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Responses of drivers and motorcyclists to congestion charge

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Abstract

To effectively mitigate traffic congestion, many densely populated and well-developed cities worldwide decided to charge in-town traffic a congestion fee and the effectiveness of the congestion charge policy has been proven. However, a successful congestion charge scheme mainly depends on a clear understanding of urban travelers' responses. To do so, this study aims to model behaviors of travelers, including car drivers and motorcyclists, in response to in-town congestion charge in Taipei City and to propose feasible in-town congestion charge scheme accordingly. Four possible choices of travelers are defined as: 1) Pay for the charge, 2) Shift to off-peak hours/Cancel the trip, 3) Shift to public transportation, and 4) Shift to other private modes. Due to the possible correlation among alternatives and the potential heterogeneity among travelers, Multinomial Logit model (MNL), Nested Logit model (NL) and Mixed nested Logit model (MXNL) are estimated and compared based on a large-scale post-mail questionnaire survey. A total of 5,906 valid questionnaires were returned, including 3,450 car drivers and 2,536 motorcyclists. Among them, a total of 355 drivers and 314 motorcyclists who have morning peak-hour commuting experiences in Taipei City were selected. The estimation results show the existence of correlation among alternatives and heterogeneity for car drivers. Additionally, motorcyclists are much more sensitive to the charge than car drivers. The proportion of drivers and motorcyclists who are discouraged by various congestion charges are also predicted based on the estimated model. Suggestions for implementation of congestion charge are then proposed accordingly.

Keywords: Congestion charge; stated preference; mixed nested Logit model.

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1. Introduction

Traffic congestion is a major problem in the daily life of citizens in many densely populated and well-developed cities. To mitigate the congestion, many cities such as London, Oslo, Bergen, Stockholm, and Singapore have decided to charge in-town traffic a congestion fee, and this economic measure has demonstrated its effectiveness in militating traffic congestion. In-town congestion charge can internalize the external cost of private motor vehicles, effectively change the urban travel behaviors and reduce traffic congestion in peak hours. However, to abruptly implement this scheme without a sound planning in advance would soon become a political disaster. A successful in-town charge scheme mainly depends on a clear understanding of urban travelers' possible responses.

Many studies have analyzed driver responses to congestion charge. Topics considered in studies of driver responses to in-town charge include changes in departure time (earlier or later), route choice, mode choice (shifting fom private transport to public transport), trip cancellation, (Borjesson, 2008; Hess et al., 2007; Jong et al., 2003; Bhat, 1997b) and/or trip frequency (Kockelman and Kalmanje, 2005). Most of studies on congestion charge (Karlstrom and Franklin, 2009; Small et al., 2005; Calfee and Winston, 1998; Bhat, 1997b) focused on urban commuters in using private cars. Some researchers (Hess et al., 2007; Jong et al., 2003) classified travelers by trip purposes during peak hours to identify their preference disparities. If the business purpose is excluded, the time value of commuter groups is generally higher than that of those with other trip purposes; therefore, they are relatively willing to pay for the charge. If the purpose of driving is shopping or recreation, travel time value is usually low (Bhat, 1997a), and they are sensitive to the charge. That is, charging may affect the spatial distribution of private car shopping trips (distributed to shopping centers outside the central area) and alter transport mode choices (shifted to public transport), even adversely influence the occurrences of trip and decrease the number of customers of shopping centers in the charging area (Schmocker et al., 2006; Hu and Saleh, 2005). Burris and Pendyala (2002) reported that commuters who have flexible working-hour systems or who are retired tend to avoid paying the charge; commuters who have a high income and fixed working-hour system are comparatively less affected by congestion charge. Washbrook (2006) pointed out that the additional expenses for commuting (congestion charge or parking fee) on self-driving commuters are likely to alter their transport modes even with the increase in travel time by shifting to public transportation. In Golob (2001), a structural equations model of the public attitude towards the congestion pricing plan found that the equity of plan is the main concern. Saleh and Farrell (2005) found that the working-hour scheme, children and activity scheduling prior to departures are associated with the commuters' decision of departure time. They concluded that the congestion charge is an inevitable burden to those with inflexible working hours scheme and family factors (taking care of children). Albert and Mahalel (2006) showed that whether a commuter would change his/her departure time or transport mode due to congestion charge is related to whether he/she could control his/she departure time and the charge period in the area; therefore, the charging policy might change current work hours arrangements (flexible hours and work at home). Washbrook (2006) indicated that a levy for congestion without the provision of public transport would burden low-income persons. Arentze and Timmermans (2007) thought that in the long run, congestion charge might transform people's housing location choice. Ben-Elia and Ettema (2009) also indicated that since the value of times on travelers are diverse, so the effects of the charge on travelers may significantly differ, thus resulting in the concern of distribution equity. Karlstrom and Franklin (2009) showed that a congestion charge in Stockholm might have different welfare distribution effects on drivers across income levels and genders inside and outside of the charging area, the welfare of low-income (25-5500 SEK/month) group increased because most of them did not consider car driving as their first choice to enter the city during the charging period. In contrast, those in the lowest income level (<2500 SEK/month) and those who live outside the charging area would have a substantial loss of welfare. Therefore, the charging policy should not only concern the solution of traffic congestions, but also has to take regional economic developments, social welfare and residents' equity into account.

