Impacts of Motorcycle Demand Management in Yangon, Myanmar

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Abstract.
This study analyzes the potential impacts of motorcycle demand management and its contribution to the transportation market in Yangon, Myanmar, where motorcycles have been banned since 2003. A vehicle ownership model with travel demand models of modal choice, destination choice, and trip frequency is estimated using a dataset comprising 8,289 households and 24,373 trips in Yangon, compiled by the Japan International Cooperation Agency in 2013. Next, a traffic demand forecast system is developed in which a traffic assignment model is integrated with a vehicle ownership model and travel demand models to evaluate the impacts of the motorcycle ban. Then, the expected impacts of the motorcycle ban are estimated by comparing multiple scenarios for 2013 and 2035. The results show that the ban could reduce traffic volume and vehicle kilometers traveled by approximately 18.0% and 26.9% in 2013, but only 4.5% and 6.0% in 2035. In other words, the ban significantly contributes to the mitigation of the current urban transportation problems; however, it would promote car ownership and the substitution of motorcycles in line with income growth, wiping out the effects of reduced motorcycle trips in the future. These findings suggest that developing cities should consider the long-term dynamics of motorcycle demand management.

Keywords: motorcycle ban, urban travel demand, developing city, Yangon

1. Introduction

Motorcycles are a key mode of urban transportation in many Asian developing cities (Barter, 1998; Tuan et al., 2005; Koizumi et al., 2013). In particular, they have been known to provide flexible and inexpensive mobility for low- and middle-income individuals. However, the growing number of motorcycles has led to severe traffic congestion and accidents in developing cities (Phan and Shimizu, 2011; Uy and Regidor, 2011). To tackle these issues, various related transportation policies have been proposed: motorcycle lanes and parking as well as improvements in motorcycle regulations (Hung, 2006; Institute for Transportation and Development Policy, 2009). A potential policy measure to regulate the number of motorcycles is introducing traffic demand management of motorcycles (Barter, 1998; Lai, 2007), including a ban on motorcycles in specific areas, regulation of motorcycle ownership and parking, and cordon pricing for motorcycle users. Although motorcycle demand management could contribute toward solving traffic problems in developing cities, its impacts have not been sufficiently studied, possibly because few cities have implemented policies that regulate motorcycle ownership and use (Ye et al., 2009). An exception, however, is Yangon City, the former capital of Myanmar, where motorcycle use has been prohibited in most urban areas since 2003 (JICA, 2014; Kojima et al., 2015a).

Thus, this study analyzes the potential impacts of motorcycle demand management and its contribution to the transportation market in Yangon. To do so, a traffic demand forecast system is developed using large-scale travel data collected by the Japan International Cooperation Agency (JICA) in 2013. The expected impacts of a motorcycle ban are then estimated using a scenarios analysis, in which traffic demand is simulated with a demand forecast system. An advantage of this study is that it empirically analyzes the potential impacts of a motorcycle ban from the viewpoint of not only a modal shift but also changes in vehicle ownership, trip generation, and destination choice using a consistent model framework. This approach is expected to provide an understanding of the overall impacts of a motorcycle ban in a systematic manner, which could facilitate a holistic discussion on policy implications.

The remainder of this paper is organized as follows. Section 2 reviews the extant literature. Section 3 describes the current conditions of the urban transportation market in the Yangon metropolitan area and presents the data used in the empirical analysis. Section 4 formulates the models of an individual's vehicle ownership and travel behavior and presents the estimation results of the model. Section 5 develops the travel demand forecast system using the estimated models and presents the simulation results of the impact analysis. Section 6 summarizes the findings and suggestion for future research.

2. Literature Review

Some studies have demonstrated the importance of motorcycle ownership management and use in developing cities. For example, Hung (2006) assessed traffic management measures using multiple criteria and accordingly, listed strategies for motorcycle-dependent cities. The Institute for Transportation and Development Policy (2009) reviewed existing knowledge on management policies for two- and three-wheeler use and summarized recommended strategies. Ye et al. (2011) estimated the impacts of a motorcycle ban policy using travel preference data of local residents in Huizhou, China, and showed that while the policy suppresses motorcycle use, it promotes the use of other transportation modes. Xingdong et al. (2009) studied restrictions on motorcycle use across main urban areas in Guangzhou, China, since 2007 and reported that the ban decreased the use of motorcycles and increased that of public transportation, bicycles, and cars. These studies have highlighted the impact of a motorcycle ban mainly on an individual's modal choice, such as a shift from the use of motorcycles to other transportation modes. However, we expect that such a regulation also influences an individual's trip generation and/or vehicle ownership, which could significantly affect urban traffic demand. In particular, vehicle ownership is strongly connected with its usage in developing cities, where provisions of public transportation are lacking (Dissanayake et al., 2001). Thus, this study investigates the potential impacts of a motorcycle ban with an integrated travel demand model that incorporates trip generation, vehicle ownership, and modal choice in Yangon City.

Although urban transportation is one of the most critical issues in Yangon City, it has been rarely studied mainly because of poor data availability. An exception is Zhang et al. (2008), who during Myanmar's closed-market era examined the potential impacts of introducing a new public transit on individual's behavior using stated-preference data in Yangon. Similarly, Kato et al. (2010a) analyzed the route choice behavior of bus commuters using stated-preference data for Yangon, while Kato et al. (2010b) reported on the city's urban bus system, including the regulatory framework and cost structure of bus operators. Kato et al. (2011) further studied the potential impacts of introducing a bus rapid transit system in Yangon by conducting a cost-benefit analysis using urban travel demand forecast models. Since the economic liberalization of Myanmar in 2012, an increasing number of studies have highlighted urban transportation problems in Yangon. For instance, the Japan International Cooperation Agency (JICA, 2014) administered large-scale travel surveys, including the personal

trip (PT) survey in Yangon metropolitan area, and proposed mid- and long-term urban transportation investment plans. Kojima et al. (2015b) reported on the urban transportation market using data collected by JICA. Tun et al. (2015) analyzed local car ownership using an ordered logit model with local data for Yangon City. Although studies have reported on the uniqueness of motorcycle regulations in Yangon City, to the best of our knowledge, no study analyzes its impact on urban transportation demand in the city.

3. Scope of Study and Data

3.1. Scope

Fig. 1 (a) illustrates the study area, which includes Yangon City (33 townships) and a part of six adjacent townships: Thalyin, Hmawbi, Helgu, Htantabin, Twantay, and Kyauktan. The total area is approximately 1,500 km^2 and the total population is approximately 5.7 million as of 2013. The central business district (CBD) of Yangon City is located to the southern part of the city, which is adjacent to where the Yangon River and Bago River meet. As the urban population increased, the urban area was extended from the CBD to the north. Accordingly, transportation infrastructure, including highways and rail networks, were developed to connect the CBD with the northern part of Yangon City. The main residential areas are located in the north-eastern part of the city, from which many commuters travel to their workplaces in the CBD (Kojima et al., 2015b).

