Modelling departure time choice of car commuters in Dhaka, Bangladesh

Khatun E. Zannat
Institute for Transport Studies
University of Leeds
Leeds, UK, LS29JT
Email: tskez@leeds.ac.uk
Assistant Professor (On study leave)
Department of Urban and Regional Planning
Chittagong University of Engineering and Technology
Chittagong-4349, Bangladesh

Charisma F Choudhury
Institute for Transport Studies
University of Leeds
Leeds, UK, LS29JT
Email: C.F.Choudhury@leeds.ac.uk

Stephane Hess
Institute for Transport Studies
University of Leeds
Leeds, UK, LS29JT
Email: s.hess@leeds.ac.uk

ABSTRACT

Dhaka, one of the fastest-growing megacities in the world, faces severe traffic congestion leading to a loss of 3.2 million business hours/day (1). While peak-spreading policies hold the promise to reduce the traffic congestion levels, the absence of comprehensive data sources makes it extremely challenging to develop econometric models of departure time choices for Dhaka. This motivates this paper where we develop advanced discrete choice models of departure time choice of car commuters using secondary data sources and quantify how the level-of-service attributes (e.g., travel time), socio-demographic characteristics (e.g., type of job, income, etc.) and situational constraints (e.g., schedule delay) affect their choices. The trip diary data of commuters making home-to-work and work-to-home trips by personal car/ride-hailing services (957 and 934 respectively) have been used in this regard. Given the discrepancy between the stated travel times and those extracted using the Google direction API, a sub-model is developed first to derive more reliable estimates of travel time throughout the day. A mixed multinomial logit (MMNL) model and a simple multinomial logit (MNL) model have been developed for outbound and return trip respectively, to capture the heterogeneity associated with different departure time choice of car commuters. Estimation results indicate that the choices are significantly affected by the travel times, schedule delay and socio-demographic factors. The influence of the type of job on Preferred Departure Time (PDT) has been estimated using two different distributions of PDT for the office employees and self-employed people (Johnson's S_B distribution and truncated normal respectively).

In addition to being practically useful for devising peak-spreading policies in Dhaka, the proposed framework can be useful in other developing countries with similar data issues.

Keywords: Departure time choice, Discrete Choice Model, Schedule Delay, Developing country, Dhaka, Bangladesh

INTRODUCTION

Dhaka, the capital of Bangladesh is home to more than 15 million people. The population of Dhaka (within the RAJUK[1] jurisdiction area) is projected to be 26.3 million by the year 2035, predominantly due to migration from rural to urban areas (2). To meet the mobility demand of this rapidly growing population, the number of motorized vehicles in the city, private cars in particular, is increasing at an alarming rate. According to the statistics of the Bangladesh Road Transport Authority (BRTA), a total of 145,000 private cars, 20,000 trucks, 14,000 buses and minibuses are currently registered in the Dhaka Metropolitan Area which is expected to grow at a rate of 34% annually. This escalating growth of the motorized vehicle coupled with the increasing usage of private vehicles is associated with the severe traffic congestion that cripples the city and results in a loss of 3.2 million business hours per day (3).

The traffic congestion levels in Dhaka are worst during the morning and evening peak hours. According to the World Bank (1), the average speed on Dhaka's urban network during the peak hours is approximately 8.75km/h, indicating that the travel time during the peak hours is almost triple the travel time during the off-peak hours. A large share of the trips made during these periods is presumed to be mandatory trips by commuters that are often hard to cancel or reschedule. However, different types of commuters are expected to have different levels of flexibility in their start times at the workplaces as well as commitments at home. It is, therefore, crucial to develop an understanding of the factors affecting the departure time choice decisions made by the commuters and how it varies with the type of their job and socio-demographic characteristics. It then boils down to identifying the appropriate modelling specifications that can reflect the behaviour of decision-makers about departure time choice that can be used to design policies to flatten the peak demand.

Although departure time choice is a crucial determinant in measuring the temporal and spatial distribution of travel demand (4), it has received less attention than mode or route choice (5; 6). For example, previous travel demand models developed focusing on Dhaka city discussed methodological issues in developing the mode choice model (7) but there has not been similar research done in the context of departure time choice. Key challenges to develop departure time choice model in the case of Dhaka (as well as many countries in the developing world) include the following:

(1) lack of dependable data sources to calculate the travel time for different origin-destination pairs.

(2) different opening and closing times of different types of institutions making it harder to infer the preferred departure time choice.

In the context of developed countries[2], several modelling approaches have been used to model departure time choice. Bhat and Steed (9) have developed a continuous time model for urban shopping trips. In parallel, a large number of studies have used discrete choice models to investigate departure time choice by dividing the continuous departure time variable into a finite set of discrete intervals. For example, Small (10), McCafferty and Hall (11), Hendrickson and Plank (5), Holyoak (12) have used simple multinomial logit (MNL) structures to model departure time choices of commuters. MNL models have also been used to model time of day choice in the context of trips made during weekends and holidays (13; 14). In addition to the single facet model, Bhat (15) have used a joint multinomial logit (MNL) and ordered generalized extreme value formulation for integrated models of mode and departure time choices. The study however focused only on non-commute trips. De Jong et al. (16) and Hess et al. (17) have used mixed multinomial logit (MMNL) models to capture influences of unobserved factors in the time of day switching in the context of mode and departure time choices. However, all these studies and their applications focus on countries in North America and Europe which have very different socio-economic composition (e.g., income and age distribution, gender roles, household size and family structure, etc.), work-culture (e.g., inflexible working hours, recording of arrival time at workplace, etc.), state of technological advancement

[1] Rajdhani Unnayan Kartripakkha (RAJUK) is the Capital Development Authority of the Government of Bangladesh

[2] Developed countries are the sovereign state with a very high Human Development Index (HDI) rating. World Bank uses a threshold for the classification between developed and developing country i.e., per capita income level of US$6,000 in 1987 prices (8). Developing countries are typically characterized by little industrial and economic activity and where people have low-income level (8).

(e.g., reliable internet access and uninterrupted power supply to work from home) and transport landscape (e.g. car-ownership levels, public transport accessibility, paratransit, etc.). All these lead to significant differences in activity and travel behaviour (7; 18; 19) and affect the transferability of the models (18-20). Further, modelling frameworks formulated for the developed countries are very often not directly applicable in the context of developing countries where detailed socio-demographic information and fine-scale spatial and temporal data are not available (7).

Very few studies have discussed the methodological issues and data challenges of modelling departure time choice in the context of developing countries (21; 22). Anwar (21) have proposed a departure time choice model in the context of Dhaka using primary data with a pre-defined classification of timeslots within a narrow range (7:30 – 8:50). The collected data was used to develop ordered logit models of departure time choice. However, the study focused only on officials who had office hours from 9:00 to 17:00 ignoring the rest of the working population. Further, the travel times used in calibrating the model lacked adequate temporal and spatial granularity.

This motivates this research where we develop advanced discrete choice models of departure time choice of car commuters using secondary data sources. We propose approaches to account for the data limitations and quantify how the level-of-service attributes (e.g., travel time), socio-demographic characteristics (e.g., type of job, income etc.) and situational constraints (e.g. schedule delay, activity duration) affect the departure time choices of different types of commuters. Trip diary data of commuters making home-to-work and work-to-home trips by personal car/ride-hailing services (957 and 934 respectively) have been used in this regard. It may be noted that though stated preference data have been used in some of the departure choice modelling studies (6; 16; 17; 22; 23), it is prone to hypothetical bias and behavioural incongruence (24) and hence revealed preference (RP) data has been deemed to be the better option. To the best of our knowledge, this is the first study that highlights the key challenges and methodological issues to model departure time choice using RP data from developing countries and proposes ways to address these issues.

The rest of the paper is organized as follows: the next section describes the data sources used in this study. The modelling issues are presented next followed by the description of the model structure and the estimation results. The findings are summarized in the end along with directions for future research.