Many statistical methods have been used to investigate the effects of congestion charge on travel behaviors during peak and off-peak hours, such as Multinomial Logit models (MNL) and Nested Logit (NL) (Karlstrom and Franklin, 2009; Arentze and Timmermans, 2007; Albert and Mahalel, 2006; Washbrook et al., 2006; Hu and Saleh, 2005; Saleh and Farrell, 2005; Brownstone et al., 2003; Burris and Pendyala, 2002; Golob, 2001; Calfee and Winston, 1998), Ordered Logit models (Schmocker et al., 2006), Ordered Probit models (Ben-Elia and Ettema, 2009; Podgorski and Kockelman, 2006; Kockelman and Kalmanje, 2005), Mixed Logit (ML) or Error Component Logit models (ECL) (Borjesson, 2008; Hess et al., 2007; Small et al., 2005; Jong et al., 2003; Bhat, 1997b). The travel behavior changes of commuters under congestion charging can be modeled by the above models, by the willingness-to-pay charge level, and by the travel time value of road users with various trip purposes.

The two major attributes used to model travel behaviors in the discrete choice model are travel cost and travel time. However, definitions of perceived travel cost and travel time vary. For example, congestion charge, fuel cost, and parking fee can be considered in total or separately, as a part of travel cost. However, if they are separately modeled, special attention is needed to interpret the definitions of values along with their estimates. In addition to travel time varies under peak and off-peak hours, schedule delay caused by the changed departure time decisions needs to be considered under congestion charge schemes. On the other hand, the observable and unobservable characteristics of travelers also influence the measurement accuracy of the driver's attitude towards congestion charge (Borjesson, 2008; Hess et al., 2007; Jong et al., 2003; Bhat and Castelar, 2002; Bhat, 1997b). The observable characteristics refer to the measurable socioeconomic characteristics of travelers, such as income, gender and age; the unobservable characteristics refer to the unobservable heterogeneity (taste variation) among travelers or the correlations among choice alternatives. If the model cannot accommodate the heterogeneity among travelers, erroneous estimations may cause misjudgment of policy implications.

Since the congestion charge policy is closely related to the people's daily life, the public opinions should be taken into account, and validated survey methods should be considered (Podgorski and Kockelman, 2006). To access new traffic management strategies, many studies collect stated preference data of the surveyed people. Additionally, in the scenario design, in additional to travel cost, travel time and schedule delay, different studies have different situations and attributes as they have different analysis purposes. Calfee and Winston (1998) used stated preference models to estimate the value that commuters are willing to pay to save travel time. They found that even high-income commuters, having adjusted to congestion through their modal, residential, workplace, and departure time choices, simply do not value travel time savings enough to benefit substantially from tolls. The research scheme design of Bhat and Castelar (2002) considered the peak and off-peak hours, total number of passengers and the competition with the rapid transit system. The SP scheme design of Jong et al. (2003) considered the departure time of commuters, the length of stay of commuters, and the competitiveness of public transport. Saleh and Farrell (2005) defined the departure time of commuters as advanced departure, delayed departure and unchanged schedule. Arentze and Timmermans (2007) took the housing area as the selection scheme, so as to determine the effect of levying congestion charge on the commuters selecting resident area. Albert and Mahalel (2006) distinguished respondents by arrival time and then designed congestion charge and parking fee systems at different rates. Washbrook et al. (2006) considered the mode choices of self-driving, ride sharing and shuttle bus with the attributes of parking fee and walking time. Hess et al. (2007) combined multiple possible schemes from departure time, transport and commuter characteristics in Britain and the Netherlands. To reflect the behavior of possible advanced or delayed arrival at the destination of commuters, the design also considered the schedule-delay attribute. Borjesson (2008) considered walk/bicycle scheme, and the commuting attributes considered the variability of travel time and specific departure time (7:30 AM).

Notably, the above discussions are from the perspective of car users and do not consider regions where the motorcycle is the prevailing transportation mode. The automobile and motorcycle are popular in Taipei City, although with well-developed and designed mass rapid transit (MRT) and bus service, there is still severe traffic congestion during morning peak hours. Therefore, this study investigated travel behavioral changes by discrete choice modeling based on stated preference survey on users of private motor vehicles (cars and motorcycles), so as to assess the efficiency and equity of charging policy based on the behavioral responses of different motor vehicles commuters during peak hours (change in transport and departure time).

The cities of Taiwan, especially in Taipei City, are densely populated because land available for buildings and roads is limited. Rapid increases in commuting traffic caused by urbanization of neighboring cities have seriously reduced the efficiency of roadway networks during peak hours. Some studies have advocated levying a congestion charge to reduce private vehicle traffic entering the city, to improve the traffic congestion and enhance the patronage of public transportation, and to increase local tax revenue. The successful planning of congestion charge is to acknowledge the behavioral responses of urban commuters under different charge levels. However, the policy may have negative social and economic impacts if most of travelers are insensitive to the congestion charge and traffic is still seriously congested under congestion charge, or in contrast, too many commuters are discouraged and cancel their trips due to congestion charge. Therefore, it is important investigate and collect public opinions from the influenced area to serve as the basis for congestion charge planning (Podgorski and Kockelman, 2006).

