Modelling of Income Effect over Household Vehicle Ownership in a Motorcycle Dominant Environment: A Case Study of Khon Kaen City, Thailand

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Abstract: This study aims at examining the effect of income over vehicle ownership in a mid-sized motorcycle dominant environment city using Khon Kaen City, Thailand, as a case study. Multinomial logit models are employed based on a dataset collected in early 2010. Two different model structures to incorporate car and motorcycle ownership are introduced and results from both models are compared. A sensitivity analysis is also used to examine the effect of income exerting influence on each model. With different model structures, both approaches provide somewhat identical results at the aggregate level. Yet, some differences can be found in the specific alternative level. Finally, some discussions are given on the feasibility of introducing price mechanism policies and high quality public transit in order to restrain the vehicle ownership in mid-sized cities of Thailand.

Keywords: Vehicle ownership, Motorcycle dominant environment, Mid-sized City, Thailand

1. INTRODUCTION

Over the last few decades, there have been many transport planning studies discussing private vehicle ownership and usage in many urban areas around the world. In most regions of the world, and especially in developed countries, a majority of private vehicles are private cars so the car ownership was the focus of attention in previous studies. In the last couple of decades, an economic boom in Southeast Asia has led countries in the region to a new situation that may be termed the ‘Asian developing countries’. As a result, the need for travel in those countries has been rapidly increasing, a trend that continues today. As a considerable proportion of population in Southeast Asian countries are low income, the countries themselves exhibit large socioeconomic disparity and a general lack of urban public transport services (Hayashi, 2006; Townsend, 2003; APEC, 2006; ISEAS, 2010). Small motorcycles including scooters are low-cost private transport modes which have become a majority of private vehicles in these countries. Although the motorcycle provides many benefits to the user (e.g. less cost, lower fuel consumption, better manoeuvrability and door-to-door transport), the mode also leads to many serious transport issues including road accidents and discouragement of the use of public transit and other sustainable modes. For this reason, in recent years both understanding the nature of motorcycle ownership and the identification of policies to control use of the motorcycles in Southeast Asia have become more popular research topics as can be seen from the number of recent vehicle ownership studies in the region, e.g. Leong and Mohd-Sadullaha (2007), Tuan and Shimizu (2007), Hsu *et al*. (2007), Lai and Lu (2007), Senbil *et al.* (2007) and Wedagama (2009). Nevertheless, the number of such studies is still quite small, relative to those in developed countries.

Among these previous studies, most studies have supported the view that household socio-demographic and economics, e.g. income and household size, and number of other competing modes, such as number of cars in household and public transit service provision, could be important factors influencing motorcycle ownership. For instance, Leong and Mohd-Sadullaha (2007) undertook a study in Penang, Malaysia and found that household income, number of cars in household, number of driving licence holders and household size were the main parameters influencing motorcycles ownership. The study indicated that the motorcycle is the major mode for low and middle income people. In contrast, the level of motorcycle ownership in high income households which already own multiple cars was falling, implying that cars and motorcycles in household may have an inverse relationship with each other. Tuan and Shimizu (2007) conducted another study in Hanoi City, Vietnam, and their study found that the greater the household income, the greater the degree of household motorcycle ownership, a result that is opposed to the study in Penang which suggested that at high income levels, the degree of motorcycle ownership dropped. Hsu *et al*. (2007) undertook a study in three major cities in Taiwan and concluded that income also has a large influence on motorcycle ownership. The reported research indicates that higher incomes lead to a higher degree of car ownership and lower degree of motorcycle ownership in households, supporting the findings of Leong and Mohd-Sadullaha (2007). Hsu *et al*. (2007) also found that motorcycle ownership is negatively related to quality of public transit services. Lai and Lu (2007) conducted another study in Taipei and found a strong relationship between numbers of motorcycles, cars and income in households, quite similar to the findings of Hsu *et al*. (2007). In the same year, Senbil *et al*. (2007) examined motorcycle ownership in Jabotabek, Indonesia, and showed that the degree of motorcycle ownership is likely to increase with income until the income reaches a particular level. Once income exceeds that level the degree of motorcycle ownership is likely to reduce and the degree of car ownership will eventually surpass it. Wedagama (2009) conducted a motorcycle ownership study in Bali, Indonesia, confirming that there could be a relationship between household income and degree of motorcycle ownership.