Currently, a vast majority of urban transporters in Yangon rely on the bus system (Zhang, 2008; Kato, 2010a). A factor driving the increase in the modal share of buses is the motorcycle ban introduced in 2003 (31 townships and areas to the south of the CBD, namely Dala and Seik Gyi Ka Naung Toe, were not included) to reduce the number of traffic accidents (Myanmar Times, 2014). Fig. 1 (b) shows the motorcycle ban area, that is, where the use motorcycles is not permitted.

Source: JICA, 2014

Fig. 1. (a) Study Area in Yangon.

Source: Kojima et al., 2015

Fig. 1. (b) Motorcycle and Bicycle Ban Areas in Yangon.

Note that bicycle use is also prohibited in the CBD. The penalty for violating the motorcycle ban is 20,000 Myanmar Kyats (MMK) (approximately US $20) and that for not wearing a helmet is 10,000 MMK (approximately US $10) as of 2014 (Myanmar Times, 2014). The motorcycle ban has been considered to contribute to significantly reducing motorcycle ownership in Yangon (Kojima et al., 2015a). Kojima et al. (2015a) also reported that the mobility of Yangon's citizens does not largely depend on motorcycles and bicycles. First, this is because the surrounding areas are well connected with the CBD by public transportation and second, lower income people who reside to the south of the CBD across the Yangon River use ferries to access the district.

3.2. Data

This study uses a dataset compiled in the Project for Comprehensive Urban Transport Plan of Greater Yangon (YUTRA) project (JICA, 2014) organized by JICA in 2013. The YUTRA project team, which includes one of the authors, implemented eleven surveys intended to capture the travel patterns of local people and the level of transportation services such as travel speed, traffic volume by transportation mode, and socioeconomic attributes of trip makers (e.g., age, gender, occupation, car ownership, and income). One of the eleven surveys is the PT survey interviewed 44,988 individuals from 11,286 households in the 39 townships in Yangon from February to August 2013. The respondents were requested to maintain a daily travel diary, mention the socioeconomic and demographic characteristics of their households, and state opinions about transportation policies. Details of the PT survey are available in JICA (2014) and Kojima et al. (2015a).

Table 1 presents the descriptive statistics of household vehicle ownership by household monthly income and location of settlement, that is, inside or outside the motorcycle ban area. Note that this dataset was constructed using a random re-sampling process from the original dataset where the sample rate is controlled to account for 0.5–0.7% of the total households in each township as of 2013. This is because the sample rates of the original dataset greatly vary among townships. As a result, 8,289 households comprising 7,356 households within and 933 households outside the motorcycle ban area were obtained. First, this shows that motorcycle owners can be seen across income levels, although the motorcycle ownership rate marginally increases with income level, especially outside the ban area. This indicates that motorcycles are popular as an inexpensive transportation mode even in Yangon. Second, the motorcycle ownership rate within the ban area is significantly lower than that outside it. Although this is reasonable, 4.7–7.9% households within the ban area may still own motorcycles because individuals living along the border can ride their motorcycles outside it. Third, the car ownership rate increases with income level. Finally, the car ownership rate inside the ban area is higher than that outside it, except among the lowest income subgroup (Table 1). This is possibly because car ownership is promoted inside the ban area as a substitute for motorcycles.

Table 2 shows the descriptive statistics of respondents' modal share by vehicle ownership and trip origin, that is, inside and outside the ban area. Here as well, this dataset was constructed using a random re-sampling process of the original dataset, in which the sample rate is controlled to account for 0.4–0.6% out of the total households in each township as of 2013. In addition, non-motorized transportation modes are excluded from the dataset because they are mainly used for intra-zone short travels. Thus, 24,373 trips consisting of 22,591 trips from inside and 1,782 trips from outside the ban area were obtained.

Table 1. Descriptive statistics of household vehicle ownership by settlement location and household income.

Settlement area	Household monthly income	Car & Motorcycle		Car		Motorcycle		None		Total
	kyat/month	Obs.	%	Obs.	%	Obs.	%	Obs.	%	Obs.
Inside the ban area	100,000 or lower	2	0.2	30	3.0	52	5.2	919	91.6	1,003
	100,001 - 200,000	10	0.3	124	4.3	227	7.9	2,528	87.5	2,889
	200,001 - 300,000	15	0.9	186	10.9	135	7.9	1,369	80.3	1,705
	300,001 – 400,000	13	1.7	147	19.0	53	6.8	561	72.5	774
	400,001 – 500,000	5	1.3	106	27.5	27	7.0	248	64.2	386
	500,001 or higher	12	2.0	249	41.6	28	4.7	310	51.8	599
	Total	57	0.8	842	11.5	522	7.1	5,935	80.7	7,356
Outside the ban area	100,000 or lower	0	0.0	1	0.5	51	23.0	170	76.6	222
	100,001 - 200,000	7	1.5	11	2.3	156	33.2	296	63.0	470
	200,001 - 300,000	7	4.8	8	5.5	66	45.2	65	44.5	146
	300,001 – 400,000	6	10.7	5	8.9	24	42.9	21	37.5	56
	400,001 – 500,000	1	7.7	1	7.7	5	38.5	6	46.2	13
	500,001 or higher	3	11.5	1	3.8	16	61.5	6	23.1	26
	Total	24	2.6	27	2.9	318	34.1	564	60.5	933

First, it shows that car use is promoted by car ownership. Car owners inside the ban area use their vehicles more than those outside it. This is probably because the road infrastructure outside the ban area is so poorly maintained that car owners have lower incentive to use their vehicles. Second, motorcycle use is promoted by motorcycle ownership (Table 2). Motorcycle owners inside the ban area use motorcycles less than those outside it simply because it is prohibited. Third, the modal share of car or motorcycle owners in bus use is lower than the share of those who do not own vehicles. In other words, car or motorcycle ownership suppresses public transportation demand. Finally, the modal share of car owners in taxi use is higher than the share of those who do not own a vehicle both inside and outside the ban area. This is probably because the household income of car owners is sufficiently high for them to afford taxi charges.

Table 2. Descriptive statistics of modal share by trip origin and vehicle ownership.