DATA

In this study, we used the travel diary survey data conducted across the Dhaka Metropolitan Region (RAJUK area) by TYPSA (https://www.typsa.com/en/) as part of the Dhaka Subway Project. The data was collected from Monday to Saturday[3] between 28th February 2019 to 4th May 2019. A total of 35,000 households were surveyed in the RAJUK Area. A stratified sampling procedure with proportional allocation was applied to determine the number of households will be surveyed in each sub-divided area. About 25,000 households were surveyed in the Dhaka City Corporation area, with the remaining 10,000 household interviews conducted in the rest of the RAJUK area. During the surveys, each household member was asked about trips made during the previous working day (from Sunday to Thursday). The questionnaire survey was divided into two parts: the first part focused on general household information (e.g. age, gender, education, occupation, income, car ownership) and the second part focused on trip-related information (e.g. departure time, travel mode, travel time) for each household member who has made at least one trip on the previous working day. Very short trips (less than 10 minutes of walking distance) and trips made by children (under 6 years) were not recorded. The survey was well planned to avoid trips made on Fridays, Saturdays, public holidays, hartal (strike days), election days, major events (like Ijtema), and during Ramadan. From the full dataset, only commuting trips by car-based modes (private car and ride-hailing services like *uber*/*pathao* car) have been considered for this study. Before the survey in each zone, the survey correspondents had communicated with local representatives including the ward commissioners, in order to gain approval of, and assistance for, the surveys. This survey yielded a total of 957 unique home-to-work

[3] Friday is the generic weekly holiday in Bangladesh. Educational institutes and some offices are closed on Friday and Saturday.

trips and 934 unique work-to-home trips[4]. Commuting trips with origins outside Dhaka have not been considered. The socio-demographic characteristics of the commuters are summarized in Table 1.

TABLE 1: Summary of socio-demographic characteristics of the commuters in the sample

	Percentage	*Percentage*
	Home-to-work trip respondents (n=957)	**Work-to-home trip respondents (n=934)**
Gender		
Male	83.28	82.87
Female	16.72	17.13
Age		
<26	3.97	4.18
26 -40	37.93	38.00
41-60	47.23	47.43
>60	10.87	10.39
Monthly income		
<10,000 BDT *	1.07	0.87
10,000-20,000 BDT	4.06	3.71
20,001-30,000 BDT	5.34	5.35
30,001-40,000 BDT	9.71	9.72
40,001-60,000 BDT	17.93	18.12
>60,000 BDT	61.89	62.23
Level of education		
Below primary (Year 5)	3.66	3.64
Years 6-10	5.96	5.89
Secondary School Certificate	6.06	5.78
Higher Secondary School Certificate	9.51	9.64
Bachelors	17.76	17.77
Masters	54.75	54.93
Others	2.30	2.35
Occupation		
Employed in public services	20.69	21.09
Employed in private jobs	35.63	35.44
Self-employed	43.68	43.47
Car ownership rate		
Do not have a car	12.54	7.50
Have at least one car	87.46	92.5

*1 BDT= 0.012 USD

It may be noted that though the original sample was representative of the population of Dhaka city, the sample used in the departure time choice models of this paper is expected to be biased towards high income and educated segments of the population as it focuses only on car users (who have higher affordability than the others).

MODELLING ISSUES

Choice Set Specification

The number and length (i.e. duration) of alternative time periods play an important role in the computation, interpretation and transferability of the departure time choice models (25). In a usual

[4] There is an imbalance in the number of home-to-work and work-to-home commute trips by car as some travellers have used public transport and non-motorized modes in one of the legs of the trip

specification, a separate alternative specific constant (ASC) is recommended for each possible combination of home to work (outbound) and work to home (inbound) time period to capture the unexplained time preference of travellers. However, this can lead to a compounding problem of higher computational cost and complex parameter identification. For example, using 1-hour time periods (*N=24*) would lead to a requirement for 300 constants (following the rule *N(N+1)/2*), of which 299 (*N(N+1)/2-1)* can be estimated (17). To reduce this computational cost, we have used a separate set of alternatives for the outbound (home-to-work) and return (work-to-home) trip. The choice set for the outbound (home-to-work) trips is assumed to range between 06:00-18:00. Between 06:00-12:00, we have used 1-hour intervals (since the majority of the trips are likely to be made before 12:00) and 2-hour intervals are used for the rest. The choice set for the return (work-to-home) trips is assumed to range between 10:00-24:00. Between 16:00-20:00, we have used 1-hour intervals (since the majority of the trips are likely to be made before 20:00) and 2-hour intervals are used for the rest. In the time choice model, the off-peak hours (6:00 – 7:00, 10:00 – 12:00) are considered as base alternatives.

Calculation of Travel Time

Departure time choice models require the calculation of travel times between origins and destinations for the chosen and unchosen time periods. In many cities, the Google Maps, Open Street Maps, etc. provide reliable travel times for each alternative time period inadequate spatial and temporal granularity. Examples include departure time choice models developed in the context of the USA (4; 24) where Google Maps Distance Matrix API/Direction API has been used for deriving travel times during different time periods for different origin-destination pairs. Since Google Maps uses historical data to predict future traffic, it is considered that future traffic conditions based on Google Maps are more stable and represent better trends in traffic than real-time information. However, in the context of a developing country, it is hard to infer travel time accurately from Google Maps. For example, in Dhaka, both motorized and non-motorized vehicles share a common right-of-way making the travel times very sensitive to the proportion of different types of vehicles. Further, in Dhaka, traffic intersections are manually operated by traffic police which also makes it harder to reliably infer travel times between a specific origin-destination pair. Moreover, there are multiple types of public transport and paratransit services (e.g., human hauler, 'tempo's etc.), who tend to allow passengers to board and/or alight at almost any place. These also make it almost impossible to reliably predict travel times across the network. Finally, though Google Map can show the shortest path in Dhaka, the use of navigation technology is not widespread among car users. A major share of the cars is chauffeur-driven, and the chauffeurs use their intuition to select the route to travel instead of choosing the quickest or shortest path that would have been recommended by a navigation device. For these reasons, instead of providing a single predicted travel time between an origin-destination pair, Google Maps direction API provides three different travel time suggestions: best guess[5], pessimistic[6] and optimistic[7]. Comparison of the stated travel time (only available for the chosen time of travel) and the three different predicted travel times showed variations in fit depending on the time of the day and origin-destination pair. This prompted us to estimate a sub-model to establish a relationship between the stated travel time and the best guess, pessimistic and optimistic travel times.

The proposed relationship among the stated travel time and predicted travel time using models from direction API can be expressed as follows:

$$T_{stated\ travel\ time} = W_1 T_{Best\ guess} + W_2 T_{Optimistic} + W_3 T_{Pessimistic} + \varepsilon \quad (1)$$

Where,

$T_{stated\ travel\ time}$ = Travel time stated by the respondents

[5] Best guess model returns the duration in traffic using both historical traffic conditions and live traffic. Live traffic becomes more important the closer the departure time is to now

[6] Pessimistic model returns the duration in traffic, usually that should be longer than the actual travel time on most days, though occasional days with particularly bad traffic conditions may exceed this value

[7] Optimistic model returns the duration in traffic, usually that should be shorter than the actual travel time on most days, however, occasional days often with a good traffic condition could be faster than this value

$T_{Best\ guess}$ = Travel time from the best guess model of google direction API at the chosen alternative time period

$T_{Optimistic}$ = Travel time from the optimistic model of google direction API at the chosen alternative time period

$T_{Pessimistic}$ = Travel time from the pessimistic model of google direction API at the chosen alternative time period

W indicates the systematic scale differences between the stated and measured time, ε represents the random part of the error. W_1 and W_2 were estimated keeping W_3 as a reference point (with their sum fixed to 1). The relationship among W and weight of different models in the different time periods can be expressed as:

$$W = \frac{\sum_{n=1}^{n} e^{\beta_{nj} t_n}}{\sum_{j=1}^{j} \sum_{n=1}^{n} e^{\beta_n t_n}} \tag{2}$$

Here, n is the number of alternative time period (n=7 for home to work and n=5 for work to home trip) and j refers to the number of models (j=3) considered for travel time prediction. Weights calculated from different Google map models are presented in Table 2.