From this review, it appears that most reported studies support each other in the notion that income should have a significant effect on household vehicle ownership. Motorcycles seem to be the right answer for low and medium income people while the popularity of private cars is greater for high income households. Although the results of Tuan and Shimizu (2007) differ from other studies, this could be due to the lower average income in Hanoi compared to the other study areas. One further observation can be made here; all of studies reviewed were undertaken in cities with populations exceeding one million. However there are many mid-sized cities in Southeast Asia which the nature of vehicle ownership has not been investigated. For instance, in Thailand, a country with a high degree of motorcycle ownership, Bangkok is the only city with a multi-million population and there are more than 20 major regional cities which are classified as mid-sized cities with between 100,000 and 500,000 populations (DOPA, 2010). Since the average incomes of such cities are observably lower than that in a large city like Bangkok while the living cost is also cheaper, the nature of vehicle ownership in mid-sized cities might well be different. Further, the mid-sized cities tend not to have well developed public transport systems.

Motorcycle ownership models developed in Southeast Asia can be generally classified into two types; 1) single-modal motorcycle ownership models and 2) joint car-motorcycle ownership models. Similar to some sophisticated discrete choice car ownership models previously developed, e.g. Golob and Burns (1978), Han (2001), Soltani (2005) and Whelan (2007), a motorcycle ownership only model gives the output as a predicted probability of each output category of household motorcycle ownership, such as 0, 1, 2 and 3+ motorcycles in household. Explanatory variables of these models include household characteristics and related attributes such as number of other alternative modes in the household. Previous studies using such a single-modal motorcycle model are, for instance, Tuan and Shimizu (2007), Leong and Mohd-Sadullaha (2007), Wedagama (2009) and Prabnasak *et al*. (2010). On the other hand, a joint car-motorcycle ownership model offers output as predicted probability of each combination category of cars and motorcycles in household, for example, ‘0 car 0 motorcycle’, ‘1 car 2 motorcycles’ and ‘2 cars 0 motorcycle’, and so on. Some studies using such a joint model are Senbil *et al.* (2007) and Lai and Lu (2007). Typically, the structure of a joint model is likely to be more complicated and unstable than the first type of models since the numbers of categories and parameters are mostly greater. Yet it could be argued that joint models might have a greater advantage as they allow full interaction between variables governing car and motorcycle ownership, which could potentially result in more realistic outputs than from the single-model models. Meanwhile, a joint model might provide a better representation of the trade-off between car and motorcycle ownership. There might be a possibility of simply unifying the two first types of models with one as a motorcycle ownership model and another one as a car ownership model, into a single model, and this approach might permit final model results as close or similar to joint models while maintaining a simple model structure and stability as an ordinary type one model.

This study attempts to investigate the nature of car and motorcycle ownership within a motorcycle dominant environment, focusing on mid-sized cities and paying attention mainly to examining the influence of income over the ownership levels as well. Two models are developed using data obtained from a household vehicle ownership survey recently undertaken in Khon Kaen City, Thailand. The first model is structured as a joint car-motorcycle ownership model and the other model represents a unification of two single-modal models – one car-only ownership model and one motorcycle-only ownership model. Both models are based on the Multinomial Logit (MNL) choice model and all models’ explanatory variables represent household socio-demographic and economic characteristics. The rest of this paper is organized as follows. Section 2 presents the methodology including mathematical derivation and model specification. Section 3 reviews the data used in this study and model estimation results and a brief interpretation of the results are then presented in Sections 4. A test of the income effect over car and motorcycle ownership in the study area is given in Section 5 and finally, conclusions and recommendations from the study are provided in Section 6.

2. METHODOLOGY

According to previous studies, e.g. Bhat and Pulugurta (1997), Han (2001), Soltani (2005), Leong and Mohd-Sadullaha (2007), Lai and Lu (2007), Potoglou and Kanaroglou (2008) and Wedagama (2009), household vehicle ownership can be treated as an allocation to a discrete ownership category under the assumption that each is potentially influenced by various socio-demographic and economic characteristics, activities and environmental factors of each household. To model such discrete categories, one widely used approach is the Multinomial

Logit (MNL) model. This study develops two different models based on the ordinary MNL model structure: 'Approach 1', a common joint car-motorcycle ownership model; and 'Approach 2', a combined model of two single-modal ownership sub-models (the first sub-model is car ownership model and the second sub-model is motorcycle ownership model). Output of the Approach 1 model is probabilities of various combinations of cars and motorcycles in household as an ordinary MNL model. The final output of the Approach 2 model is a product of two sub-model output probabilities. Outputs of both approaches are compared in order to examine the performance in terms of behavioural explanation and prediction of the model unification technique used in Approach 2. As suggested by several previous studies regarding the influence of household income over vehicle ownership, in this study a sensitivity analysis of household income is also used to examine the effect of the variable over both developed models.

