1	0.000	-
μ_2	0.608	2.961*
μ_3	2.683	9.110*
Goodness of Fit Measures		
Log-likelihood at zero (LL (0))	- 121.251	
Log-likelihood estimated (LL (β))	- 81.812	
Likelihood ratio index $\rho^2 = 1 - LL(\beta) / LL(0)$	0.325	

* Significance at 99% level; ** Significance at 95% level; *** Significance at 90% level

The estimations results of Table 4 indicates that travel time is the dominant explanatory variable with coefficients of 3.455 and t statistic of 4.441 indicating that a higher travel time leads to greater probability of experiencing higher earlier departure in journey to work.

Another important explanatory variable is the dummy variable Chil5. When child = 0, there is no children under 5 years old, when it is equals 1, the household has children under 5 years old. Given the large t statistic (3.146) and the coefficient is negative, it means that the person who has children under 5 years old prefer lower earlier departure time.

Since the latent variable in the ORP model (Equation 1) has a linear relationship with the explanatory variables, positive signs for the estimated parameters can be interpreted as an increase of *earlier departure time*. In this sense, the estimated results show the likelihood that a commuter who experienced higher travel time before may get involved in another travel time increases. Having children under 5 years old and modal preference are also observed to be more important for departure time choice decision than having children from 5 to 10 years old, income level, occupation pattern driving, safety margin and flexibility about on time arrival. A negative parameter sign means that *earlier departure time* will decrease with increasing value of the corresponding variable. It is observed that the *extremity of higher earlier start* decreases when a commuter is male. At the same time, travel cost is more sensitive to decrease the higher earlier start for work.

The estimated threshold variables (μ_2 and μ_3) are very significant with t-statistics of 2.961 and 9.110 respectively indicating the ordered probit model with 4 different departure time choices is highly appropriate. The overall fit of the model is also reasonable with a log likelihood ratio index ($\rho 2$) of 0.325 which means all variables included in the model are statistically significant.

Table 4 shows the estimation results. All estimated parameters are significant at 99%, 95% and 90% confidence level. Parameters (β) and asymptotic *t*-statistics were calculated by maximum likelihood estimation, using LIMDEP (LIMited DEPendent). To assess the performance (i.e., the goodness-of-fit) of the estimated model, an adjusted Rho-squared (ρ^2) is also presented in Table 4.

Based on the estimated results, a number of inferences can be made based:

- The availability of a flexible work schedule is important for people planning to arrive exactly on time and extremely important for those planning a late work arrival.

- Motorized vehicle (MV) travelers are not more likely to depart with lower earlier start from their house to work place, while non-motorized vehicle (NMV) travelers are likely to depart with lower earlier start.

- The non-government service holder typically avoids importance of departure time such that travel time is increased.

- The higher income workers have a definite interest in arriving at or slightly before the official work start time, therefore they start their journey to work with higher earlier departure time.

- The younger workers are more inclined to depart with lower earlier start time so as to arrive on time.

- Individuals with very young children (under 5 years) in their households are unlikely to arrive on time due to settle down their children at home for whole day regarding food and safety.

- Individuals with children above 5 years in their households, on the other hand, are most likely similar situation as it is required to send their children to school.

- In context of level-of-service variables, travel time is more concerned by the commuters. On the other hand, safety margin consideration and travel time variability consideration are also not well thought-out by the commuters when they make a trip for journey to work.

Table 5: Univariate statistics (Probability of alternative choices)

Alternative choice	Probability of choice	Standard Deviation of probability	Variance of probability	Skewness of probability	Kurtosis of probability
LES	0.13646	0.15501	0.024027	2.49434	5.43254
MES	0.38087	0.16316	0.026622	0.10786	-1.04746
HES	0.41652	0.13928	0.019400	-0.38729	-0.58688
EHES	0.066151	0.022121	0.00048933	-0.38729	-0.58688

Table 5 depicts the departure time choice probability for journey to work trip in Dhaka city. According to the results estimation, the highest probability belongs to HES (0.416). In terms of standard deviation, the dispersion among choice probabilities of the trip makers is very negligible among four departure time choice categories. It means that the choice probability varies very marginally from one departure choice to another. On the other words, it means that the probability of departure time choice of the trip makers is homogeneous among the different discrete departure time choices. Skewness and kurtosis of the probability have been also shown in Table 5. If the skewness value is not equal to zero it means that the distribution is not normal and somehow it is skewed. But in the real world, normal distributions are hard to come by. Therefore, the probability distribution is skewed to the right; longer tail to the right if the value is positive (in this case, LES and MES) and skewed to the left; longer tail to the left with the negative value (in this case, HES and EHES). In terms of kurtosis, a positive kurtosis value (case of LES) means that the tails are heavier than a normal distribution and the distribution is said to be leptokurtic (with a higher, more acute "peak"). A negative kurtosis value (case of others) means that the tails are lighter than a normal distribution and the distribution is said to be platykurtic (with a smaller, flatter "peak").