TABLE 2: Calculated weights of different model used for travel time calculation
(a) Home to Work Trip

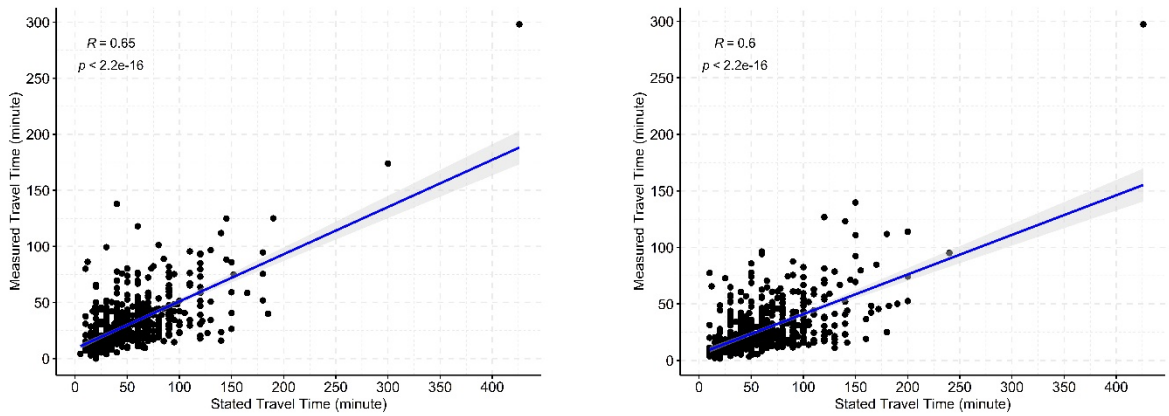
Departure Time	Google Maps Model	Estimates (β)	Exp (β)	Weight (W)
		$\sigma = 31.4626$		
	Best Guess	14.2567	1554555.173	0.99958522[(a)]
Before 7:00	Optimistic	6.4678	644.0652237	0.000414137
	Pessimistic	0	1	6.43004E-07
		∑	1555200.238	1
	Best Guess	-15.9892	1.13757E-07	2.63623E-08
7:00 – 8:00	Optimistic	1.1985	3.315140481	0.768257814
	Pessimistic	0	1	0.23174216
		∑	4.315140594	1
	Best Guess	-12.567	3.48515E-06	1.53532E-06
8:00 – 9:00	Optimistic	0.239	1.269978537	0.559466341
	Pessimistic	0	1	0.440532123
		∑	2.269982022	1
	Best Guess	-12.567	3.48515E-06	1.53532E-06
9:00 –10:00	Optimistic	0.239	1.269978537	0.559466341
	Pessimistic	0	1	0.440532123
		∑	2.269982022	1

Departure Time	Google Maps Model	Estimates (β)	Exp (β)	Weight (W)
10:00 – 11:00	Best Guess	-1.8409	0.158674555	0.055933598
	Optimistic	0.5177	1.678163432	0.591561252
	Pessimistic	0	1	0.35250515
		∑	2.836837986	1
11:00 – 12:00	Best Guess	0.0022	1.002202422	0.499689173
	Optimistic	-5.6696	0.003449245	0.001719763
	Pessimistic	0	1	0.498591065
		∑	2.005651666	1
12:00 and after 12:00	Best Guess	-0.7994	0.449598642	1.76382E-08
	Optimistic	17.0538	25490082.17	0.999999943[(b)]
	Pessimistic	0	1	3.92309E-08
		∑	25490083.62	1

(b) Work to Home Trip

Departure Time	Google Maps Model	Estimates (β)	Exp (β)	Weight (W)
10:00 – 12:00	Best Guess	0.0022	1.002202422	0.499689173
	Optimistic	-5.6696	0.003449245	0.001719763
	Pessimistic	0	1	0.498591065
		∑	2.005651666	1
12:00 – 14:00	Best Guess	1.763	5.829900889	0.000898438
	Optimistic	8.7768	6482.101226	0.998947454[(c)]
	Pessimistic	0	1	0.000154109
		∑	6488.931127	1
16:00 – 18:00	Best Guess	-9.1197	0.000109488	9.28015E-05
	Optimistic	-1.7165	0.179693977	0.1523084
	Pessimistic	0	1	0.847598799
		∑	1.179803465	1
18:00 – 19:00	Best Guess	-5.1375	0.005872352	0.000662464
	Optimistic	2.0616	7.85853341	0.886526815
	Pessimistic	0	1	0.11281072
		∑	8.864405762	1
19:00 – 24:00	Best Guess	7.1876	1322.924374	0.98801963
	Optimistic	2.7108	15.04130375	0.011233524
	Pessimistic	0	1	0.000746845
		∑	1338.965678	1

Note: Given the close to 1 weight, only the Best Guess model has been used in (a) and only the Optimistic model has been used in (b) and (c) instead of the weighted models.



(a): Home-to-work trip (b): Work-to-home trip

Figure 1: Correlation between stated and measured travel time

Further, the fit of the results has been tested by comparing the measured travel times (calculated using the estimated weights) with the stated travel times for each origin-destination pair (Figure 1). The correlation coefficients (0.65 and 0.6 for home-to-work and work-to-home trips respectively) signify the substantial positive association between the estimated and measured travel times.

Accounting for Schedule Delay

Schedule delay, which captures the disutility caused by travelling at times other than the desired time of travel, is a key variable in modelling departure time choice. Usually, the actual departure and travel times are recorded in RP surveys and the preferred arrival and preferred departure times (PAT and PDT) are missing in the data source. Asking direct questions to extract the information can also be biased due to potential subjective justification towards the actual or the intended arrival time (i.e., respondents may try to justify to themselves and/or the interviewer their actual behaviour is the optimum). Different studies have used different modelling approaches to model schedule delay. Koppelman, Coldren and Parker (26) assumed that preferred departure time follows the same trend as the observed departure time. Though this assumption could be realistic for the air traveller, for regular commuters, it could be stringent. Ben-Akiva and Abou-Zeid (25) suggested two methods: 1) assumption of a constant desired time of travel by market segment as PDT and 2) assumption of a latent desired time of travel assuming a probability density function for the latent (unobserved) PDT. While these methods yield good results in cities with homogeneous starting times of offices and businesses, the situation in Dhaka (as well as many other countries in the Global South) is more complicated. For instance, in the RP data used in the current study, the occupations are reported in three categories: public, private, and business (i.e., self-employed). However, depending on job type, the starting time of offices and the working hours very often vary within the single market segment. For example, in Dhaka, the opening times of public banks, administrative offices, etc. are 10:00 am, whereas public universities/schools/colleges have different start times. Therefore, it is not worthwhile to consider a constant time for a specific market segment in such a complex situation. Hence, we considered a latent desired time of travel for each market segment and estimate the parameters of the distribution of the PDT along with the other model parameters.

THEORETICAL MODEL

Our modelling framework is based on the random utility framework. Random utility theory suggests that individual decision is followed by rationality and complete information. Decision-makers choose each alternative time with the highest utility, where the utility of an alternative i to a person n has the form:

$$u_n(i) = u(x_{in}, s_n, \beta) \quad (3)$$

Where, x_{in} is the vector of the attribute of alternative i and for individual n, s_n is the vector of characteristics of person n and β is the parameter vector that would be estimated using the available choice data. McFadden (27) proposed that this utility has the linear-in-parameters separable form:

$$u(x_{in}, s_n, \beta) = V(x_{in}, s_n, \beta) + \varepsilon_{in} \tag{4}$$

Where, V is the observed component of utility and ε_{in} is the unobserved error term. Based on the schedule delay theory, in our model, the generic form of the observed component can be expressed linearly as a function of variables available for the departure time utility equation such as travel time, corresponding schedule delay, activity duration and other sociodemographic attributes. Therefore, the equation can be expressed as follows:

$$V_{in} = \beta_{TT} * TT_{in} + \beta_{SDE} * SDE_{in} + \beta_{SDL} * SDL_{in} + \cdots \tag{5}$$

Where, TT_i is the travel time at alternative i. The early and late schedule delay can be defined as:

$$SDE_{in} = \max\,(0, PDT_n - DT_i) \tag{6}$$

and

$$SDL_{in} = \max\,(DT_i - PDT_n, 0) \tag{7}$$

Where, PDT_n is the preferred departure time and DT_i is the midpoint of the departure time interval of alternative time i in terms of hours (e.g., for 7:00 to 8:00 time interval DT corresponds to 7:30). In the absence of PDT_n in the available RP data, we used statistical distributions. From a behavioural perspective, it is assumed that the earliness and lateness disutility is lower around the preferred departure time and higher when departure time spreads further away from the preferred departure time. Therefore, it is assumed that the schedule delay is symmetric in terms of earliness and lateness and follow a parabolic function (as this functional form give better consistency (24)). After adjusting the schedule delay term, the deterministic part of the utility equation can be expressed as:

$$V_{in} = \beta_{TT} * TT_{in} + \alpha(PDT_n - DT_i)^2 \tag{8}$$

Where, α is the parameter to be estimated and representing the sensitivity to delay. It is expected that α will have a negative sign.