2.1 Multinomial Logit Model (MNL)

The objective of the MNL model is to determine the probabilities of choice from alternative ownership categories based on utility functions that are estimated for each alternative. As mentioned earlier, this study uses MNL model to examine the relationships between household socio-demographic characteristics and degrees of car and motorcycle ownerships in household in the mid-sized city of Khon Kaen, Thailand. For all models developed in this study, a model with J categories and K explanatory variables can be expressed directly in terms of alternative probabilities (P_i) as follows (Hensher *et al.*, 2005):

$$P_i = \frac{\exp(\alpha_i + \sum_{k=1}^{K} \beta_{ik} X_k)}{\sum_{j=1}^{J} \exp(\alpha_j + \sum_{k=1}^{K} \beta_{jk} X_k)} \qquad j = 1, \dots, i, \dots, J \quad \text{and} \quad k = 1, \dots, K \tag{1}$$

where,

α_i : an Alternative Specific Constant (ASC) of the ownership category *i*,
β_{ik} : a coefficient of an explanatory variable k for the ownership category *i, and*
X_k : an explanatory variable *k.*

Using Maximum Likelihood estimation (Louviere *et al.*, 2000), a set of utility function coefficients which makes the model best fit the calibration dataset are estimated. Also, explanatory variables can be chosen to remain in or out of the model in order to optimize the performance. Coefficients with t-statistics value greater than 1.96 (significance value 0.05) are judged statistically significant. The coefficients estimated are subsequently used for interpreting the relationships between explanatory variables and degrees of car and motorcycle ownerships in household. For the model specification, calibration and validation, the full dataset is randomly divided into two sets. The first set contains 55 per cent of all observations (about 450 observations). This dataset is mainly used for calibrating all models in this study. Model performance is indicated by several statistical values, such as the Log-likelihood estimate, Pseudo R^2 value, Akaike's information criterion (AIC), Chi-square and prediction accuracy. The model structure and utility functions which provide the greatest satisfactory values for those criteria will be chosen. The other 45 per cent of the observations are used to evaluate how fit of the selected model to a different set of observations.

2.2 Approach 1 Model Structure

As it has been concluded in previous studies, e.g. Lai and Lu (2007), that a number of ownership categories are defined as a variety of car-motorcycle combinations in household, e.g. '0 car 0 motorcycle', '1 car 0 motorcycle' and '0 car and 2 motorcycles', and so on. One constraint used to limit number of the categories is the number of observations matching each category in the dataset. Insufficient observations for a category might cause model instability or provide a faulty solution. According to our dataset, it is observed that households with no cars and no motorcycles and households with the number of cars or motorcycles larger than two do not present in sufficient numbers to warrant a classification in the choice alternatives. The MNL structure of Approach 1 model is therefore established as presented in Figure 1. From this figure it can be observed that the 'Approach 1' MNL model structure provides the household with a discrete allocation to one of eight car/motorcycle ownership combinations.

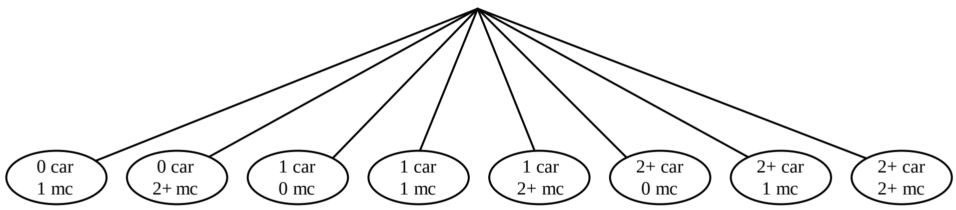

Figure 1. Approach 1 model structure

2.3 Approach 2 Model Structures

Car and motorcycle ownership sub-models established in this study use a simple MNL structure similar to several single-modal vehicle ownership models previously developed, such as Han (2001), Leong and Mohd-Sadullaha (2007), Wedagama (2009) and Prabnasak *et al.* (2010). There are four ownership categories defined for each sub-model and the structures of both sub-models are demonstrated in Figure 2.