Although Taiwan is well-developed, due to the low cost and convenience of motorcycles, motorcycles are the most favorable transportation mode and prevail across unban streets. Applying the in-town congestion charge only to cars may not resolve traffic congestion due to the high motorcycle traffic volume, along with increased motorcycle traffic shifting from the discouraged car drivers.

To investigate whether the effective congestion charge policy should be applied to both cars and motorcycles, this paper modeled the travel behaviors of car drivers and motorcycles in response to congestion charge. The remainder of this paper is organized as follows. Section 2 briefly describes the survey data and descriptive statistics. Section 3 presents the analytical models adopted in this paper. Section 4 compares model performance and discusses their estimation results. Section 5 analyzes the responses of car drivers and motorcyclists under various charge rates based on the estimated results of the best performing model. Finally, Section 6 concludes the study and suggests future works.

2. Model

To model the travel behaviors of car drivers and motorcyclists in response to congestion charge, four travel choice alternatives are defined and MNL, NL, and mixed nested logit (MXNL) models are respectively estimated, where NL and MXNL models aims to account for the potential correlation among alternatives. Hess et al. (2007) demonstrated that the behavior sensitivity of transport mode choice shifting is obviously lower than departure time shifting for city commuters, while travelers facing congestion pricing are likely to change departure time without switching their transport modes. Based on this, the proposed nested structure of the travel choice alternatives is depicted as Fig. 1, which attempts to accommodate the departure time correlation among choice alternatives due to the similarity shared in the common feature of peak-hour trip. The alternatives of traveling during peak hours (remain original departure time) and traveling during off-peak hours or trip cancellation (change departure time) are in separate nests.

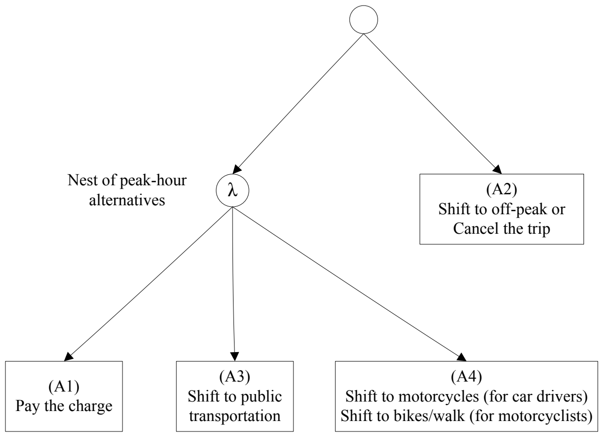


Fig.1. The nested structure of travel choice alternatives

The general application considers a general two-level NL model with *k* non-overlapping nests of alternatives. The NL probability that alternative *i* in nest *k* chosen by a driver/ motorcyclist *n* is following:

$$P_{ni} = P_{ni/B_k} P_{nB_k} = \frac{e^{V_{ni}/\lambda_k} \left(\sum_{j \in B_k} e^{\frac{V_j}{\lambda_k}} \right)^{\lambda_k - 1}}{\sum_{l=1}^{K} \left(\sum_{j \in B_l} e^{V_{nj}/\lambda_l} \right)^{\lambda_l}} \tag{1}$$

where, $V_i=\beta X_{ni}$, the alternative utility V_i within the nest B_k, and a vector of observed variables specific to a driver/ motorcyclist n and alternative i, X_{ni} are the explanatory variables associated with parameters β. P_{ni/B_k} is the probability of choosing alternative i conditional on choosing the nest B_k, P_{ni/B_k} is the marginal probability of choosing nest B_k of which i is within, B_l is the subsets of all alternatives included in nest B_k, λ_k is the logsum or inclusive value parameter for the nest B_k. The NL model is consistent with the principle of utility maximization if the conditions, $0 < \lambda_k \leqq 1$, are satisfied for all λ_k. If $\lambda_k=1$, the MNL is a special case of NL. For further discussions of NL models see Train (2009).

To acknowledge the heterogeneity in the perceived congestion charge among travelers (unobserved factors that may vary across unobserved travelers), the mixed variant of the NL model (MXNL) is estimated by setting a random parameter specified to congestion charge. The MXNL class of models involves the integration of the NL formula over the distribution of unobserved random parameters, as expressed below:

$$P_{ni}(\theta) = \int L_{ni}(\beta) f(\beta \mid \theta) d\beta \tag{2}$$

where, $L_{ni}(\beta)$ is the NL probability; β is parameter that are random realizations from a density function $f(.)$ and θ is a vector of underlying moment parameters characterizing $f(.)$.

Accordingly, the MXNL probability is a weighted average of the standard NL evaluated at different values of β, with the weights regarding its distribution $f(\beta)$. Since the integrand has no closed form, the values of β, are drawn from a simulation procedure which is repeated many times and the results are averaged. The simulated probabilities enter the likelihood function to give a maximum simulated log-likelihood estimator. For further details of estimation issues also see Train (2003).