Trip origin area	Vehicle ownership	Car		Motorcycle		Bus		Taxi		Total
		Obs.	%	Obs.	%	Obs.	%	Obs.	%	Obs.
Inside the ban area	Car owner	1,990	43.9	65	1.4	1,690	37.3	786	17.3	4,531
	Motorcycle owner	144	7.6	528	27.8	1,066	56.2	158	8.3	1,896
	No vehicle owner	606	3.7	222	1.3	13,833	84.0	1,806	11.0	16,467
	Total	2,740	12.0	815	3.6	16,589	72.5	2,750	12.0	22,894
Outside the ban area	Car owner	28	16.1	24	13.8	111	63.8	11	6.3	174
	Motorcycle owner	10	1.3	443	59.5	278	37.3	14	1.9	745
	No vehicle owner	20	2.2	127	13.7	763	82.1	19	2.0	929
	Total	58	3.1	594	32.1	1,152	62.3	44	2.4	1,848

4. Models

4.1. Vehicle ownership model

The vehicle ownership model is formulated as a discrete choice model (Ben-Akiva and Lerman, 1985) in which an individual is assumed to choose an option maximizing his/her utility function from a choice set. The model is specified to be a two-level nested logit model (Louviere et al., 2000): the upper level of the choice set consists of car or no-car and the

lower level comprises Car&Motorcycle or Car under the car ownership option and Motorcycle or No Motorized Vehicle under the no-car option. The utility functions of each option are assumed to be

$$V_n^o = V_{a,n} + V_{b,n} + V_{ab,n}, \tag{1}$$

where $V_{o,n}$ is the utility function of household *n* under the condition that the household owns a vehicle *o* (Car&Motorcycle, Car, Motorcycle, or None). $V_{a,n}$ is a partial utility function of household *n* if the household chooses an upper level option *a*, $V_{b,n}$ is the partial utility function of household *n* if the household chooses a lower-level option *b*, and $V_{ab,n}$ is the partial utility function of household *n* determined by the upper and lower levels of options *a* and *b*.

The probability of choosing a vehicle ownership status *o* for household *n* in the nested logit is expressed as

$$P_n^o = \frac{\exp\left(V_{b,n} + V_{ab,n}\right)}{\sum_{b'} \exp\left(V_{b',n} + V_{ab',n}\right)} \cdot \frac{\exp\left(V_{a,n} + \theta_\Lambda \Lambda_{a,n}\right)}{\sum_{a} \exp\left(V_{a,n} + \theta_\Lambda \Lambda_{a,n}\right)}, \tag{2}$$

where $\Lambda_{a,n}$ is a log-sum variable defined as

$$\Lambda_{a,n} = \ln \sum_b \exp\left(V_{b,n} + V_{ab,n}\right) \tag{3}$$

and θ_Λ is a coefficient related to the log-sum variable. Unknown coefficients are estimated using the full-information maximization likelihood method (Louviere et al., 2000).

4.2. Modal choice model

The modal choice model is formulated as the discrete choice model in which an individual is assumed to choose an option maximizing his/her utility function from a modal choice set. The individual's choice set is assumed to consist of car, motorcycles, buses, and taxis. It is specified as a standard logit model (Ben-Akiva and Lerman, 1985) in which the utility function is expressed as

$$V_{ijm,n} = \beta_{GC} GC_{ijm,n} + \sum_k \beta_k V_{mk,n}, \tag{4}$$

where $V_{ijm,n}$ is the utility function of individual *n* under the condition that he/she chooses a transportation mode *m* from origin *i* to destination *j*. $GC_{ijm,n}$ is the generalized travel cost of transportation mode *m*, $V_{mk,n}$ is the *k*th explanatory variable, and β is the unknown coefficient. Then, the probability of choosing a transportation mode *m* for individual *n* who owns *o* from origin *i* to destination *j* is

$$P_{ijm,n} = \frac{\exp\left(V_{ijm,n}\right)}{\sum_{m'} \exp\left(V_{ijm',n}\right)}. \quad (5).$$

The unknown coefficients are estimated by maximizing the likelihood function derived from equation (5).

4.3. Destination choice model

A destination choice model is formulated as the discrete choice model in which an individual is assumed to choose an option maximizing his/her utility function from a destination choice set. It is specified as a standard logit model incorporating the log-sum function derived from the modal choice model. The utility function is assumed to be

$$V_{ij,n} = \sum_{l} \gamma_l V_{ijl,n} + \gamma_\Lambda \Lambda_{ij,n}, \quad (6)$$

where $V_{ij,n}$ is the utility function of individual *n* under the condition that he/she travels from origin *i* to destination *j*, $V_{ijl,n}$ is the *l*th explanatory variable, γ is the unknown coefficient, and $\Lambda_{ij,n}$ is a log-sum variable from origin *i* to destination *j*, which is expressed as

$$\Lambda_{ij,n} = \ln \sum_{m} \exp\left(V_{ijm,n}\right). \quad (7).$$

The probability of choosing destination *j* for individual *n* from origin *i* is expressed as

$$P_{ij,n} = \frac{\exp\left(V_{ij,n}\right)}{\sum_{ij'} \exp\left(V_{ij',n}\right)}. \quad (8).$$

The unknown coefficients are estimated by maximizing the likelihood function derived from equation (8). The log-sum variable of equation (7) is formulated using the utility function of the modal choice model with the estimated coefficients. Thus, the estimation process of modal choice and destination choice models can be regarded the sequential estimation of the nested logit model (Hensher, 1986).

4.4. Trip frequency model

A trip frequency model is formulated as an aggregated linear regression model that explains the daily trip frequency generated from origin *i*. One of the explanatory variables is the log-sum variable derived from the destination choice model. As the log-sum variable represents the expected maximum utility level or expected indirect utility (Williams, 2002), the induced demand can be incorporated into the trip frequency. This is expressed as

$$F_{i,n} = \sum_q \eta_q V_{iq,n} + \eta_\Lambda \Lambda_{i,n}, \tag{9}$$

where $F_{i,n}$ is the daily trip frequency of individual n traveling from origin i , $V_{iq,n}$ is the qth explanatory, η is the unknown coefficient, and $\Lambda_{i,n}$ is the log-sum variable of origin i, which is expressed as

$$\Lambda_{i,n} = \ln \sum_j \exp\left(V_{ij,n}\right). \tag{10}$$

The unknown coefficients are estimated using the ordinary least squared method.

4.5. Model estimation

First, the study area of 39 townships was divided into 156 traffic analysis zones (TAZs) and a representative centroid is assumed in each TAZ. Next, a transportation network in Yangon is assumed, including major roads, secondary roads, selected local roads, and rail networks, with 1,862 nodes and 2,314 links. Then, sociodemographic and socioeconomic data are prepared for each TAZ and travel time and travel cost data are prepared on the basis of the transportation network.

The unknown coefficients in the vehicle ownership, modal choice, destination choice, and trip frequency models are estimated using the dataset. The explanatory variables in each model are selected using a trial-and-error process to achieve the best fitted results from a statistical viewpoint.

Table 3 shows the estimation results of the vehicle ownership model. *HH monthly income* denotes household monthly income (kyat/month). *MC ban area* equals 1 if a household resides within the ban area and 0 otherwise. *Over five-year stay in MC ban area* takes the value of 1 if a household has resided in the motorcycle ban area for more than five years and 0 otherwise. *Well-maintained road infrastructure area* equals 1 if a household resides in a township where road infrastructure is well maintained and 0 otherwise. *Poor bus service area* equals 1 if a household resides in a township where urban bus services are poorly provided and 0 otherwise.