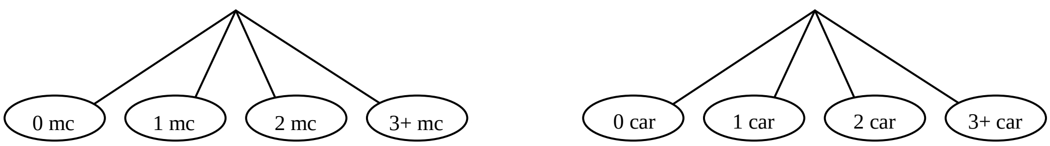

Figure 2. Approach 2 sub-model structures

Given that the output of each sub-model is a set of probabilities predicted for all ownership categories in the model, it might be possible to unify the outputs of two sub-models into a new set of joint ownership categories as an outer product of two column vectors – the first vector is the output probability matrix of car ownership sub-model while the other vector is the output probability matrix of motorcycle ownership sub-model. A diagram of model unification and matrix algebra are shown in Figure 3 and Equation (2). With the model structure presented in Figure 3, the maximum number of ownership categories could be 16 categories with up to '3+ cars' and '3+ motorcycles' – The reason to configure sub-models to four categories is that to allow in examining behaviour of '3+ cars' and '3+ motorcycle' by using the estimation results from each sub-model individually. Because of the sample size limitation which allows Approach 1 model to have ownership categories up to '2+ cars' and '2+ motorcycles' only. In order to compare Approach 1 and Approach 2 in a straightforward manner, in Approach 2's model structure the categories with '2 cars' and '3+ cars' are therefore merged into '2+cars', and as the same for motorcycle sub-model also. Nevertheless, according to Figure 3 and Equation (2) the margin of error may be larger in the category '0 car 2+ motorcycles' than other categories,. This needs to be considered while analysing results.

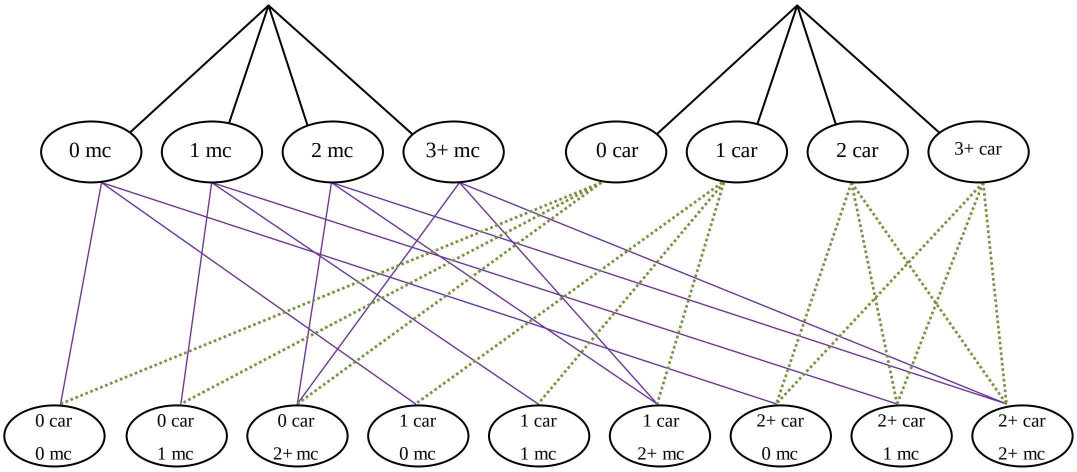

Figure 3. Approach 2 final model structure

$$A \otimes B = AB^T = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix} \begin{bmatrix} b_1 & b_2 & \cdots & b_m \end{bmatrix} = \begin{bmatrix} a_1b_1 & a_1b_2 & \cdots & a_1b_m \\ a_2b_1 & a_2b_2 & \cdots & a_2b_m \\ \vdots & \vdots & \ddots & \vdots \\ a_nb_1 & a_nb_2 & \cdots & a_nb_m \end{bmatrix} \quad (2)$$

where,

A, B : car and motorcycle sub-models,
a, b : the output probability of car and motorcycle sub-models,
n, m : the number of model categories in car and motorcycle sub-models, and
T : the matrix transpose.

Equation (2) is used to produce the final output probability of the Approach 2 model as well as the projected vehicle ownership demand (see Section 5). Because the Equation (2) is a matrix algebra of model outputs not the outputs straight from MNL models, it is noted that the Approach 2 may not well represent the pattern of substitution between car and motorcycle ownerships if exists.