In addition, it is two scenarios that each individual had faced in the SP questionnaire, provided the more flexibility observing the two choices from a respondent. The simulated probability for n individuals and two responses by each individual is rewritten as following (Train, 2009):

$$P_{n\ell} = \int L_{n\ell}(\beta) f(\beta) d\beta \tag{3}$$

where $L_{n\ell}(\beta) = \prod_{t=1}^{2} P_{nit}$, and P_{nit} is the NL probability calculated at choice situation t.

In this paper, the models are coded by the GAUSS software, and the BFGS algorithm are applied (Aptech, 2006) for the log-likelihood optimization. The MXNL model was run with 150 Halton draws in the simulated log-likelihood estimation for conservative reason, though Bhat(2001) had demonstrated 125 Halton draws enough produced accurate parameters. Additionally, we observed that there are no significant differences in the estimation results as increase the draws above 100. Relevant mathematical details about Halton draws are available in Bhat (2001; 2003), and Train (2009).

3. Data

The empirical data were obtained from our previous study (Chiou et al., 2009), which performed a nationwide household questionnaire survey of car and motorcycle owners. A total of 20,000 questionnaires were post-mailed to car and motorcycle owners during September 1-30, 2008. The car and motorcycle owners were sampled based on a proportionally stratified random sampling method. A total of 4,871 valid questionnaires were returned from Taiwan 23 cities/counties, including 3,001 car owners and 1,870 motorcycle owners (valid response rate=24.4%).

Since Taipei city Metropolitan has well-developed public transportation systems with the potential and possibility to implement congestion charge schemes, only the returned valid samples within the vicinity of Taipei Metropolitan are selected for the following analysis. Additionally, those who did not enter Taipei City during morning peak hours are also excluded. Therefore, the results for a survey of 355 drivers and 314 motorcyclists are used in the following analysis.

In this survey, numerous socio-demographic and trip features regarding principal drivers/motorcyclists in households were collected, especially for their responses to various congestion charge rates. The purpose of the questionnaire item was to survey preferred travel behavior changes during the morning peak hours (7:00~9:00 am).

However, since congestion charge has never been implemented in Taiwan, the stated preference (SP) method is adopted in questionnaire design. Each respondent were asked to answer 2 randomly assigned scenarios. Additionally, the level information of fee provided NT $50 and NT $100 for drivers, NT$25 and NT $50 for motorcyclists. For further details about the questionnaires, see Chiou et al. (2009).

Table 1. Demographic breakdown of selected drivers and motorcyclists

Item	Category	Car driver Counts	%	Motorcyclist Counts	%
Gender	Female	51	14.4	67	21.3
	Male	304	85.6	247	78.7
Age	≤ 30	36	10.1	129	41.1
	31~50	168	47.3	124	39.5
	≥ 51	151	42.5	61	19.4
Education years	≤ 9	67	18.9	75	23.9
	10~12	88	24.8	90	28.7
	13~16	159	44.8	129	41.1
	≥17	41	11.5	20	6.4
Occupation	White-collar	222	62.5	208	66.2
	Blue-collar	66	18.6	39	12.4
	Other	67	18.9	67	21.3
Monthly income (NT$ 1,000)	> 20	53	14.9	85	27.1
	20-40	105	29.6	118	37.6
	40-60	113	31.8	83	26.4
	60-80	48	13.5	14	4.5
	≥ 90	36	10.1	14	4.5
Distance to the nearest public transport station	≤ 50 m	95	26.8	84	26.8
	150~50 m	62	17.5	60	19.1
	350~150 m	67	18.9	75	23.9
	550~350 m	61	17.2	46	14.6
	≥ 550 m	70	19.7	49	15.6
Frequency of driving/riding to work or school per week	None	115	32.4	94	29.9
	1~4	64	18.0	50	15.9
	5	106	29.9	102	32.5
	6~7	70	19.7	68	21.7
Frequency of driving/riding for leisure or visiting per week	None	94	26.5	130	41.4
	1	121	34.1	77	24.5
	2	102	28.7	59	18.8
	≥3	38	10.7	48	15.3
Number of cars	None	0	--	90	28.7
	1	237	66.8	170	54.1
	2	94	26.5	43	13.7
	≥3	24	6.8	11	3.5
Number of motorcycles	None	75	21.1	0	--
	1	133	37.5	91	29.0
	2	90	25.4	106	33.8
	≥3	57	16.1	117	37.3
Number of bikes	None	136	38.3	85	27.1
	1	109	30.7	109	34.7
	2	71	20.0	64	20.4
	≥3	39	11.0	56	17.8
Total		355	100.0	314	100.0

The travel alternatives in response to congestion charge include: “(1) do not change the original travel decision, and pay the charge”, “(2) change departure time or cancel the trip”, “(3) shift to public transportation”, and “(4) shift to other private modes (Drivers: Motorcycles; Motorcyclists: Bikes/Walk)”.

Table 1 presents the demographic characteristics of the sampled drivers and motorcyclists. Notably, most drivers and motorcyclists were male, and the proportion of male motorcyclists is even 5% greater than that of drivers. The age distribution was older in drivers ("31~50" and "≥ 51") than in motorcyclists ("≤ 30" and "31~50"). The "Education level" could not be found significant discrepancy between car drivers and motorcyclists. The income distribution of car drivers is also higher than that of motorcyclists. Regarding the distance to the nearest public transport terminal/stop (regardless of vehicle type), over 60% of selected owners lived within 350m, and over 80% of selected owners lived within 550m, suggesting the convenience of public transportation in Taipei.