The estimation results show that all coefficients are statistically significant. The model has theoretical consistency and high goodness of fit: the coefficient of a log-sum variable is between 0 and 1, while McFadden R^2 is sufficiently high. *HH monthly income* positively influences the utility of Car&Motorcycle, Car, and Motorcycle, given that higher income households can afford to purchase vehicles. The coefficient of *ln (HH monthly income/100,000)* is the highest for Car&Motorcycle, followed by Car and Motorcycle because a car is more expensive than a motorcycle. *MC ban area x ln (HH monthly income/100,000)* is significantly negative for Car&Motorcycle. This possibly means that a household is less motivated to own both a car and motorcycle if it is inside the ban area, which is reasonable given the ban on motorcycle use in the area. In the case of Motorcycle, *over five-year stay in MC ban area x ln (HH monthly income/100,000)* is significantly negative, while *over five-year stay in MC ban area* is significantly positive. Since more than 85% of households have monthly income of over 100,000 kyats per month (Table 1), *over five-year stay in MC ban area* negatively influences mid- and high-income households' motorcycle utility. This suggests that motorcycle ownership is suppressed inside the ban area. *Poor bus service area* is significantly negative for Car&Motorcycle and Motorcycle, while *well-maintained road infrastructure* is significantly positive for Car, which is reasonable.

Table 3. Estimation results of vehicle ownership model.

Variable	Option	Coefficient	t-statistic
ln (HH monthly income/100,000)	Car&Motorcycle	4.458**	5.41
ln (HH monthly income/100,000)	Car	3.725**	4.38
ln (HH monthly income/100,000)	Motorcycle	0.792 **	6.38
MC ban area x ln (HH monthly income/100,000)	Car& Motorcycle	–0.776 *	–2.05
Over five-year stay in the MC ban area x ln (HH monthly income/100,000)	Motorcycle	–0.438**	–2.98
Poor bus service area	Car& Motorcycle	0.721*	2.55
Poor bus service area	Motorcycle	1.525**	15.08
Over five-year stay in the MC ban area	Car	0.829*	2.34
Over five-year stay in the MC ban area	Motorcycle	0.471**	8.98
Well-maintained road infrastructure area	Car	2.493**	4.80
Log-sum	All	0.372**	4.49
Constant	Car& Motorcycle	–11.896**	–4.42
Constant	Car	–10.502**	–3.54
Constant	Motorcycle	–3.946**	–5.61
Number of observations		8289	
Initial log-likelihood		–11491.0	
Final log-likelihood		–4906.5	
Adjusted ρ^2		0.572	

Note: ** and * mean $p < 0.01$ and $p < 0.05$.

Table 4 presents the estimation results of the modal choice model. *Car ownership* equals 1 if an individual's household owns a private car and 0 otherwise. *Motorcycle ownership* equals 1 if a household owns a motorcycle and 0 otherwise. *MC ban area* equals 1 if a trip starts from a TAZ, which is located inside the ban area and 0 otherwise. *CBD* takes the value of 1 if a trip starts from the CBD and 0 otherwise. *Periphery area* takes the value of 1 if a trip starts from a periphery area and 0 otherwise. *Generalized cost* is defined as monetary cost plus time cost estimated using the value of time and travel time. The value of time is estimated from the average wage rate. The results show that all coefficients are statistically significant and McFadden's R^2 is sufficiently high. *Car ownership* is significantly positive for car use, while *MC ownership* is positive for motorcycle use. In other words, car and motorcycle owners prefer using their vehicles to travel. *MC ban area* is significantly negative for motorcycle use, which means individuals starting their trip from within the ban area are less likely to use a motorcycle. *CBD* is significantly positive for taxi use, whereas *Periphery area* is significantly negative for taxi use. This is because a trip starting from the CBD is mainly a business one in which an individual has higher willingness to pay for travel, whereas a trip traveling from peripheral areas is mainly a non-business trip. *Generalized cost* is significantly negative, which is reasonable.

Table 5 shows the estimation results of the destination choice model. *Daytime population* is the population during the daytime. *CBD* takes the value of 1 if the destination TAZ is the CBD district and 0 otherwise. *Major road* equals 1 if the destination TAZ is located along major roads and 0 otherwise. *Riverside* takes equals 1 if the destination TAZ is located next to major rivers and 0 otherwise. *Outside rivers* equals 1 if the destination TAZ is located beyond the major rivers from

the CBD and 0 otherwise. *Periphery area* takes the value of 1 if the destination TAZ is categorized as a periphery area and 0 otherwise. The results show that all coefficients are significant in t-value. The coefficient of the log-sum variable is between 0 and 1, while McFadden's R^2 is large enough. *ln (Daytime population)* is significantly positive because the daytime population mainly represents travelers commuting to workplaces. *CBD* is significantly positive because most offices and commercial facilities are located in the CBD. *Major road* is significantly positive because the areas along major roads have better accessibility while *outside rivers* is significantly negative owing to poorer accessibility. *Riverside* and *Periphery area* are significantly negative because these areas have fewer offices or commercial facilities.

Table 4. Estimation results of modal choice model.

Variable	Option	Coefficient	t-statistic
Car ownership	Car	2.880**	59.82
Motorcycle ownership	Motorcycle	3.657 **	47.02
MC ban area	Motorcycle	–1.950**	–23.69
CBD	Taxi	0.403**	8.64
Periphery area	Taxi	–0.918**	–11.08
Generalized cost	All	–0.00089**	–50.04
Constant	Car	–1.743**	–38.29
Constant	Motorcycle	–2.578**	–29.22
Constant	Taxi	–0.364**	–7.37
Number of observations		24267	
Initial log-likelihood		–33641.2	
Final log-likelihood		–18095.4	
Adjusted ρ^2		0.462	

Note: ** and * mean $p < 0.01$ and $p < 0.05$.

Table 5. Estimation results of destination choice model.

Variable	Coefficient	t-statistics
ln (Daytime population)	0.515**	25.63
CBD	0.510**	9.30
Major road	0.823**	22.78
Riverside	–0.815**	–9.09
Outside rivers	–0.721**	–3.24
Periphery area	–0.759**	–9.77
Log-sum	0.801**	69.50
Number of observations	4935622	
Initial log-likelihood	–24892.4	
Final log-likelihood	–21006.6	
Adjusted ρ^2	0.156	

Note: ** and * mean $p < 0.01$ and $p < 0.05$.

Finally, Table 6 presents the estimation results for the trip frequency model. *Daytime population density* is defined as the population per hector during the daytime. *CBD* takes the value of 1 if the TAZ is located in the CBD and 0 otherwise. *Major road* equals 1 if the TAZ is located along major roads and 0 otherwise. *Riverside* equals 1 if the TAZ is located next to major rivers and 0 otherwise. *Outside rivers* equals 1 if the TAZ is located beyond the major rivers from the CBD and 0 otherwise. *Periphery area* takes the value of 1 if the TAZ is categorized as a periphery area and 0 otherwise. All coefficients are significant in t-value and R^2 is high enough. All explanatory variables' signs are reasonable.