Different assumptions about the distribution of the unobserved error term ε_{in} lead to different model structures, thus offering different functional forms for the choice probabilities. In our model, ε_{in} is assumed to be independent and identically distributed across alternatives and respondents, following a Type I Extreme Value distribution (Gumbel). Therefore, the choice probability for an individual can be estimated using the multinomial logit model (27). The choice probabilities for each alternative i in MNL can be expressed as (for detail see (28)):

$$P_{in}(\beta, \alpha, PDT_n) = \frac{exp(\beta_{TT} * TT_{in} + \alpha(PDT_n - DT_i)^2)}{\sum_{j \in C_n} exp\left(\beta_{TT} * TT_{jn} + \alpha(PDT_n - DT_j)^2\right)} \tag{9}$$

Where, C_n is the choice set of individual n. As the PDT_n is not observed, statistical distributions are assumed to reflect the heterogeneity of PDT across the travellers. The density of PDT_n can be defined as $f(PDT|\Omega)$, here, Ω is the vector of parameters (mean and covariance) of the distribution. In this case, choice probabilities are estimated using the following form:

$$P_n(\beta, \alpha, \Omega) = \int_{PDT} P_{in}(\beta, \alpha, PDT_n) * f(PDT|\Omega) dPDT \tag{10}$$

Since Equation 10 does not have a closed-form, a simulated log-likelihood is used using "Halton draws" from the specified distribution (normal distribution for Johnson's distribution and uniform distribution for truncated normal distribution) to calculate the logit probabilities, which are then averaged over the number of draws. To keep the simulation variance lower in the estimated parameter and at the same time, to reduce the computation run time, we have used Halton draws. The number of draws has been gradually increased starting from 50 till they were found to be stable for different starting values. The final model was estimated with 300 Halton draws (29).

$$SSL = \sum_{n=1}^{N}\sum_{j=1}^{J} d_{nj} ln\, \breve{P}_{nj}(\beta, \alpha, PDT_n) \tag{11}$$

Here,

$$\breve{P}_{in} = \frac{1}{R}\sum_{r=1}^{R} L_{ni}(\beta, \alpha, PDT_n)^r \tag{12}$$

Where, R is the number of draws and $\breve{P}_{in}$ is the unbiased estimation of P_{in}. For the PDT distribution, we have used Johnson's S_B distribution for office employees and truncated normal distribution bounded between the limits of the analysis period (morning to evening) for the self-employed personnel. The S_B distribution has been preferred for the former one as it has a more flexible functional form than truncated normal and log-normal distribution (30).

RESULTS AND DISCUSSION

Models have been estimated using the "Apollo" package R, applying the Maximum Likelihood Estimation with the BFGS optimization algorithm (31). Model estimation is done for both outbound and return commuting trips separately. Base outbound and a return models are developed first, which are simple MNL models. The base models are then extended to advanced MMNL models that acknowledge the heterogeneity in preferred departure time. Both in the base and advanced MMNL models, the effects of different socio-demographics have been considered. These effects are allowed to vary among the alternative time-periods. It is important to note that in the survey data, respondents who work at the office have been categorized as public and private employees and no further details about the profession have been recorded. We have aggregated these two categories to a single category ('office employees') as we are modelling the choices of the car and ride-hailing commuters (who are likely to be 'white collar' workers). Developed outbound and return models (both MNL and MMNL) include three broad types of independent variables: individual socio-demographics, household-level socio-demographics, and level-of-service attributes. Individual socio-demographic variables included in the model are gender, usage of ride-hailing service[8] (a proxy of car availability), observed activity duration (<3hours or not). Since in the data employees' job flexibility information was missing, we have included observed activity duration as a dummy variable to capture its effect on the departure time choice. Household socio-demographics explored in the model specification include a dummy variable for income (household income >60,000BDT per month or not). The level of service attribute includes travel time which is estimated for different alternative periods where the observed and unobserved travel times have been calculated using the sub-model described in section 4.2. To distinguish the influence of different occupations, at the outbound and return MMNL models different distributions of PDT have been defined. The modelling results from the outbound (home-to-work) and return (work-to-home) model are shown respectively in Table 3 and Table 4. The signs of the parameter estimates are plausible, supporting the hypotheses and are consistent with those in previous studies. Most of the variables considered are statistically significant at 95% confidence interval (Table 3 and Table 4). However, some parameters which are not statistically significant, corresponding coefficients have been retained in the model for the sake of comparison between simple MNL and MMNL model, and intuitive interpretation of each co-efficient.

Outbound model

For the outbound model, 10 discrete time intervals are grouped under four broad discrete time intervals such as early morning (before 7:00), morning peak (7:00 – 10:00), morning off-peak (10:00 –12:00),

[8] Ride-hailing services include *uber* or *pathao* car use and considered as a proxy of car-availability.

afternoon off-peak (12:00 – 16:00) and evening (after 16:00). These groupings are done considering the sign and magnitude of more disaggregate time-period-specific parameters.

Overall, most of the socio-demographic variables considered in the two specifications of the outbound models show similar trends. It is observed that different socio-demographic determinants have a significant influence in determining the departure time choice of car commuters for the home-to-work trips. For example: the results from both outbound models show that compared to male commuters or female self-employed personnel, the utility associated with departing for the outbound trip is larger for the morning peak (7:00 – 10:00) and morning off-peak (10:00 – 12:00) for female office commuters compared to early morning, afternoon off-peak and evening (Table 3). This is intuitive due to the potential consequence of increased obligation of housework and safety concerns[9]. A similar trend is observed in both models that for office commuters with monthly income greater than 60,000BDT - the utility of departure for outbound is highest during the morning peak which is followed by morning off-peak time compared to the other periods. On the contrary, for self-employed personnel with monthly income greater than 60,000BDT – the utility is highest during the morning off-peak followed by morning peak. This implies the greater privilege of self-employed personnel to avoid peak time congestion and travel in the period of reduced travel time. In both models, office commuters and self-employed personnel who have activity durations less than three hours have the lowest utility to travel during the peak time. The influence of observed activity duration can be explained by the fact that shorter activity durations (<3 hours) could insinuate the flexibility of employees both at work as well as at home. The effect of travel time is captured using generic coefficients for all time periods in both specifications. In both cases, the coefficient of travel time is negative as expected indicating disutility associated with longer travel times. The variable travel time is statistically not significant in the MNL model, but significant in the MMNL model. Therefore, it has been retained in the MNL model.

The MNL and MMNL specifications however lead to different sensitivities between car and ride-hailing service users. In the MNL specification, all else being equal, the office employees using ride-hailing services tend to prefer to travel in the morning peak-time (7:00 – 10:00). While once the effect of schedule delay and preferred departure times are accounted for in the MMNL specification, they show disutility associated with travelling in the morning peak compared to other alternative time period.

It may be noted that the influence of other socio-demographic variables (e.g., age, household size, vehicle ownership, etc.) have also been tested in both specifications, but not included in the final models as their influences are not significantly different from zero. Similarly, the effects of Alternate Specific Constants (ASCs) have been also tested, but not found to be statistically significantly different from zero.