For work (and school) trip purpose and frequency, 29.9% of drivers and 32.5% of motorcyclists driving cars /riding motorcycles to work (or to school) every work days (five days a week). However, 32.4% of drivers and 29.9% of motorcyclists still preferred other transport modes to enter Taipei city (e.g. mass rapid transit, buses, and bicycles).

Finally, survey of household vehicle ownership showed similar ratios of cars to motorcycles. Most households owned one car/one motorcycle. Notably, however, the percentage of households owning more than three motorcycles was high (37.3%), which indicates the wide use of motorcycles in Taipei. Actually, car and motorcycle ownership ratios in Taipei City are the lowest among other cities in Taiwan due to the convenient public transportation system.

Table 2 shows the choice probabilities of the stated preference alternatives. Note that under the congestion charging scheme, car drivers and motorcyclists have similar patterns of choice shares. The highest choice ratios of car drivers and motorcyclists are "Shift to off-peak hours or cancel the trip", followed by "Pay the charge". Additionally, 17.2% of car drivers shift to motorcycles in town, and only 13.5% of car drivers shift to public transportation. However, 20.9% of motorcyclists will shift to public transportation and 8.8% of them will choose to ride a bike, or walk. Of course, none of the sampled motorcyclists shifted to driving a car since they have to pay higher congestion charge.

Table 2 further reports the travel time and travel cost (fuel cost or public transportation fare, but congestion charge is not included) of car drivers and motorcyclists. Notably, those who shift to public transportation tend to have the highest travel cost and travel time among other choices, suggesting those who having a longer trip prefer to shift to public transportation.

Table 2. Travel choice shares along with travel time and travel cost statistics

Travel choices	Choice shares (%)	Travel time (minutes)		Travel cost (NT$)	
		Mean	Std.	Mean	Std.
Drivers (*n*=710)					
Pay the charge	32.1	33.4	12.9	26.9	26.1
Shift to off-peak hours/Cancel the trip	37.2	26.4	10.4	26.9	26.2
Shift to public transportation	13.5	40.3	13.5	31.8	54.7
Shift to motorcycles	17.2	34.1	29.1	3.9	8.2
Motorcyclists (*n*=628)					
Pay the charge	28.3	26.8	12.3	11.6	13.1
Shift to off-peak hours/Cancel the trip	42.0	21.1	9.7	11.5	13.2
Shift to public transportation	20.9	34.8	11.8	22.9	17.3
Shift to bikes/walk	8.8	26.2	21.3	3.0	13.9

4. Results

To facilitate model estimation and comparisons, the variables significantly tested (at the significance level of α=0.10) in the MNL model are used to estimate the NL and MXNL models. Figure 1 shows the hypothesized nested structure of the NL model. Accordingly, a dissimilarity parameter was estimated to represent the correlation among the three nested peak-hour alternatives. The MXNL model further extends the NL structure to accommodate the preference heterogeneity in response to the congestion charge by assuming a normal distributed random coefficient. Tables 3-4 show estimation results of the MNL, NL, and MXNL models for car drivers and motorcyclists, respectively.

4.1. Responses of car drivers

As expected, Table 3 shows that the estimated generic variables of the MNL model, including congestion charge, travel cost, and travel time are all significant and negative. According to the estimated coefficients, the absolute value of the estimated parameter of congestion charge is much larger than that of travel cost, suggesting that car drivers are more sensitive to congestion charge than traditional travel cost (such as fuel cost and parking fee) and to level congestion charge is more effective than to increase fuel cost or parking fee. The average value of travel time is NT $246.32 dollars/hour (about $8 dollars/hour). Demographic characteristics of the driver (e.g., income, gender, education years, and work status) and characteristics of the trip (weekly frequency of driving to work, driving for leisure or visiting trip purpose, and inertia variable of public transportation for work or school) are also considered.