Table 6. Estimation results of trip frequency model.

Variable	Coefficient	t-statistics
ln (Daytime population density)	0.091**	6.79
CBD	0.571**	6.44
Major road	0.235**	2.89
Riverside	–0.240**	–2.64
Outside rivers	–0.364**	–4.32
Periphery area	–0.185 *	–2.15
Log-sum	0.174**	3.35
Constant	–1.380 *	–2.41
Number of observations	155	
Adjusted R^2	0.558	

Note: ** and * mean $p < 0.01$ and $p < 0.05$.

5. Scenario Analysis

5.1. Travel Demand Forecast System

A travel demand forecast system is developed using the estimated models with a traffic assignment in the road and public transportation network to estimate the travel demand under given scenarios. Fig. 2 illustrates the structure of the travel demand forecast system. The vehicle ownership in a zone is computed using the vehicle ownership model under given socioeconomic and sociodemographic variables, while an O-D matrix by travel mode is calculated using the trip frequency, destination, and modal choice models with socioeconomic and sociodemographic variables, which are given by scenario.

The O-D matrix by travel mode and vehicle ownership is estimated as

$$T_{ijm}^{o} = \sum_{n \in I_i} \left(P_{i,n}^{o} \cdot F_{i,n} \cdot P_{ij,n} \cdot P_{ijm,n} \right), \tag{11}$$

where I_i is a set of individuals who resides in zone *i*.

The generalized cost inserted in the modal choice model is computed through the traffic assignment in the road network because the traffic congestion of a road link influences travel time. The road traffic volume is computed on the basis of the user equilibrium principle when the O-D matrix by mode is given. The following BPR function is assumed for the link performance function in the user equilibrium assignment:

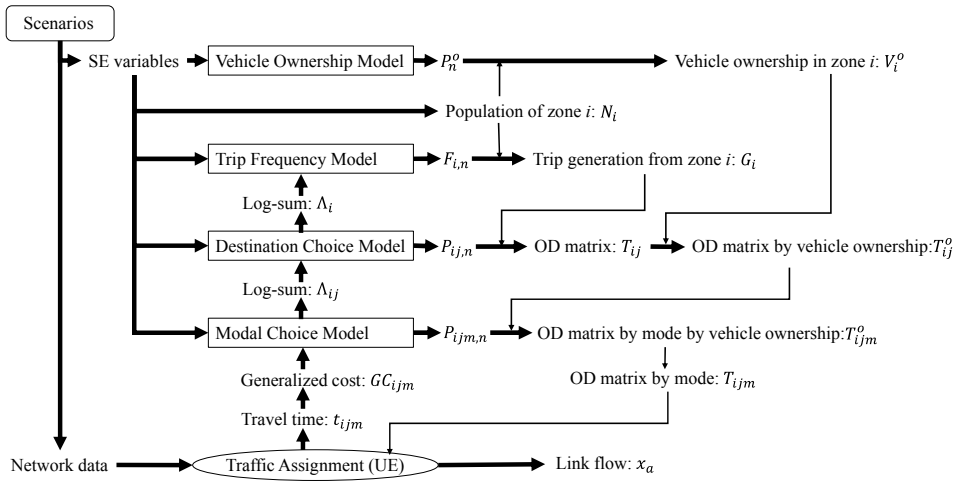

Fig. 2. Structure of Travel Demand Forecast System

$$t_a(x_a) = t_{a0}\left\{1 + \alpha\left(\frac{x_a}{C_a}\right)^{\beta}\right\}, \tag{12}$$

where t_a, t_{a0}, a, x_a, and C_a , respectively, are the travel time, free flow time, traffic volume, and capacity of link a, and α and β are parameters. α and β are assumed to be 3.0 and 4.0 following JICA (2014).

As shown in Fig. 2, our travel demand forecast system requires an iterative computation process. The convergence criterion is assumed as follows:

$$\sum_a \frac{\left|x_a^g - x_a^{g-1}\right|}{x_a^g} \le 0.05, \tag{13}$$

where x_a^g is the traffic volume of link a of the gth iteration.

Table 7 shows the observed modal share versus converged modal share estimated using the travel demand forecast system, while Fig. 3 shows the observed O-D traffic volume versus converged O-D traffic volume estimated with the travel demand forecast system. Both show that the estimated traffic demand through the travel demand forecast system is well reproduced.

Table 7. Observed modal share versus estimated modal share.

	Car	Motorcycle	Bus	Taxi
Observed modal share (%)	11.0	5.5	72.2	11.3
Estimated modal share (%)	10.9	5.5	73.0	10.6

5.2. Scenarios Analysis

The impact of the motorcycle ban on Yangon's transportation market is simulated using the developed travel demand forecast model. Four scenarios are set up for the analysis. In Scenario 1, the ban continues to exist as of 2013, which represents the current condition. In Scenario 2, the ban is lifted in 2013. In Scenario 3, the ban continues to exist in 2035,

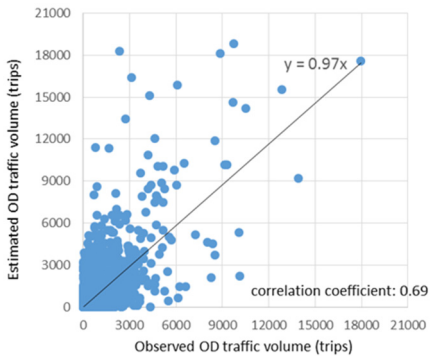

Fig. 3. Observed OD versus estimated OD traffic volume

the target year in JICA's (2014) long-term urban transportation master plan for Yangon City. Finally, in Scenario 4, the ban is lifted in 2035.

The expected changes in the sociodemographic and socioeconomic conditions and transportation network are incorporated into Scenarios 3 and 4 following the long-term master plan (JICA, 2014). First, future population is projected in each municipality and then divided into TAZs using the current share of population in each municipality. Second, the transportation network, which is extended from the current network as of 2035 and includes 2,197 nodes and 3,056 links, is assumed. This extension of transportation network includes the introduction of two urban mass transit (UMRT) lines, ten bus rapid transit (BRT) lines, urban expressways, and tunnels or bridges crossing the rivers. Third, the household income in 2035 is assumed to be 3.96 times higher than that in 2013, reflecting the projected average income growth in Yangon. Fourth, the value of time in 2035 is also assumed to be 3.96 times higher than that in 2013. Fifth, the bus service is assumed to improve such that the *poor bus service area* in the vehicle ownership model is zero in 2035. Finally, for analytical simplicity, the fare of public transport including bus, UMRT, and BRT is assumed to follow the fare table of the current bus system, while the travel time of public transport is assumed to follow the travel time of road traffic.