2.4 Model Evaluations

Both Approach 1 and Approach 2 models have their own advantages and disadvantages. Approach 1 represents a joint car-motorcycle ownership model in a straightforward way to model the behaviours of car and motorcycle ownerships in this study. A well specified model may allow all model parameters to fully interact with each other providing more realistic behaviour interpretation, such as allowing a simulation of the trade-off between car and motorcycle ownership. However, there are a few disadvantages either. Firstly, a joint model is likely to be rather complicated and quite vulnerable to parameter changes since there are a large number of categories and parameters. Secondly, the greater numbers of categories and parameters contained in a model, a larger number of observations are required for accurate model estimation. This is a crucial limitation for many studies as the sample size in the calibration dataset is insufficient to accurately establish model parameter estimates. Thirdly, since the output categories are a combination of cars and motorcycles, it does not allow a specific analysis between explanatory variables and one isolated mode ownership estimation without an influential effect from the other mode. In contrast, Approach 2 model is created by two less complex sub-models and they both operate independently. Thus, a smaller number of observations might be sufficient to build a model with acceptable stability. This approach also permits fully independent analysis for each sub-model, which cannot be done with the Approach 1 model. Although the Approach 2 model might be able to remedy the disadvantages of a joint model, it could be questioned on a lack of interaction between parameters of both sub-models and that might cause a faulty prediction, especially the lack of substantial pattern between car and motorcycle ownerships. For this reason, a comparative test of both model outputs is required.

One important concern of using MNL model is the problem of Independence of Irrelevant Alternatives (IIA) property. In this study, the IIA property of the developed MNL models was tested by using Nested Logit (NL) model (Louviere *et al.*, 2001; Hensher *et al.*, 2005). A number of NL models with different hierarchical structures were built on identical data and choice sets but none of them was found to improve the MNL models, implying that the IIA property in those MNL models was held. This test has relaxed the concern of the IIA property of the MNL models in this study. Nevertheless, it is not the focus of this paper and the results of those NL model estimations are not presented here.

3. DATA DESCRIPTION

The data set used to build models in this study is extracted from a recent household survey undertaken in Khon Kaen in early 2010, named the Khon Kaen Household Vehicle Ownership Survey 2010 (KKVOS2010). Brief descriptive statistics of the study area and a validation of KKVOS2010 using a previous household travel survey database available for the study area are provided in this section.

The metropolitan area of Khon Kaen City covers 228 km^2 with approximately 250,000+ population. The city is established as a capital city of the northeast region of Thailand. The KKVOS2010 interviewed 830 households inside the metropolitan area and 811 of them were successfully completed and used in this study (approximately one per cent of the city population). In the survey, a questionnaire was randomly distributed to households across the metropolitan area, asking for information regarding household socio-demographic and economic characteristics, vehicle ownership and attitudes to household vehicle ownership and usage. Because this is brand-new data, a validation is necessary. To validate the degree of representativeness and reliability of the KKVOS2010, several key attributes were compared with the previous Khon Kaen Household Daily Travel Survey 2007 (KKDTS2007). The KKDTS2007 was conducted by SIRDC (2008) across the metropolitan area of Khon Kaen City, using the study same area as in the KKVOS2010. A brief comparison between KKVOS2010 and KKDTS2007 is presented in Table 1.

Referring to Table 1, the average household size in 2010 is 3.45 members, roughly equal to that reported in 2007. The average household monthly income in 2010 is reported as 28,126 Thai Baht (US$940) which is approximately 10.7 per cent higher than that reported by the residents in 2007. The difference of average income between 2010 and 2007 could be a result of economic growth and inflation in the city over time between the two surveys. Gender, level of education and usual mode share in 2010 are roughly equivalent to 2007.

Small discrepancies are found in working status as in KKVOS2010 has a slightly lower proportion of students. Usual mode shares in both surveys are comparable. Consistency in the share implies that the travel pattern and lifestyle of people in the study area did not change much in last four years. Numbers of cars and motorcycles in household in 2010 are slightly higher than in 2007. The proportion of non-vehicle households also dropped from nearly four per cent in 2007 to one per cent in 2010. In addition, the proportion of households that own at least one motorcycle is found to increase from about 87 per cent in 2007 to 91 per cent in 2010. This phenomenon hints a large private vehicle dependency particularly the popularity of motorcycles in the study area and this tends to continue growing over the time. Regarding the comparison, only minor discrepancies between two surveys can be found while most common attributes seem to be comparable. Thus, it could be fairly confident with the degree of representative and reliability of KKVOS2010.