In the MMNL model, the inclusion of schedule delay leads to a significant gain in model fit. The negative coefficient of schedule delay term captures the increased disutility associated with a late arrival (i.e., after the start of the office hours). The coefficient is statistically significant for both occupation group, but the sensitivity to the schedule delay is slightly higher for the office employees ($\beta = -0.09361$) compared to self-employed personnel ($\beta = -0.07999$). The density curve of the preferred departure time derived from the outbound MMNL model outputs shows a single peak for office employees with approximately a mean value of 9:00 (Figure 2 (a)). On the other hand, for self-employed personnel, the PDT graph is almost similar to office employees (Figure 2 (b)) with a slight shift of mean value towards the right (around10:00). This can be explained by the fact that self-employed personnel can avoid office rush hours due to their increased flexibility and lower sensitivity to schedule delay. Further, higher sensitivity to schedule delay among office employees is attributed to the strict enforcement of the reporting time at the workplace (i.e., requirement to sign-in upon arrival) compared to the more flexible schedule of self-employed personnel. It may be also noted that corresponding standard deviation is statistically significant only among the office employees. This can be attributed to the fact that the start times (and subsequently reporting times) of office employees working in the public and private sector are different (it was not recorded in the data whether or not an office employee worked in the public or private sector).

[9] Majority of the cars in Dhaka are driven by male chauffeurs

TABLE 3: Base model (estimates from simple MNL model)

Outbound (Home-to-work) base MNL model			Outbound (Home-to-work) advanced MMNL model		
Parameter	Estimates	t-ratio	Parameter	Estimates	t-ratio
Socio-demographic variables					
Female-office employee			*Female-office employee*		
Morning peak (7:00 – 10:00)	1.715	4.02***	Morning peak (7:00 – 10:00)	0.981	2.63***
Morning off-peak (10:00 – 12:00)	1.811	3.98***	Morning off-peak (10:00 – 12:00)	0.956	2.15***
High income office employee			*High income office employee*		
Morning peak (7:00 – 10:00)	2.879	12.64***	Morning peak (7:00 – 10:00)	1.536	5.86***
Morning off-peak (10:00 – 12:00)	1.604	5.88***	Morning off-peak (10:00 – 12:00)	0.672	2.16***
High income self-employed personnel			*High income self-employed personnel*		
Morning peak (7:00 – 10:00)	1.873	9.34***	Morning peak (7:00 – 10:00)	0.755	3.37***
Morning off-peak (10:00 – 12:00)	2.048	9.56***	Morning off-peak (10:00 – 12:00)	1.172	4.89***
Ride-hailing service user office employee			*Ride-hailing service user office employee*		
Morning peak (7:00 – 10:00)	1.167	3.64***	Morning off-peak (10:00 – 12:00)	-0.839	-2.02***
Ride-hailing service user self-employed personnel			*Ride-hailing service user self-employed personnel*		
Morning peak (7:00 – 10:00)	0.484	1.68**	Morning peak (7:00 – 10:00)	-0.498	-1.36*
			Morning off-peak (10:00 – 12:00)	-0.698	-1.67**
Activity duration under 3 hours (office employee)			*Activity duration under 3 hours (office employee)*		
Morning peak (7:00 – 10:00)	-2.382	-3.75***	Morning peak (7:00 – 10:00)	-2.388	-4.48***
Activity duration under 3 hours (self-employed personnel)			*Activity duration under 3 hours (self-employed personnel)*		
Morning peak (7:00 – 10:00)	-0.643	-1.71**	Morning peak (7:00 – 10:00)	-0.790	-2.08***
Level of service variable					
Travel Time (minute) (β_{TT})	-0.006	-1.12	*Travel Time (minute)* (β_{TT})	-0.067	-7.15***
Situational constraint					
			Mean PDT of office employees, μ_{office}	-0.252	-2.09***
			Std. Dev. of PDT of office employees, σ_{office}	0.642	3.22***
			Schedule delay of office employees,	-0.093	-5.36***
			Mean PDT of self-employed personnel, μ_{se}	9.776	49.80***
			Std. Dev. of PDT of self-employed personnel, σ_{se}	0.872	1.45
			Schedule delay of self-employed personnel	-0.080	-4.07***
Final LL		-1888.658	LL (final)		-1739.175
Rho-square (0)		0.1429	Rho-square (0)		0.2107
Adj.Rho-square (0)		0.1379	Adj.Rho-square (0)		0.2026
AIC		3799.32	AIC		3514.35
BIC		3852.82	BIC		3601.90

*** Estimates are significant at 95% level of confidence, ** Estimates are significant at 90% level of confidence, * Estimates are significant at 80% level of confidence

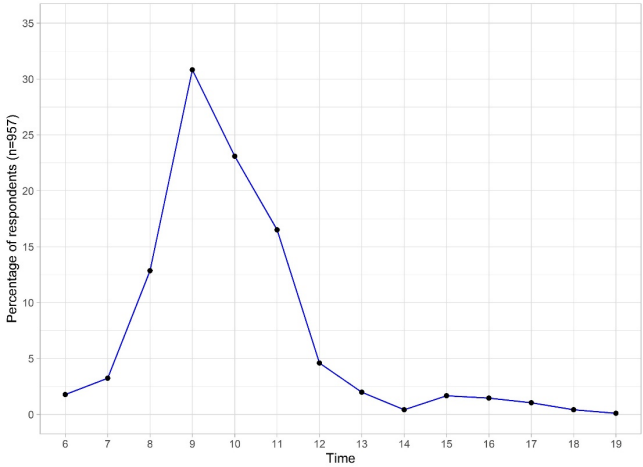


Figure 2 (a): Departure time of home to work trip

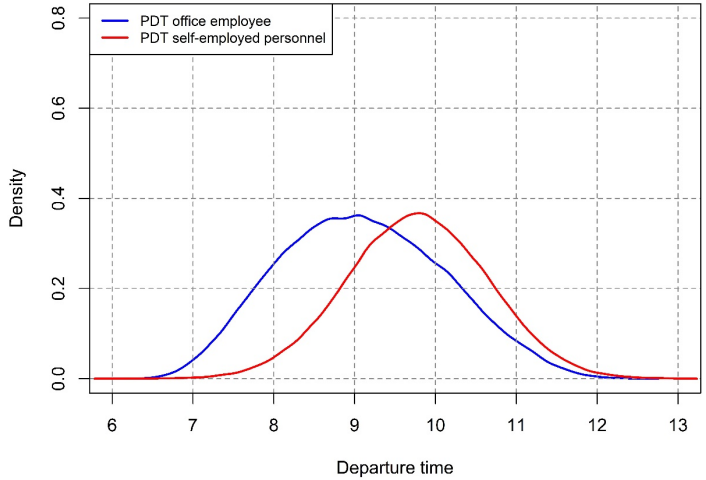


Figure 2 (b): Preferred departure time (home to work trip)

Return model

Table 4 summarizes the estimation results of the return model. In the return model, 9 discrete time intervals are considered in the choice set: 10:00 – 12:00, 12:00 – 14:00, 14:00 – 16:00, 16:00 – 17:00, 17:00 – 18:00, 18:00 – 19:00, 19:00 – 20:00, 20:00 – 22:00 and 22:00 – 24:00. Unlike the outbound model, the Alternate Specific Constants (ASCs) of most of these time intervals are found to be significantly different from zero and hence, retained in the model. Results from both MNL and MMNL specifications indicate that all else being equal, the most preferred time period is 17:00 – 18:00 followed by 20:00 – 22:00, 18:00 – 19:00, 19:00 – 20:00, 22:00 – 24:00, 14:00 – 16:00, 16:00 – 17:00, and 12:00 – 14:00 compared to the base alternative (10:00 – 12:00).

Similar to the outbound model, the return choice set is further grouped under four broad discrete time intervals such as morning off-peak (10:00 – 12:00), afternoon off-peak (12:00 – 16:00), evening peak (16:00 – 19:00) and evening off-peak (19:00 – 22:00) to capture the heterogeneity associated with departure time choice among different socio-demographic groups. The same set of socio-demographic variables tested for the outbound trips have been tested in this regard. All the socio-demographic variables considered in the two specifications of the return models (MNL and MMNL) show similar trends. Estimated shifts in the time period parameters indicate that for both specifications, the utility for departing during afternoon off-peak (12:00 – 16:00) and evening peak (16:00 – 17:00) is higher for female commuters. This might be driven by the fact that travelling after that (i.e., 19:00 – 22:00) can be associated with safety concerns and returning before 12:00 is not likely to be feasible.