To simulate the traffic demand without the ban in Scenarios 2 and 4, *MC ban area* and *over five-year stay in the MC ban area* in the vehicle ownership model are assumed to be zero. The *MC ban area* in the modal choice model is also assumed to be zero for all households and individuals. Note that the traffic volume of vehicles other than cars, motorcycles, buses, and taxis (e.g., trucks) is also considered in the traffic assignment given the possible influence on traffic congestion and travel time. Although the traffic volume of other vehicles is assumed to grow in line with economic growth in Scenarios 2 and 4, for analytical simplicity, it is assumed that whether the motorcycle ban area is introduced does not affect the traffic volume of other vehicles.

Table 8 shows the results of vehicle ownership by type of vehicle estimated in the four scenarios. Table 9 shows the traffic volume and vehicle kilometers traveled using the said travel modes for the four scenarios. Figs. 4 and 5 show traffic volume and traffic congestion in the road network with and without the ban area for 2013 and 2035. Table 8 shows that, in

2013, car (Car&Motorcycle and Car) and motorcycle owners (Car&Motorcycle and Motorcycle) account for 11.5% and 11.1% in Scenario 1 but 9.3% and 25.2% in Scenario 2. It also shows that, in 2035, car (Car&Motorcycle and Car) and motorcycle owners (Car&Motorcycle and Motorcycle) account for 34.4% and 12.5% in Scenario 3 and 31.2% and 33.3% in Scenario 4. This means that the ban promotes car ownership but suppresses motorcycle ownership.

Table 9 shows that, in 2013, the total traffic volume based on the personal car unit in the ban area is 657,483 in Scenario 1, while that outside the ban area is 802,291 in Scenario 2, which means the ban suppresses total traffic volume by 18.0%. On the other hand, in 2035, the total traffic volume in the ban area is 2,117,428 in Scenario 3, while that without the ban is 2,218,215 in Scenario 4. In other words, the motorcycle ban suppresses total traffic volume by 4.5%, despite the sharp reduction in motorcycle traffic volume by 74.7%. The impact of the ban is smaller in 2035 because by then, car traffic volume has significantly increased compared to that in 2013.

Table 9 also shows that, in 2013, the total vehicle kilometers traveled with the ban is 5,022,697 km in Scenario 1, while that without the ban is 6,873,811 in Scenario 2. In 2035, the total vehicle kilometers traveled with the ban is 21,186,150 km in Scenario 3, while that without it is 22,530,332 km in Scenario 4. This means the motorcycle ban reduces the vehicle kilometers traveled by approximately 26.9% in 2013 and 6.0% in 2035, which suggests that the ban reduces vehicle kilometers traveled in 2013 but loses its effectiveness in 2035.

Figs. 4 and 5 show changes in traffic volume from 2013 to 2035. Link traffic flows significantly increase in wider areas with congested traffic by 2035 given the growth of population and income. They also show that the ring road links have greater traffic volume in 2035 than 2013 mainly because of industrial development and rapid population growth in suburban areas.

Table 8. Vehicle ownership estimated in the four scenarios.

Scenario (%)	Car & Motorcycle	Car	Motorcycle	None
Scenario 1 (with the ban area in 2013)	1.0	10.5	10.1	78.4
Scenario 2 (without the ban area in 2013)	2.4	6.9	22.8	67.9
Scenario 3 (with the ban area in 2035)	5.0	29.4	7.5	58.1
Scenario 4 (without the ban area in 2035)	14.0	17.2	19.3	49.5

Table 9. Traffic volume and vehicle kilometers traveled by transportation mode in the four scenarios.

Scenario		Car	Motorcycle	Bus	Taxi	Total
Scenario 1	Traffic volume (PCU)	224,164	40,774	166,875	225,669	657,483
	Vehicle km	1,798,824	607,474	1,755,427	860,972	5,022,697
Scenario 2	Traffic volume (PCU)	202,290	209,923	171,648	218,430	802,291
	Vehicle km	1,696,048	2,428,442	1,849,768	899,553	6,873,811
Scenario 3	Traffic volume (PCU)	1,210,220	108,347	246,172	552,689	2,117,428
	Vehicle km	12,126,862	1,687,358	3,096,052	4,275,878	21,186,150
Scenario 4	Traffic volume (PCU)	1,035,478	427,785	235,579	519,372	2,218,215
	Vehicle km	10,275,523	5,265,165	2,976,146	4,013,498	22,530,332

Note 1: PCU is passenger car unit.

Note 2: Bus in Scenarios 3 and 4 include conventional bus and bus rapid transit.

Fig. 4 shows that the average volume or capacity with the ban is 0.31 in Scenario 1, while that without the ban is 0.38 in Scenario 2. Fig. 5 also shows that the average volume or capacity with the ban is 0.61, while that without it is 0.64. This means that the ban contributes toward reducing traffic congestion. However, the distribution of volume or capacity in Scenario 2 seems to largely differ from that in Scenario 1, while that in Scenario 4 appears similar to that in Scenario 3. Fig. 4 (a) and (b) show that the traffic congestion in Scenario 1 significantly varies from that in Scenario 2, particularly in the road network of the CBD. Thus, although the traffic congestion in the CBD is mitigated by the ban regulation in 2013, it may not be as effective in doing so in 2035.

5.3. Discussion

The results showed that the impacts of the ban on the reduction of total traffic volume and vehicle kilometers traveled are significant in 2013, although they are less significant in 2035. This suggests that the effects of the motorcycle ban could weaken in the future, possibly because household income gradually could increase with economic growth in the city, enabling the local people to purchase cars rather than motorcycles. Thus, potential motorcycle users shift to car users once they can afford to do so.

Fig. 4. (a) Traffic volume and traffic congestion in the road network with the motorcycle ban in 2013 (Scenario 1)