Table 3. Estimation results of car driver responses

Variables	Models					
	MNL		NL		MXNL	
	β	*t-value*	*β*	*t-value*	*β*	*t-value*
Constant						
A1.Pay the charge	-0.005	-0.01	-0.064	-0.21	4.994	23.19
A2.Shift to off-peak hours/Cancel trip	-0.660	-1.62	-0.830	-2.45	0.106	0.81
A3.Shift to public transportation	-2.069	-3.84	-1.573	-2.75	-4.804	-13.94
A4.Shift to other travel modes (Motorcycles)	-	-	-	-	-	-
Generic variables						
Congestion charge	-0.101	-2.99	-0.084	-2.73	-1.374	-11.02
Congestion charge (Std.)	-	-	-	-	1.594	8.00
Travel cost	-0.076	-2.49	-0.054	-1.95	-0.078	-2.18
Travel time	-0.312	-3.14	-0.256	-2.73	-0.308	-3.00
Demographics						
Income (A1 & A3)	0.092	3.01	0.068	1.99	0.178	2.37
Male (A1 & A2)	0.591	2.48	0.473	2.24	0.246	2.43
Education years (A3)	0.057	1.76	0.041	1.48	0.119	2.14
Age > 50 (A4)	0.505	2.30	0.357	1.77	0.775	5.07
Blue-collar workers (A2)	0.409	2.06	0.885	2.44	0.639	14.09
Weekly frequency						
Commuting trip (A3)	0.152	2.88	0.111	2.14	0.249	2.76
Leisure and visiting trip (A2)	0.102	1.77	0.101	1.76	0.094	1.64
Inertia						
Public transport to work/school (A3)	1.232	3.83	0.411	2.08	1.254	2.30
Dissimilarity						
Peak-hour alternatives			0.721	3.38	0.258	5.35
Value of time (*NT$/hr*)		246.32		284.44		237.15
LL (0)		-912.35		-912.35		912.35
LL (β)		-827.86		-827.15		-716.39
ρ^2		0.093		0.094		0.215
Number of samples (responders)						710 (355)

Therefore, when the congestion charge is levied in the morning peak hours, male drivers with a high income still drive in-town and pay for the charge. Blue-collar male drivers have higher intention to enter the city in the off-peak hours or to cancel the trip. The car drivers with higher education years, higher weekly frequency in commuting and original public transportation users (inertia variable) prefer to shift to public transportation. Elderly drivers (above 51 years old) prefer to shift to motorcycles.

According to the estimated NL model, the estimated dissimilarity parameter is within the reasonable range, which supports the nested structure of the proposed model. The NL model also significantly improves goodness of fit of the MNL model at the confidence level of 95%, $\chi_{1,0.05}$ = 3.84. To account for the heterogeneity in congestion charge, the estimated MXNL model significantly enhance goodness of fit in comparison to the MNL and NL models in terms of ρ^2 and the dissimilarity parameter is still within a reasonable range. Since the MXNL simultaneously considers heterogeneity and panel data processing, the estimated coefficient changes. The time value is NT$237.15 dollars/hr, which is slightly lower than the time value obtained by the MNL and NL models. This result is consistent with the empirical results of Bhat and Castelar (2002) and Daniels and Hensher (2000) that ignoring unobserved heterogeneity and/or state dependence can lead to inflated money values of travel time. The empirical data also indicate that unobserved heterogeneity and mode alternatives substitution pattern are intertwined for car drivers.

In contrast, the estimated value of congestion charge in the MXNL model increases the difference in travel cost. The perceived cost of congestion charge is 17.6 times of travel cost, suggesting that car drivers are rather reluctant to pay for the charge. The significantly tested coefficient of the standard deviation of congestion charge suggests that the responses of drivers to the congestion charge are heterogeneous. Specifically, the estimated mean and standard deviation coefficients of congestion charge depict the coefficients distribution on congestion charge effects for car drivers. While the mean coefficient of congestion charge is zero (no effect), 80% of drivers will be affected by the congestion charge (the congestion charge effects for 80% travelers are negative), and the other 20% drivers are not affected by congestion charge (the congestion charge effects for remaining 20% travelers are non-negative).

4.2. Responses of motorcyclists

Table 4 shows the estimation results for motorcyclists, which indicate that the sign and significance of congestion charge, travel cost and travel time of the MNL model are coincident with those of car drivers, but the estimated time value is only about 60% of car drivers, and congestion charge is equivalent to 2.4 times of travel cost. Blue-collar male drivers with high income and high weekly frequency to work (school) have high willingness to pay the charge. Commuters with higher education years, higher weekly frequency in riding to work (school) and originally take public transport to work or school are more likely to choose public transport mode. Younger commuters (under 31 years old) are unlikely to choose public transport. However, highly educated commuters prefer to shift to bicycling or walking. Male and blue collar motorcyclists with higher income are more willing to pay the charge, but those who with higher education years are more likely to shift to public transportation.

The nested structure of the motorcyclist NL model is confirmed in coinciding with car drivers, but the estimates for motorcyclist are reduced as well as their associated t-values. The difference indicates that the assumed NL structure may not perfectly depict the preferences of motorcyclists. Additionally, the estimated MXNL model shows the dissimilarity parameter does not significantly different from 1, suggesting that only the accommodation of unobserved heterogeneity can influence the taste variation of motorcyclist. The MXNL model (reduced to the mixed logit model, ML) has the best goodness of fit in terms of ρ^2.

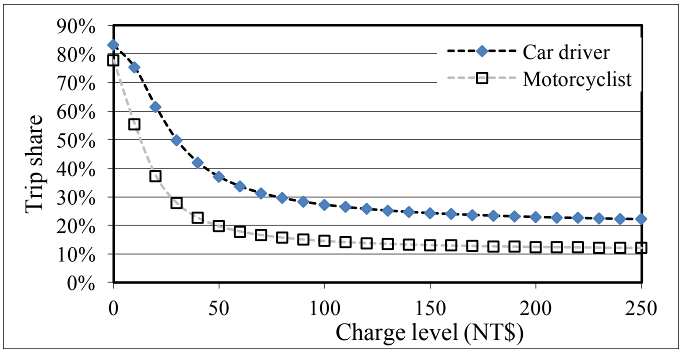
According to the estimated MXNL model, the cost of congestion charge perceived by motorcyclists is 11.4 times that of travel cost, which is much lower than that perceived by car drivers. However, the result still consistently show motorcyclists are also reluctant to pay the charge. Similarly, the coefficient of standard deviation of congestion charge has also been significantly tested, suggesting the heterogeneity of motorcyclists in response to congestion charge. The value of travel time for motorcyclists (NT$103 dollars/hr) is less than half of that for car drivers (NT$237 dollars/hr).