In terms of the availability of a personal car for return trips, the differences in preferences are tested separately for office workers and self-employed people. The shifts in the time period parameter estimates are statistically significantly different between the office employee and self-employed personnel – possibly due to the higher rate of car ownership (and hence lower propensity to use ride-hailing services) among the self-employed personnel. The estimates reveal that office employees are more likely to choose evening off-peak time (19:00 – 22:00) for return trips if they are using car-based ride-hailing services. This is likely to be driven by the propensity to avoid the peak surcharge.

In terms of income, from both MNL and MMNL model specifications, it is found that for the office employee group with monthly income greater than 60,000BDT, the utility of returning is highest during the evening peak followed by the afternoon off-peak and evening off-peak. On the other hand, for the self-employed personnel, those who have monthly income greater than 60,000BDT, the utility is highest for departing at afternoon off-peak followed by evening off-peak and evening peak compared to other alternatives. This is likely to be associated with the higher flexibility of schedule of the self-employed group.

For office commuters and self-employed personnel who have observed activity duration less than three hours, the utility for travelling during the peak time (16:00 – 19:00) is the lowest. The disutility of longer travel time of peak period might have exceeded the utility associated with short duration activity participation.

Unlike the outbound model, travel time co-efficient is a significant determinant both in the return trip MNL and MMNL model. However, it is evident that the travel time parameter has a greater influence on the outbound trip (β = -0.06737 in the MMNL model) compared to the return trip (β = -0.009347 in the MMNL model). This suggests that car commuters are less willing to spend longer time in traffic for outbound trips as compared to the return trips.

Unlike the outbound MMNL model, the inclusion of situational constraint on the return MMNL model does not lead to a statistically significant improvement in the model fit and the coefficient of schedule delay is not statistically different from zero. This can be attributed to the fact that there is more flexibility in schedule during the return segment. The parameters of the preferred departure time distribution (mean and standard deviation) are also not found to be statistically significant reflecting this flexibility. Though in the return segment MNL model outperform than the MMNL model, the density curve of the preferred departure time derived from the return MMNL model is consistent with the reality (Figure 3 (b)). It is also observed that the sensitivity to schedule delay is generally higher during the outbound when compared to the return trip. This is intuitive because late arrival on office probably has more serious consequences or penalties

than on late arrival at home. Overall, the model fit of return model has lower R-square value compared to outbound model which might be because of large number of alternatives (times) considered in the model specification. Since inclusion of situational constraint on the return MMNL model does not improve the model performance, this study recommends MNL model for the return segment.

TABLE 4: Final model (estimates from mixed logit model)

Return (Work-to-home) base MNL model			Return (Work-to-home) advanced MMNL model		
Baseline time period constants	Estimates	t-ratio	Baseline time period constants	Estimates	t-ratio
ASC (10:00 – 12:00)	0	n/a	ASC (10:00 – 12:00)	0	n/a
ASC (12:00 – 14:00)	0.540	1.58*	ASC (12:00 – 14:00)	0.529	1.42
ASC (14:00 – 16:00)	1.593	5.11***	ASC (14:00 – 16:00)	1.577	5.26***
ASC (16:00 – 17:00)	1.491	4.96***	ASC (16:00 – 17:00)	1.475	5.06***
ASC (17:00 – 18:00)	2.302	7.89***	ASC (17:00 – 18:00)	2.287	8.21***
ASC (18:00 – 19:00)	2.006	6.79***	ASC (18:00 – 19:00)	1.993	7.08***
ASC (19:00 – 20:00)	1.790	5.90***	ASC (19:00 – 20:00)	1.782	6.06***
ASC (20:00 – 22:00)	2.033	6.61***	ASC (20:00 – 22:00)	2.034	6.68***
ASC (22:00 – 24:00)	1.662	5.65***	ASC (22:00 – 24:00)	1.679	4.94***
Shifts in time period constants			*Shifts in time period constants*		
Female-office employee			*Female-office employee*		
Afternoon off-peak (12:00 – 16:00)	2.195	2.94***	Afternoon off-peak (12:00 – 16:00)	2.194	2.65***
Evening peak (16:00 – 19:00)	1.605	2.20***	Evening peak (16:00 – 19:00)	1.604	2.03***
Evening off-peak (19:00 – 22:00)	1.220	1.62*	Evening off-peak (19:00 – 22:00)	1.220	1.50*
Female-self-employed personnel			*Female-self-employed personnel*		
Afternoon off-peak (12:00 – 16:00)	1.992	1.88**	Afternoon off-peak (12:00 – 16:00)	1.991	2.22***
Evening peak (16:00 – 19:00)	1.780	1.67**	Evening peak (16:00 – 19:00)	1.780	1.92**
Evening off-peak (19:00 – 22:00)	1.129	1.01	Evening off-peak (19:00 – 22:00)	1.128	1.19
High income office employee			*High income office employee*		
Afternoon off-peak (12:00 – 16:00)	0.555	1.61**	Afternoon off-peak (12:00 – 16:00)	0.556	1.99***
Evening peak (16:00 – 19:00)	0.979	3.22***	Evening peak (16:00 – 19:00)	0.980	3.71***
Evening off-peak (19:00 – 22:00)	0.306	0.93	Evening off-peak (19:00 – 22:00)	0.303	1.08
High income self-employed personnel			*High income self-employed personnel*		
Afternoon off-peak (12:00 – 16:00)	0.711	2.17***	Afternoon off-peak (12:00 – 16:00)	0.711	2.17**
Evening peak (16:00 – 19:00)	0.260	0.86	Evening peak (16:00 – 19:00)	0.260	0.65
Evening off-peak (19:00 – 22:00)	0.680	2.14***	Evening off-peak (19:00 – 22:00)	0.680	1.78**
Ride-hailing service user office employee			*Ride-hailing service user office employee*		
Evening off-peak (19:00 – 22:00)	0.795	2.97***	Evening off-peak (19:00 – 22:00)	0.795	3.03***
Ride-hailing service user self-employed personnel			*Ride-hailing service user self-employed personnel*		
Evening peak (16:00 – 19:00)	-0.656	-1.89**	Evening peak (16:00 – 19:00)	-0.656	-1.85**
Evening off-peak (19:00 – 22:00)	-0.531	-1.37*	Evening off-peak (19:00 – 22:00)	-0.531	-1.38*
Activity duration under 3 hours (office employee)			*Activity duration 3 hours (office employee)*		
Evening peak (16:00 – 19:00)	-1.742	-3.11***	Evening peak (16:00 – 19:00)	-1.742	-3.07***
Evening off-peak (19:00 – 22:00)	-1.390	-2.03***	Evening off-peak (19:00 – 22:00)	-1.390	-1.99***

Return (Work-to-home) base MNL model			Return (Work-to-home) advanced MMNL model		
Parameter	Estimates	t-ratio	Parameter	Estimates	t-ratio
Activity duration under 3 hours (self-employed personnel)			*Activity duration under 3 hours (self-employed personnel)*		
Evening peak (16:00 – 19:00)	-2.195	-3.93***	Evening peak (16:00 – 19:00)	-2.194	-3.89***
Evening off-peak (19:00 – 22:00)	-2.190	-3.47***	Evening off-peak (19:00 – 22:00)	-2.190	-3.46***
Level of service variable					
Travel Time (minute) (β_{TT})	-0.009	-2.11***	*Travel Time (minute)* (β_{TT})	-0.009	-2.06***
Situational constraint					
			Preferred Departure time (μ)	15.487	0.44
			Preferred Departure time (σ)	1.577	0.25
			Schedule delay	-0.0006	-0.67
Final LL		-1848.716	LL (final)		-1848.716
Rho-square (0)		0.0992	Rho-square (0)		0.0992
Adj.Rho-square (0)		0.0855	Adj.Rho-square (0)		0.0841
AIC		3753.43	AIC		3759.43
BIC		3888.94	BIC		3909.45
Estimated parameters		28	Estimated parameters		31

*** Estimates are significant at 95% level of confidence, ** Estimates are significant at 90% level of confidence, * Estimates are significant at 80% level of confidence