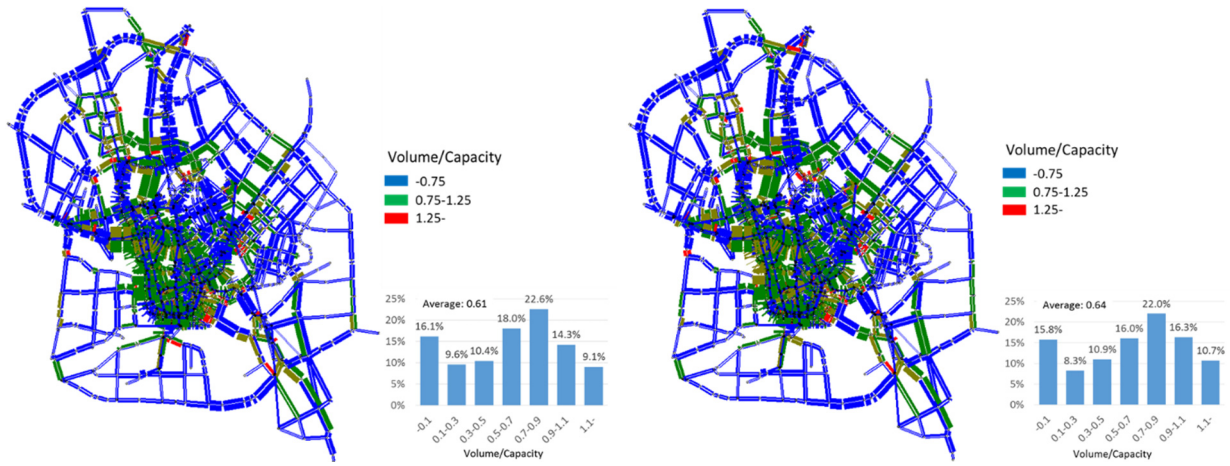

Fig. 5. (a) Traffic volume and traffic congestion in the road network with the motorcycle ban in 2035 (Scenario 3)

In other words, policies must account for long-term traffic demand management in developing cities. Dynamic policy implementation is a key issue, particularly in developing countries, as pointed out by Acharya (2005); however, the dynamics of a traffic management policy have been rarely discussed. A possible reason is that studies discussing traffic management policies tend to focus on developed cities, where economic development is rather stable. In addition, JICA (2014) presented the short-, mid-, and long-term urban transportation plans, in which different traffic management policies were proposed for the Yangon metropolitan area. However, the short- and mid-term transportation plans highlighted car parking management rather than the current motorcycle ban regulation, reflecting the traffic capacity constraints caused by on-street parking in the downtown area of Yangon.

Our analysis reveals that, in the near future, the motorcycle ban policy should be replaced by other transportation policy measures such as car bans or congestion charges for both motorcycles and cars. In addition, an expanded transportation network and improved public transit system should be highlighted, as pointed out by Morichi (2005). One of the reasons underlying this shift from motorcycles to cars is the difficulty public transportation faces in attaining sufficient ridership owing to its poor service quality. Although individuals may have to opt for the bus or railways in the early stage of development, they are expected to gradually switch their travel mode from public to personal transportations (e.g., cars). Additionally consistency of urban transportation policy with other related strategies may be also required. Particularly, the car import strategy should be harmonized with the motorcycle management policy. The car ownership would increase significantly in accordance with the income growth if the car import would be inappropriately deregulated. One of the challenges in Yangon towards the consistent policy development is a fragmented organizational system relating the urban transportation issues. For instance, currently, the Yangon Regional Government is responsible for the motorcycle ban while the Yangon City Development Committee is responsible for other urban transportation policies. To pursue the integrated transportation policy, poor institutional structure should be properly improved, such as the establishment of a new organization that handles comprehensively the Yangon's urban transportation.

Another issue in the dynamic urban transportation strategy is consensus building among stakeholders to change the existing policy. It is widely known that a newly introduced traffic demand management often faces strong oppositions from locals, tough debates among stakeholders, and varying attitudes from different groups (Schlag and Teubel, 1997; Sdhlag and Schade, 2003; Whittles, 2003; Winslott-Hiselius et al., 2009; Xiao and Lu, 2013). This is also the case in developing cities (Mahendra, 2011). Similar challenges are expected in the removal or replacement of the current motorcycle ban. In the PT survey, respondents were asked if they thought the current limitation on the use of motorcycles in Yangon should continue, to which 58% respondents supported the regulation that could possibly impair citizen's convenience; in particular, the residents in the CBD and surrounding areas favored the ban (Kojima et al., 2015b). This implies that people recognize that the motorcycle and bicycle ban improves traffic safety in the CBD. Under this condition, it may be difficult for policy makers to change the existing regulation. Thus, a careful monitoring of vehicle ownership and urban traffic demand is required to make a decision regarding the removal of the motorcycle ban and to do as at the most appropriate time so that the decision is accepted by the public.

6. Conclusion

This study analyzes the potential impacts of motorcycle demand management and its contribution to the transportation market in Yangon, where motorcycle use has been prohibited since 2003. To do so, a traffic demand forecast system is

developed, where the vehicle ownership model and travel demand models are estimated using large-scale data collected in Yangon. The expected impacts of the ban are analyzed for both 2013 and 2035 using a scenarios analysis, in which the traffic demand is simulated using a demand forecast system. The results imply that the motorcycle ban policy contributes to the mitigation of urban transportation problems in the early stage of economic development; however, in the mid and long term, it would promote car ownership or use, reducing or even eliminating the positive impacts of reduced motorcycle traffic. This suggests a strong requirement to develop long-term dynamic transportation strategies, particularly in developing cities. As shown in this study, the effects of motorcycle demand management is expected to dynamically change in line with income growth. Thus, the motorcycle ban regulation should be well managed in conjunction with additional transportation policies or should be replaced by other transportation policies such as an additional traffic management of cars and/or an improved public transportation

Numerous issues need to be addressed in future research. First, this study uses cross-sectional data, making it difficult to confirm the reliability of future transportation demand forecast. Studies could examine whether individuals or households really change their decisions regarding their travel behavior in a static manner. For instance, in the context of our study, those who resided in the area with the ban for several years are likely to have become accustomed to daily travel patterns in which no motorcycles are used. In this case, even if the ban was lifted, individuals' attitudes or preferences may not significantly increase motorcycle traffic volume, as shown in our scenario analysis. On the other hand, motorcycle users may continue to use motorcycles, despite potentially aggressive improvements in public transport (Tuan, 2014). Next, a combination of multiple policies should be discussed, such as the motorcycle ban as well as public transit investment. Many studies have highlighted integrated transportation strategies, such as May and Roberts (1995) and Hull (2005, 2008). As discussed by Morichi and Acharya (2012), such integrated transportation policies are critical to overcome traffic problems in developing cities. In addition, since the timing of introducing a mass transit system should be harmonized with traffic demand management, the time schedule of long-term urban transportation strategies should be carefully analyzed. Finally, from the long-term perspective, the interaction of urban transportation system with land-use patterns and/or industrial structure should be examined.

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References

Acharya, S. R., 2005. Motorization and Urban Mobility in Developing Countries Exploring Policy Options through Dynamic Simulation. Journal of the Eastern Asia Society for Transportation Studies 6, 4113–4128.

Barter, P. A., 1998. An International Comparative Perspective on Urban Transport and Urban Form in Pacific Asia: the Challenge of Rapid Motorization in Dense Cities. Doctoral Dissertation, Murdoch University.

Ben-Akiva, M., Lerman, S., 1985. Discrete Choice Analysis: Theory and Application to Travel Demand, MIT Press, Cambridge.

Deng, X., Xu, J., Wang, B., 2009. Traffic Countermeasures Research for Guangzhou City in Traffic Mode Transferring Period after "Motorcycle Forbidden Ban Effect." Journal of Transportation Systems Engineering and Information Technology 9(4), 145–150.