5. Applications

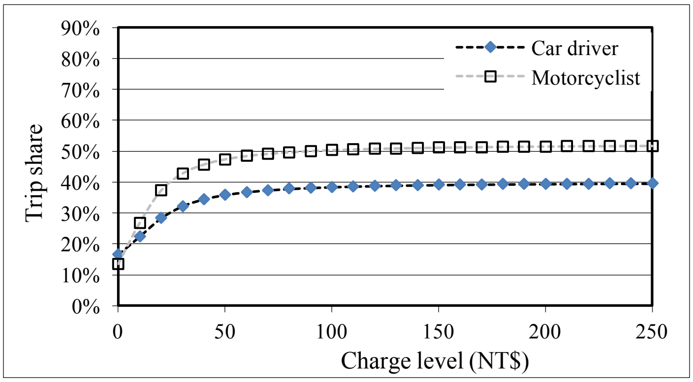
Based on the best performing model, MXNL model, the travel behaviors of car drivers and motorcyclists in response to various congestion charge rates are predicted as shown in Fig. 2. From Fig. 2(a), the usage rates of cars and motorcycles rapidly decrease, but as the charge exceeds NT$ 50 dollars, the only slight reduction in usage of cars and motorcycles, suggesting that NT$ 50 dollars may be considered as a good reference rate for the policy. Most of these discouraged travelers shift to depart during off-peak hours or cancel the trip, implying the difficulty to shift them to public transportation, especially for car drivers, because they prefer shifting to motorcycles rather than public transportation.

Table 4. Estimation results of motorcyclist responses

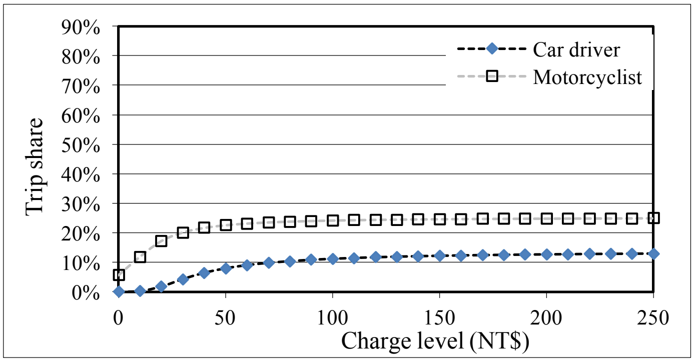
Variables	Models					
	MNL		NL		MXNL	
	β	*t-value*	*β*	*t-value*	*β*	*t-value*
Constant						
A1.Pay the charge	0.848	1.64	0.136	0.71	1.586	33.23
A2.Shift to off-peak hour/Cancel trip	1.313	3.00	0.015	0.06	1.479	34.41
A3.Shift to public transportation	-0.140	-0.60	-0.169	-1.51	-0.274	-2.71
A4.Shift to other travel modes	-	-	-	-	-	-
Generic variables						
Congestion charge	-0.309	-4.91	-0.106	-1.90	-1.130	-9.50
Congestion charge (Std.)					0.917	11.64
Travel cost	-0.127	-2.25	-0.047	-1.62	-0.099	-2.28
Travel time	-0.294	-2.53	-0.131	-1.94	-0.169	-2.48
Demographics						
Income (A1)	0.078	1.94	0.025	1.28	0.168	3.73
Male (A1)	0.513	2.02	0.157	1.38	0.745	16.31
Education years (A3 & A4)	0.714	2.77	0.235	1.50	0.679	8.04
Age < 31 (A3)	-0.621	-2.28	-0.185	-1.41	-0.702	-17.86
Blue-collar workers (A1)	0.651	3.03	0.256	1.82	0.988	9.91
Weekly frequency						
Commuting (A1 & A3)	0.126	3.80	0.044	1.44	0.167	5.52
Inertia						
Public transport to work/school (A3)	0.845	1.95	0.259	1.27	0.927	13.29
Dissimilarity						
Peak-hour alternatives			0.264	1.98	1.000	-
Value of time (NT/hr)		138.90		167.23		102.46
LL (0)		-802.58		-802.58		-802.58
LL (β)		-724.71		-713.41		-697.71
ρ^2		0.097		0.111		0.131
Number of cases (responders)						628(314)