Table 1. A brief comparison between KKVOS2010 and KKDTS2007

Attribute	KKVOS2010	KKDTS2007
Observations		
households	811	873
individuals	2,793	2,986
Household size	3.45	3.42
Household monthly income, THB [30 THB = 1 USD]	28,126	25,416
Working status		
working	56.2%	63.7%
studying	25.8%	20.3%
unemployed	12.2%	12.8%
other	5.8%	3.2%
Gender [Male]	46.30%	47.90%
Education		
Primary school	29.80%	30.60%
High school, TAFE and Undergrads	62.50%	64.40%
Postgrads	3.40%	3.10%
Other	4.30%	1.90%
Mode share (exclude minor modes)		
motorcycle	52.8%	50.3%
public transit	12.4%	12.4%
private car	34.8%	37.3%
Number of cars in household		
Average (cars/household)	0.88	0.81
No car	36.0%	38.6%
1 car	45.9%	47.4%
2 cars	13.3%	10.3%
3 cars or more	4.8%	3.6%
Number of motorcycles in household		
Average (motorcycles/household)	1.48	1.38
No motorcycle	9.4%	12.6%
1 motorcycle	47.7%	50.2%
2 motorcycles	31.8%	27.4%
3 motorcycles or more	11.1%	9.8%
Household vehicle ownership classification		
Households with no car and no motorcycle	1.0%	3.7%
Households with motorcycle(s) only	35.0%	34.9%
Households with car(s) only	8.4%	8.9%
Households with car(s) and motorcycle(s)	55.6%	52.5%

4. MODEL ESTIMATION RESULTS

The following section of this paper is divided into two parts. The first part presents model estimation results for the Approach 1 model while the second part presents model estimation results for the two sub-models in the Approach 2 model. Although the main objective of this paper is not to examine influences of all explanatory variables apart from the household income, a brief interpretation of those explanatory variables are given. Besides, one limitation of datasets used in this study is the lack of information about ownership and usage costs of cars and motorcycles in the study area. Thus, the models developed in the study may not be able to measure impact of changes in such costs straightforwardly. As mentioned in the review of previous literature (Section 1), impacts of the costs can be indirectly reflected by household income comprised in the models.

4.1 Approach 1 Model Estimation Results

Model estimation results for the Approach 1 model are presented in Table 2. The model consists of eight household categories, 11 explanatory variables and 69 parameters. According to the reported estimation results, this model can provide satisfactory degree of model fit and accuracy in prediction with a Pseudo R^2 value of 0.502. The correct prediction on the calibration dataset is 50.2 per cent and for the validation dataset is 41.0 per cent. Although correct prediction on the validation dataset is observably lower than the calibration dataset, it is still considerably high when compared to the ASC model at 15.1 per cent correct. A cause of the drop in accuracy may be related to the size of validation dataset, which is relatively small while the model is quite complex.

Among the parameters, a total of 23 are estimated to be statistically insignificant at 95 per cent confidence interval level. The only ownership category for which the utility function does not contain any insignificant parameters is ‘2+ car 0 motorcycle’. There are only two explanatory variables (‘square root household income’ and ‘number of potential drivers in household’), for which all parameters are significant for all categories.

The square root of household income parameter has a positive sign for all parameters values and the magnitude of the coefficient is greater if the number of cars in household is larger and/or number of motorcycles in household is smaller. This implies that, in this study area, income might be positively related to number of cars in household and/or negatively associated with number of motorcycles in household, as previous mentioned studies have found. The number of potential drivers in a household is the other variable with all parameters being significant and magnitudes of parameters observed to be in some way related to the number of cars in the household. For the remaining variables, household size is found to have a relationship only with the households where the motorcycle ownership dominates. This implies that larger household sizes have a greater degree of motorcycle ownership. As is expected, the number of potential riders has a negative correlation with non-motorcycle households, while number of car driving licences is found to influence the level of car ownership in households. Some household members’ occupations exert influence over some ownership categories also; however, patterns of the sign and parameter magnitude are not uniform across the model. From this brief model explanation, although this model is complicated, most of the outputs are found to agree with logical expectations and reported results from previous studies. Thus, a greater degree of confidence is possible in this model’s predictive capabilities.