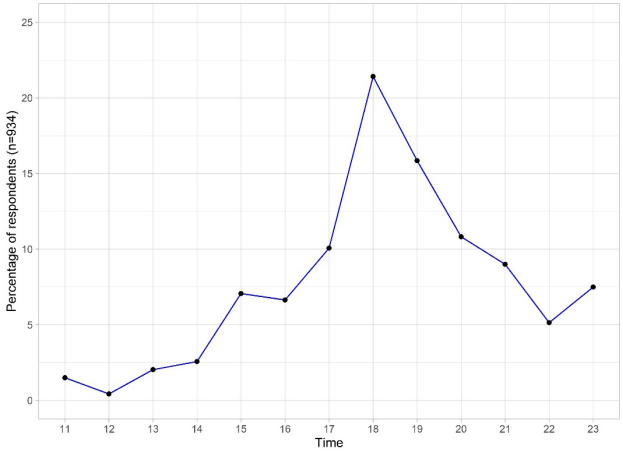


Figure 3 (a): Departure time of car commuters for the return trip

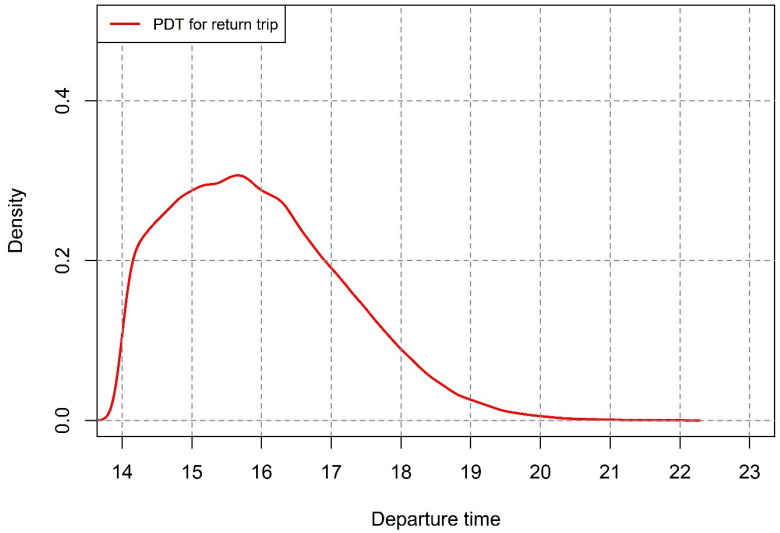


Figure 3 (b): Preferred departure time (work to home trip)

Time value of schedule delay

Generally, commuters encounter scheduled disutility due to early arrival or late arrival at workplace. Hence, commuters attempt to choose the appropriate departure time by making a trade-off between travel time and schedule delay. For instance, they can choose the alternative with the 'best travel time but large schedule delay' or 'worst travel time with no schedule delay' or anything in-between. Hence, to get better insight from our developed model, we have further estimated the time valuation of schedule delay (TVSD) to understand the sensitivities to schedule delay versus travel time. TVSD is estimated using the formulation proposed by Bwambale, Choudhury and Hess (*24*). It is estimated as the ratio of partial derivatives of utility equation (Equation 8) with respect to schedule delay and travel time. The following equation has been used and the average of the estimated output is shown in Table 5. Since, schedule delay term is insignificant for the return trip, TVSD is only estimated for the outbound trip.

$$TVSD_{occupation} = \frac{\partial V_{in}/\partial SD_{in}}{\partial V_{in}/\partial TT_{in}} = \frac{\alpha_{occupation} * 2(PDT_n - DT_i)}{\beta_{TT}} \quad (13)$$

The estimated TVSD is the unitless metric represents the amount of delay a commuter is willing to experience for a unit reduction in travel time. The TVSD is lower for office employees compared to self-employed personnel. This value signifies the fact that office employees have very less willingness to accept schedule delay – potentially due to the very inflexible working hours in the office. On the other hand, the self-employed personnel have the flexibility to choose longer schedule delay for the sake of reducing travel time. It may be noted that it was not possible to validate these due to absence of supplementary source of information. However, according to literature, the time valuation of schedule delay in European countries varies between 0.81 to 1.71 (32). Hence, the estimated output seems logical as the time valuation in developing countries will be lower than the developed countries.

TABLE 5: Time valuation of schedule delay

Direction	Office employee	Self-employed personnel	Weighted Average
Outbound	0.103	0.83	0.422

Policy insights

The estimated model parameters can be utilized in formulating peak spreading policies for car travel in Dhaka, Bangladesh. Some proposals have been suggested below in this regard:

- The coefficients of gender reveal that female office employees have a higher propensity to travel by car during the morning and evening peak hours. Targeted incentives for female employees (e.g., flexibility of the start times, working from home privileges, discounted transport cost during the off-peak and/or public transport, etc.) can hence be taken under consideration.
- The coefficients of income reveal that high-income office employees (household income >60,000BDT per month) are more likely to choose the peak time to travel when the schedule delay is minimum, but travel time is worst. This same group has higher affordability and hence are less likely to be price sensitive. Therefore, a congestion pricing policy targeting the peak time traveler, though an effective way for revenue generation, may not be effective to shift this group from travelling in the peak. This revenue can be useful means of funding efficient and dependable public transport services..
- The propensity to travel during the peak and off-peak time is very subtle for the users of ride-hailing services (e.g., Uber, Pathao Car). Changing the pricing structure of ride-hailing services to make peak-travel much more expensive compared to the off-peak can serve as the incentive to travel during the off-peak time
- The higher sensitivity to schedule delay of the office employee and their lower willingness to accept schedule delay (i.e., lower time value of schedule delay) reflects the strictness of their schedule. Hence, enhancing the flexibility of working hours of office employees (e.g., staggered start and end times, flexible start times, etc.) is a critical pre-requisite before the implementation of congestion pricing policies. To do so, the transport authority can work in collaboration with the employers to estimate the required ratio

of employee needed at a time in the office premises and offer flexibility to the rest so that they can travel during the off-peak time if needed

- The schedule delay was not found to have a significant effect for the work-to-home trips. Therefore, the afternoon peak is likely to be easier to flatten compared to the morning peak.

CONCLUSION

In this research, the key challenges in modelling the departure time choice model in the context of Dhaka, Bangladesh have been identified and solutions have been proposed. Separate departure time choice models of home-to-work and work-to-home of commuters using personal car/ride-hailing service have been developed to demonstrate the proposed solution approached to overcome the limitations of using RP data in modelling departure time choice. The methodological contributions include the following:

(1) A new method to estimate the travel time for the full range of alternative time periods using Google Maps API and stated travel times when the Google Maps API is not deemed to be a reliable stand-alone source of travel time information.

(2) Extension of the state-of-the-art method for representing PDT. Instead of assuming a constant value for a specific market segment or a generic statistical distribution, the proposed method includes two different statistical distributions for office workers and self-employed people acknowledging the high level of heterogeneity between and within each group. The estimation results support the hypothesis that a significant difference exists among different occupation groups in terms of their departure time choice.

Based on the results, an advanced MMNL model is recommended for outbound trips to account for the heterogeneity in schedule delay among the travelers. A simple MNL model was found to be adequate for return trip segment where the schedule delay was not found to have a significant effect. The key aspects of the study are listed below:

- The estimation results provide empirical evidence that departure time choices in Dhaka are significantly affected by activity duration, and schedule delay in addition to travel time. The results also reveal substantial heterogeneity depending on the type of job
- The results indicate that preferred departure times/arrival times, though unobserved in the RP data, are important aspects of departure time choice models. The proposed modelling framework to estimate the unobserved preferred departure time through the assumed distribution parameters (mean and standard deviation) using a mixed logit framework can be an effective way to address the unobserved preferred departure time issue, even in cross-sectional data. The framework can be also applied in case of passively generated data sources (e.g., GPS, mobile phone data, etc.) as well which also has the unobserved preferred departure time problem.
- Along with the distribution parameters we have estimated the sensitivities to schedule delay of different occupation groups which can be critical inputs in designing effective peak spreading policies in Dhaka city. Results highlight the fact that schedule delay and preferred departure time parameters are significant in the home-to-work trip, but not in the work-to-home trip segments. This finding can have important policy implications.
- Further, result suggests that car commuters are sensitive to travel time for both outbound and return trips. Therefore, policies aiming to reduce traffic congestion such as road pricing, inbound flow control etc. will enable the commuters to adopt their preferred departure time at the expense of minimal schedule delay
- Results indicate that schedule delay is the dominant factor for home-to-work trips and the time-value of schedule delay is much less compared to European countries (i.e., a commuter is willing to accept less unit of schedule delay per unit reduction in travel time). The effect of income (high- income office employee dummy) is found to be more substantial than that of gender (female office employee dummy) for the home-to-work trips – but the trend is opposite in case of the return trip. The results thus

strengthen the notion regarding the problems associated with transferability of the models between and developing countries.