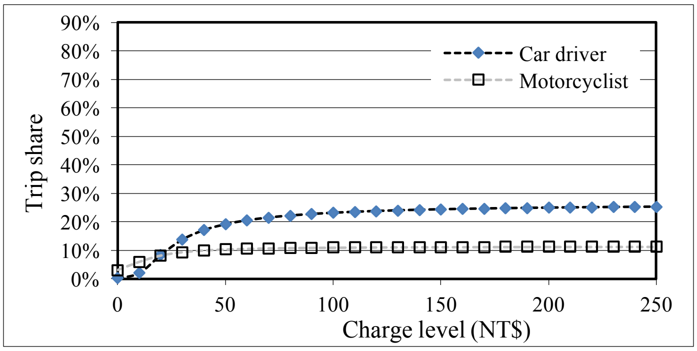
(a) Pay for the charge



(b) Shift to off-peak hours/Cancel the trip



(c) Shift to public transportation



(d) Shift to other private travel modes (Drivers: Motorcycles; Motorcyclists: Bikes/Walk)

Fig. 2. Predicted shares of four alternatives under various charge level

Figure 2 shows the travel behaviors of car drivers and motorcyclists in response to various congestion charge rates according to the best performing model, MXNL model. Figure 2(a) shows that the usage rates of cars and motorcycles rapidly decrease, but as the charge exceeds NT$ 50 dollars, the only slight reduction in usage of cars and motorcycles, suggesting that NT$ 50 dollars may be considered as a good reference rate for the policy. Most discouraged travelers shift their departure time to off-peak hours or cancel the trip, which implies that they have difficulty shifting to public transportation, especially for car drivers, because they prefer shifting to motorcycles rather than public transportation.

Table 5 shows elasticities of congestion charge, travel cost and travel time of corresponding alternatives according to the MXNL model. Since congestion charge only considers the alternative of A1, the direct elasticities of other three alternatives can be ignored.

Table 5. Elasticities of drivers and motorcyclists based on the estimated MXNL model

Attributes	Drivers	Motorcyclists
Congestion charge		
A1.Pay the charge	-0.802	-1.114
Travel cost		
A1.Pay the charge	-0.042	-0.082
A2.Shift to off-peak hour/Cancel trip	-0.210	-0.106
A3.Shift to public transportation	-0.170	-0.325
A4.Shift to other private travel modes	-0.021	-0.072
Travel time		
A1.Pay the charge	-0.206	-0.318
A2.Shift to off-peak hour/Cancel trip	-0.824	-0.330
A3.Shift to public transportation	-0.779	-0.864
A4.Shift to other private travel modes	-0.697	-1.136

As shown in Table 5, the response of motorcyclists to congestion charge is more elastic (elasticity > 1) compared to the response of car drivers; specifically, motorcyclists are much more sensitive to congestion charge than car drivers. Although the elasticities of car drivers regarding travel cost are all rather low, elasticities regarding travel time are much higher, suggesting that car drivers are insensitive to travel cost, but sensitive to travel time, especially shift to off-peak, trip cancellation, public transportation, and motorcycles. But for motorcyclists, only the elasticities regarding travel time while shift to public transportation and bikes are higher.

6. Conclusions

This study investigated travel behaviors of drivers and motorcyclists in Taipei in response to congestion charge based on a stated preference questionnaire survey. Three discrete choice models, MNL, NL and MXNL, are estimated to account for the correlation among peak-hour alternatives and heterogeneity among travelers.

The results for car drivers show that the MXNL model performs best, suggesting the proposed nested structure and heterogeneity of congestion charge are applicable for car users. Since the MXNL for motorcyclists is reduced into MXL, the proposed NL structure may not accurately depict the preferences of motorcyclists. The results also show that the effect of congestion charge is not the same as the increase of travel cost (e.g. fuel cost, parking fee and public transportation fare). That is, the effect of congestion charge is much larger than a simple increase in fuel cost or parking fee (17.6 times for car drivers and 11.4 times for motorcyclists). The irrational high perceived cost of congestion charge indicates the effectiveness of the congestion charge and the strong against opinions may be raised. Careful design and promotion of congestion charge policy is essentially important prior to the implementation.

The estimated model shows that the congestion charge reaches NT$50 per entry can effectively curtail the usage of cars and motorcycles entering Taipei CBD. However, the deterrent effects rapidly decrease as congestion charges increase. That is, charging NT$50 fee per entry for travelers can be substantial enough to alter their travel choices. Car drivers and motorcyclists have similar congestion charge responses. The largest proportion of drivers and motorcyclists prefer to pay for the charge or change their departure time to off-peak hours. Only a small percentage of them are willing to shift to public transportation. That is, changing their travel mode is more difficult than changing their departure time. Additionally, blue-collar male drivers and high income motorcyclists are rather willing to pay the charge and keep their travel behaviors unchanged, while higher education level commuters are likely to shift to public transportation. Since motorcyclists are more sensitive to the charge compared to drivers, many discouraged drivers may shift to using motorcycles in town.

The estimated models can be used to "optimize" the congestion charge by considering traffic volume and capacity of roadways entering Taipei CBD during morning rush hours. Meanwhile, travel time can be reduced due to the discouraged traffic under congestion charge. Therefore, the intertwining relationship between congestion charge rate and travel time deserves to be further investigated. This study also showed high heterogeneity in the response to congestion charge, which suggests vertical equity dilemma should be especially examined. If the charge policy largely discourages a specific group of travelers, such as the economic disadvantaged and residents in remote areas, strong resistance should be expected.

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