Concluding Remarks

A number of conclusions were drawn based on the departure time study discussed in this paper. It was found that children under 5 years, travel time, travel cost and mode choice preference variables influence departure time choice strongly. The flexibility of on time arrival is also important determinants of commuter departure time choice.

The estimation of departure time choice model for journey to work that, includes motorized vehicles users, represents a potentially important contribution for policy analysis. Because this model can be used to analyze the effects of various policies on MV traffic users' departure times, the results can conceivably, be used to study transit system as well as other motorized modes peak load requirements and how MV peak load problems can be eased by implementing policies that redistribute MV use more uniformly during the peak period.

There are a number of other policy contexts, where this analysis framework might be useful. For example, the policy of allowing flexible work hours can be represented in this framework by altering the inputs for the work arrival time flexibility and other variables like children under 5 years old, travel time etc. For a situation where planners are considering restricting private motorized vehicles travel within the CBD, the resulting change in mode split may also impact the time at which people travel. This impact could be measured by modifying the inputs to the mode split variables in the departure time choice model.

References

Abkowitz, Mark D. 1981. 'An Analysis of the Commuter Departure Time Decision', *Transportation*, vol. 10, pp. 283-297.

Bhat, C. R. and Steed, J.L. 2000. *Modeling departure time choice for home based non-work trip*. Thesis, Center for Transportation Research, University of Texas at Austin.

Ben-Akiva, M. and Lerman, S.R. 1985. *Discrete Choice Analysis.* The MIT press.

Chin, Anthony T. H. 1990. 'Influences on Commuter Trip Departure Time Decisions in Singapore', *Transportation Research A: Policy and Practice*, vol. 24, no. 5, pp. 321-333.

Greene, W. H. 2000. *Econometric Analysis*, Fourth Edition. New Jersey, Prentice Hall.

Hendrickson, C. and Plank, E. 1984. 'The Flexibility of Departure Times for Work Trips', *Transportation Research A: Policy and Practice*, vol. 18, no. 1, pp. 25-36.

Hunt, J. D., and Patterson, D. M. 1996. 'A Stated Preference Examination of Time of Travel Choice for a Recreational Trip', *Journal of Advanced Transportation*, vol. 30, no. 3, pp. 17-44.

Machmias, D. and Nachmias, C. 1976. *Research Methods in the Social Sciences*, New York: St. Martin's Press.

Mannering, F.L. 1989. 'Poisson Analysis of Commuter Flexibility in Changing Routes and Departure Times', *Transportation Research B: Methodological*, vol. 23, no. 1, pp. 53-60.

Mannering, F.L., and Hamed, M.M. 1990. 'Occurrence, Frequency, and Duration of Commuters' Work-to-Home Departure Delay', *Transportation Research B: Methodological*, vol. 24, no. 2, pp. 99-109.

McFadden, D., Talvitie, A., Cosslett, S., Hasan, I., Johnson, M., Reid, A. and Train, K. 1977a. *Demand Model Estimation and Validation.* The Urban Travel Demand Forecasting Project, Volume V, ITS, University of California at Berkeley.

McFadden, D., and Talvitie P. A. 1977_b. *Demand Model Estimation and Validation and Associates Urban Travel Demand Forecasting Project*, Phase 1, Final Report Series, Vol. V, The Institute of Transportation Studies, University of California Berkeley and Irvine.

McCafferty, D., and Hall, F.L. 1982. 'The Use of Multinomial Logit Analysis to Model the Choice of Time to Travel', *Economic Geography*, vol. 36, no. 3, pp. 236-246.

Palma, A. de, de A., Fontan, C., and Mekkaoui, O. 2000. 'Trip Timing for Public Transportation', working paper, Université de Cergy-Pontoise

Rosenbloom, S. 1978. 'Peak-period traffic congestion: a state-of-art analysis and evaluation of effective solutions', *Transportation,* vol. 7, pp. 167-191.

Small, K.A. 1982. 'The Scheduling of Consumer Activities: Work Trips', *The American Economic Review*, vol. 72, no. 3, pp. 467-479.

Small, K. A. 1978. 'The scheduling of consumer activities: work trips', Princeton

University, prepared for presentation to the Econometric Society Annual Meeting, Chicago.