Dissanayake, D., Morikawa, T., 2001. Transport Policy Analysis for Developing Countries using Nested Logit Model of Vehicle Usage, Mode Choice and Trip-chain. Journal of the Eastern Asia Society for Transportation Studies 4, 161–173.

Hensher, D. A., 1986. Sequential and Full Information Maximum Likelihood Estimation of a Nested Logit Model. The Review of Economics and Statistics 68(4), 657–667.

Hull, A., 2005. Integrated Transport Planning in the UK: From Concept to Reality. Journal of Transport Geography 13(4), 318–328.

Hull, A., 2008. Policy Integration: What Will It Take to Achieve More Sustainable Transport Solutions in Cities? Transport Policy, 15(2), 94–103.

Hung, K. V., 2006. Traffic Management in Motorcycle Dependent Cities. Doctoral Dissertation, Darmstadt University of Technology.

Institute for Transportation & Development Policy (2009) Best Practices on Regulation and Design for Motorized and Non-Motorized Two and Three Wheelers in Urban Traffic, http://cleanairasia.org/portal/system/files/23_Wheeler_Best_Practices_DraftFinal_22Oct09.pdf, last accessed on March 31, 2015.

Japan International Corporation Agency (JICA)., 2013. Project for the Strategic Urban Development Plan of the Greater Yangon (SUDP).

Japan International Corporation Agency (JICA)., 2014. Project for Comprehensive Urban Transport Plan of the Greater Yangon (YUTRA).

Kaneko, Y., Fukuda, A., Srisurapanon, V., Oda, T., 2001. Estimation of the Impact of Area License Scheme with Multi-Class User Equilibrium Model. Journal of the Eastern Asia Society for Transportation Studies 4, 277–291.

Kato, H., Inagi, A., and Htun, P. T. T., 2010a. Route Choice Analysis of Bus-use Commuters in Yangon, Myanmar, Proceedings of the 7th International Conference on Traffic and Transportation Studies, Kunming (China), Aug. 2010.

Kato, H., Inagi, A., Saito, N., Htun, P. T. T., 2011. Feasibility Analysis for the Introduction of a Bus Rapid Transit System in Yangon, Myanmar. Journal of the Eastern Asia Society for Transportation Studies 9, 914–929.

Kato, H., Saito, N., Inagi, A., Myint, U. A., 2010b. Regulatory Framework and Operational System of Urban Bus Transportation in Yangon, Myanmar. Presented at the Transportation Research Board 2010 Annual Meeting, Washington D. C. (U. S.), Jan. 2010.

Kojima, M., Futose, T., Binh, P. L., Kato, H., 2015a. Yangon's Urban Transportation: Traffic Demand and its Quality of Service. Presented at the 11th Eastern Asia Society for Transportation Studies, Cebu (Philippines), Aug. 2015.

Kojima, M., Futose, T., Binh, P. L., Kato, H., 2015b. Urban Transport in Yangon, Myanmar: Evidence from Large-Scale Surveys. Presented at the Transportation Research Board 2015 Annual Meeting, Washington D. C. (U. S.), Jan. 2015.

Koizumi, Y., Nishimiya, N., Kaneko M., 2013. Urban Transportation Characteristics and Urban Mass Transit Introduction in the Cities of Developing Countries. Journal of the Eastern Asia Society for Transportation Studies 10, 81–99.

Lai, W.T., Lu, J. L., 2007. Modeling the Working Mode Choice, Ownership and Usage of Car and Motorcycle in Taiwan. Journal of the Eastern Asia Society for Transportation Studies 7, 869–885.

Louviere, J. J., Hensher, D. A. Swait, J. D., 2000. Stated Choice Methods, Cambridge: Cambridge University Press.

Mahendra, A., 2011. Options for Travel Demand Management: Traffic Bans versus Pricing. In: Dimitriou, H. T., Gakenheimer, R., (Eds.) Urban Transport in the Developing World: A Handbook of Policy and Practice, Edward Elgar Publisher, 548–588.

May, A. D., Roberts, M., 1995. The Design of Integrated Transport Strategies. Transport Policy, 2(2), 97–105.

Morichi, S., 2005. Long-term Strategy for Transport System in Asian Megacities. Journal of the Eastern Asia Society for Transportation Studies 6(1), 1–22.

Morichi, S., Archarya, S. R., 2012. Transport Development in Asian Megacities: A New Perspective, Springer.

Myanmar Times., 2014. Ban on Motorbikes Lingers, 4 July 2014. http://www.mmtimes.com/index.php/special-features/162-wheels-2013/5788-ban-on-motorbikes-lingers.html, last accessed on July 4, 2015.

Schlag, B., Teubel, U., 1997. Public Acceptability of Transport Pricing. IATSS Research 21, 134–142.

Sdhlag, B., Schade J., 2003. Acceptability of Urban Transport Pricing Strategies. Transportation Research Part F: Traffic Psychology and Behaviour 6(1), 45–61.

Tun, N., Kanitpong, K., Jiwattanakulpaisarn, P., Kato, H., 2015. Study of Vehicle Ownership in Yangon using Household Data. Presented at the 8th ATRANS Symposium: Young Researcher's Forum 2015, Bangkok (Thailand), Aug. 2015.

Tuan, V. A., Shimizu, T., 2005. Modeling of Household Motorcycle Ownership Behavior in Hanoi City. Journal of the Eastern Asia Society for Transportation Studies 6, 1751–1765.

Tuan, V. A., 2014. Possibilities of Modal Shift to Public Transport in Developing Asian Cities – An Empirical Examination in Hanoi City. Presented at the 7th ATRANS Symposium: Young Researcher's Forum 2014, Bangkok (Thailand), Aug. 2015.

Whittles, M., 2003. Urban Road Pricing: Public and Political Acceptability, Ashgate Publication Ltd.

Williams, H. C. W. L., 2002. On the Formation of Travel Demand Models and Economic Evaluation Measures of User's Benefit. Environment and Planning A 9, 285–344.

Winslott-Hiselius, L., Brundell-Freij, K., Vagland, A., Byström, C., 2009. The development of public attitudes towards the Stockholm congestion trial. Transportation Research Part A 43, 269–282.

Xiao, H., Lu, J., 2013. A comparative study of public and academic attitudes to TDM measures: Evidence from Nanjing, Procedia – Social and Behavioral Sciences 96, 693–703.

Ye, L., Wang, Q., 2011. Case Study of Motorcycle Use and Policy Analysis in Huizhou, China. Journal of Transportation Engineering 137, 831–836.

Zhang, J., Fujiwara, A., Thein, S., 2008. Capturing Traveler's Stated Mode Choice Preferences under Influence of Income in Yangon City, Myanmar. Journal of Transportation Systems Engineering and Inform