It may be noted that the effect of travel cost has been explored as well. But travel cost has not been recorded in the data and in absence of information about the vehicle type and the type of the driver[10] it was not possible to estimate the cost in a reliable manner. This can be explored in future using primary data or appropriate supplementary data. Further, the current study focuses only on commute trips made by car which are the biggest contributors to traffic congestion in Dhaka. In future, this can be extended to commute trips made by public transport and paratransit modes and include other trip purposes.

However, even in its current form, the research findings can be practically useful for devising peak-spreading policies in Dhaka – either as a stand-alone tool to test the impact of varied start-times of offices in different locations or within an agent-based simulation tool to test the impact of different congestion pricing policies. In addition, the proposed framework can be useful in other developing countries with similar data issues.

ACKNOWLEDGEMENT

The funding for the research has been provided by the Faculty for the Future Program of the Schlumberger Foundation. Charisma Choudhury's time has been partially supported by the UKRI Future Leader Fellowship. The data used for the study has been made available by the Dhaka Transport Coordination Agency (DTCA). We acknowledge the help from Mr Anisur Rahman and Mr Dhrubo Alam of DTCA for providing clarifications regarding the data.

AUTHORS CONTRIBUTION

The authors confirm contribution to the paper as follows: study conception and design: KZ; data collection: KZ, CC; analysis: KZ; interpretation of results and model refinement: KZ, CC & SH; draft manuscript preparation: KZ. All authors reviewed the results and the responses and approved the final version of the manuscript

REFERENCE

[1] WB. Open Transport Development and Integration of ICT and Transport.In, World Bank, 2015.

[2] DTCA. *The Project on the Revision and Updating of the Strategic Transport Plan for Dhaka (RSTP)*, 2015.

[3] Siddique, M. A. B., C. F. Choudhury, and P. K. Mondal. Modelling the Behavioural Response to Congestion Pricing in Dhaka.In, 2014.

[4] Dong, H., and C. Cirillo. Space-time dynamics: A modeling approach for commuting departure time on linked datasets. *Journal of Transport Geography,* Vol. 82, 2020, p. 102548.

[5] Hendrickson, C., and E. Plank. The flexibility of departure times for work trips. *Transportation Research Part A: General,* Vol. 18, No. 1, 1984, pp. 25-36.

[6] Arellana, J., A. Daly, S. Hess, J. de Dios Ortúzar, and L. I. Rizzi. Development of surveys for study of departure time choice: two-stage approach to efficient design. *Transportation Research Record,* Vol. 2303, No. 1, 2012, pp. 9-18.

[7] Enam, A., and C. F. Choudhury. Methodological issues in developing mode choice models for Dhaka, Bangladesh. *Transportation research record,* Vol. 2239, No. 1, 2011, pp. 84-92.

[8] Fantom, N. J., and U. Serajuddin. The World Bank's classification of countries by income. *World Bank Policy Research Working Paper*, No. 7528, 2016.

[9] Bhat, C. R., and J. L. Steed. A continuous-time model of departure time choice for urban shopping trips. *Transportation Research Part B: Methodological,* Vol. 36, No. 3, 2002, pp. 207-224.

[10] Most cars in Dhaka are chauffeur-driven and there can be a substantial variation in the cost depending on the skill-level of the chauffer

[10] Small, K. A. The scheduling of consumer activities: work trips. *The American Economic Review,* Vol. 72, No. 3, 1982, pp. 467-479.
[11] McCafferty, D., and F. L. Hall. The use of multinomial logit analysis to model the choice of time to travel. *Economic Geography,* Vol. 58, No. 3, 1982, pp. 236-246.
[12] Holyoak, N. Departure time choice for the car-based commute.In, Planning and transport research centre (PATREC), 2008.
[13] Chaichannawatik, B., K. Kanitpong, and T. Limanond. Departure time choice (DTC) behavior for intercity travel during a long-holiday in Bangkok, Thailand. *Journal of Advanced Transportation,* Vol. 2019, 2019.
[14] Yang, F., X. Jin, and R. Liu. Tour-Based Time-of-Day Choices for Weekend Nonwork Activities. *Transportation Research Record,* Vol. 2054, No. 1, 2008, pp. 37-45.
[15] Bhat, C. R. Analysis of travel mode and departure time choice for urban shopping trips. *Transportation Research Part B: Methodological,* Vol. 32, No. 6, 1998, pp. 361-371.
[16] De Jong, G., A. Daly, M. Pieters, C. Vellay, M. Bradley, and F. Hofman. A model for time of day and mode choice using error components logit. *Transportation Research Part E: Logistics and Transportation Review,* Vol. 39, No. 3, 2003, pp. 245-268.
[17] Hess, S., J. W. Polak, A. Daly, and G. Hyman. Flexible substitution patterns in models of mode and time of day choice: new evidence from the UK and the Netherlands. *Transportation,* Vol. 34, No. 2, 2007, pp. 213-238.
[18] Cervero, R. Linking urban transport and land use in developing countries. *Journal of transport and land use,* Vol. 6, No. 1, 2013, pp. 7-24.
[19] Dimitriou, H. T., and R. Gakenheimer. Urban transport in the developing world: A handbook of policy and practice. 2011.
[20] Zannat, K. E., K. Ashraful Islam, D. S. Sunny, T. Moury, R. D. Tuli, A. Dewan, and M. S. G. Adnan. Nonmotorized Commuting Behavior of Middle-Income Working Adults in a Developing Country. *Journal of Urban Planning and Development,* Vol. 147, No. 2, 2021, p. 05021011.
[21] Anwar, A. M. Departure time choice analysis using ordered response probit model: journey to work trip in Dhaka City of Bangladesh. 2012.
[22] Arellana, J., J. de Dios Ortúzar, and L. I. Rizzi. Survey data to model time-of-day choice: methodology and findings.In *Transport Survey Methods: Best Practice for Decision Making*, Emerald Group Publishing Limited, 2013.
[23] Thorhauge, M., E. Cherchi, J. L. Walker, and J. Rich. The role of intention as mediator between latent effects and behavior: application of a hybrid choice model to study departure time choices. *Transportation,* Vol. 46, No. 4, 2019, pp. 1421-1445.
[24] Bwambale, A., C. F. Choudhury, and S. Hess. Modelling departure time choice using mobile phone data. *Transportation research part A: policy and practice,* Vol. 130, 2019, pp. 424-439.
[25] Ben-Akiva, M., and M. Abou-Zeid. Methodological issues in modelling time-of-travel preferences. *Transportmetrica A: Transport Science,* Vol. 9, No. 9, 2013, pp. 846-859.
[26] Koppelman, F. S., G. M. Coldren, and R. A. Parker. Schedule delay impacts on air-travel itinerary demand. *Transportation Research Part B: Methodological,* Vol. 42, No. 3, 2008, pp. 263-273.
[27] McFadden, D. Conditional logit analysis of qualitative choice behavior. 1973.
[28] Train, K. E. *Discrete choice methods with simulation*. Cambridge university press, 2009.
[29] Train, K. Halton sequences for mixed logit. 2000.
[30] Train, K., and G. Sonnier. Mixed logit with bounded distributions of correlated partworths.In *Applications of simulation methods in environmental and resource economics*, Springer, 2005. pp. 117-134.
[31] Hess, S., and D. Palma. Apollo: A flexible, powerful and customisable freeware package for choice model estimation and application. *Journal of choice modelling,* Vol. 32, 2019, p. 100170.
[32] Wardman, M., P. Chintakayala, G. de Jong, and D. Ferrer. European wide meta-analysis of values of travel time. *ITS, University of Leeds, Paper prepared for EIB*, 2012.