Table 2. Approach 1 model estimation results

	[0Cr/2$^+$MC]		[1Cr/0MC]		[1Cr/1MC]		[1Cr/2$^+$MC]		[2$^+$Cr/0MC]		[2$^+$Cr/1MC]		[2$^+$Cr/2$^+$MC]	
	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat
Constant	-8.62	-6.87	-8.83	-4.76	-6.66	-5.48	-10.07	-6.95	-18.99	-7.34	-16.98	-8.41	-15.75	-7.80
Sqrt household income	0.02	2.48	0.03	2.56	0.03	3.63	0.03	3.15	0.05	4.96	0.04	4.17	0.03	3.70
Household size	1.14	3.75	-	-	0.19	0.99	0.93	3.75	-	-	-	-	-	-
Highest education in household	-	-	2.02	3.38	0.24	0.72	-0.38	-0.97	2.58	3.48	2.08	3.55	1.12	1.92
No of potential riders	1.21	4.31	-2.60	-5.95	-0.21	-0.93	0.79	3.02	-1.77	-4.05	-	-	1.38	4.09
No of car licences	-2.89	-3.37	2.87	2.33	1.34	1.77	1.49	1.80	2.72	2.62	1.49	1.78	1.34	1.59
No of potential drivers	1.56	2.25	1.03	0.87	1.81	2.55	1.48	1.99	2.57	2.52	2.93	3.67	2.59	3.31
No of students	-0.71	-2.30	-0.47	-1.28	-	-	-0.34	-1.34	-	-	-0.43	-1.44	-0.88	-2.60
*Head of family working as a gov. officer	-0.53	-0.93	-1.01	-1.62	-0.03	-0.07	0.72	1.38	-1.63	-2.29	0.07	0.11	-0.33	-0.58
*Head of family working as a business owner	-0.02	-0.05	-0.85	-1.49	0.09	0.25	0.24	0.53	-0.98	-1.56	-0.15	-0.27	-0.70	-1.39
*Head of family working in a private company	-0.49	-0.72	-0.40	-0.53	-1.27	-2.11	-2.08	-2.23	-0.17	-0.21	-1.87	-1.88	-0.21	-0.28
*†Head of family holding other occupations	(1.04)	-	(2.25)	-	(1.21)	-	(1.13)	-	(2.77)	-	(1.95)	-	(1.24)	-
Observations	450													
Number of parameters	69													
Log-likelihood function														
at convergence	-887.41													
at market share	-441.59													
Pseudo R^2 value	0.502													
Akaike's Information Criterion (AIC)	2.269													
Crosstab: accuracy in prediction														
with the calibration dataset (55%)	50.2%													
with the validation dataset (45%)	41.0%													

* effect coding parameters

† $\beta_i = -(\beta_j+\beta_k+\beta_l)$ where *i* is reference parameter; and *j*, *k* and *l* are effect coding parameters

4.2 Approach 2 Model Estimation Results

Estimation results for the Approach 2 car ownership and motorcycle ownership sub-models are presented in Table 3 and Table 4 respectively. For the car-ownership model component (Table 3), the structure includes four alternatives, six explanatory variables and 17 parameters. This model provides a satisfactory degree of model fit and accuracy in prediction with a Pseudo R^2 value of 0.498 and a correct prediction of 66.7 per cent on the calibration dataset and 65.4 per cent on the validation dataset. All parameters included in the model are statistically significant at the 95 per cent confidence interval level.

When considering the estimated coefficients, the income parameter estimation results provide a similar finding to that of the Approach 1 model results, where there is a considerable positive relationship between income and the degree of car ownership. Household size parameters for '1 car' and '2 cars' categories can be removed from model without greatly disturbing the model performance.

Table 3. Approach 2 car-ownership sub-model estimation results

	[1 Car]		[2 Cars]		[3^+ Cars]	
	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat
Constant	-3.49	-5.31	-11.73	-8.80	-18.45	-7.58
Sqrt household income	0.01	3.04	0.02	4.00	0.04	4.88
Household size	-	-	-	-	-0.74	-2.08
Highest education	-	-	1.16	3.46	1.86	3.21
No of potential drivers	-	-	0.87	2.74	2.70	4.39
No of car driving licences	3.71	9.88	4.15	8.09	3.52	5.51
No of motorcycle driving licences	-0.64	-3.71	-0.87	-3.95	-1.03	-3.51
Observations	450					
Number of parameters	17					
Log-likelihood function						
at convergence	-533.58					
at market share	-267.60					
Pseudo R^2 value	0.498					
Akaike's Information Criterion (AIC)	1.265					
Crosstab: accuracy in prediction						
with the calibration dataset (55%)	66.7%					
with the validation dataset (45%)	65.4%					

However, household size is found to negatively interact with the '3+ cars' category, which may be an unexpected result. After closer examination of the calibration data, it is found the households with three cars or more are mostly mid-sized families (3-4 members) with a higher income while large households (more than four members) have mainly low to medium incomes, causing the model to provide a negative sign on the parameter. Level of education is found positively related to the degree of car ownership in household. According to UNESCO (2004) and Hurtubia *et al.* (2010), the level of education in household can be a factor reflecting activities, quality of life, attitude and level of income in household, which potentially gain the need of cars in household as a consequence. Numbers of potential car drivers also provide a result from the model in the same manner as the highest level of education. The number of car driving licences held in household is positive to all households with at least one car, relative to household with no car. Number of motorcycle driving licences is found to have a negative sign as may be expected with a high number of motorcycle driving licences relating to the number of potential riders and also demand of motorcycle usage against degree of car ownership in household.

For the motorcycle-ownership component of the Approach 2 model structure (Table 4) there are four alternatives, 13 explanatory variables and 30 parameters. This model also provides an acceptable degree of model fit and accuracy in prediction Pseudo R^2 value of 0.361 and prediction of the calibration dataset is 54.4 per cent, while prediction on the validation dataset is slightly lower at 49.3 per cent. Among the parameters, nine of them are statistically insignificant at 95 per cent confidence interval level. Income is found to have a negative sign and insignificant for all alternatives, relative to households with no motorcycles. This result may suggest that a higher income may lead to a lower degree of motorcycle ownership; however, this circumstance is not clear and not always true.

Table 4. Approach 2 motorcycle-ownership sub-model estimation results

	[1 Motorcycle]		[2 Motorcycles]		[3^+ Motorcycles]	
	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat
Constant	5.15	3.90	1.85	1.27	-3.31	-1.76
Sqrt household income	-0.005	-1.08	-0.003	-0.50	-0.004	-0.65
Household size	0.30	1.29	0.68	2.50	1.37	4.07
Highest education in household	-1.58	-3.42	-1.94	-3.83	-2.18	-3.74
No of potential riders	1.95	5.10	2.88	6.86	3.27	6.98
No of car licences	-1.69	-4.63	-2.35	-5.94	-2.52	-5.82
No of motorcycle licences	0.56	1.90	0.79	2.49	0.70	2.07
No of members working as gov.officers	-0.87	-2.90	-0.90	-3.15	-	-
No of members working in family's business	-	-	-	-	0.59	2.22
*Head of family working as a gov.officer	1.65	3.53	1.49	3.02	1.63	3.18
*Head of family working as a business owner	0.13	0.35	-0.01	-0.04	-0.40	-0.77
*†Head of family holding other occupations	(-1.78)	-	(-1.48)	-	(-1.23)	-
Observations	450					
Number of parameters	30					
Log-likelihood function						
at convergence	-549.91					
at market share	-351.63					
Pseudo R^2 value	0.361					
Akaike's Information Criterion (AIC)	1.696					
Crosstab: accuracy in prediction						
450 Observations used for calibration	54.4%					
353 Observations used for validation	49.3%					

* effect coding parameters,

† $\beta_i = -(\beta_j+\beta_k)$ where i is reference parameter; and j and k are effect coding parameters

As is expected, a positive relationship between household size and motorcycle ownership has been found, a phenomenon that could be indirectly related to household income and car ownership. As found for the car ownership model, rich households are quite likely to satisfy all travellers in the household by car. However, for households with moderately high incomes, some members will use cars whereas other members will use motorcycles instead. When income is limited, larger households may have greater number of members who are cannot use cars so that the number of motorcycles in household is likely to be larger. Both numbers of potential riders and motorcycle driving licences affect the degree of motorcycle ownership in a positive way; however, the relative magnitudes of the parameters imply that the number of potential riders has the greater impact on the degree of motorcycle ownership. Number of car driving licences on the other hand, has a negative sign within the model. The number of workers in a household and occupancy are found to affect the model in various ways. Even though the 'head of family working as business owner' parameter is statistically insignificant for all ownership categories, removing this factor mathematically reduces performance and accuracy in prediction of the model so that it is kept in the model.

For model interpretation in this section; even though all models are derived differently and contain some different explanatory variables, the results from all models appear to support each other and also agree with several previously mentioned studies. Also, all models perform quite well in both model fit and accuracy in prediction. Therefore, it is possible for the modeller to be rather confident with these models.

5. MODELLING EFFECT OF HOUSEHOLD INCOME ON VEHICLE OWNERSHIP

In this section, the two sets of estimated car/motorcycle ownership probabilities from Approach 2's sub-models are unified as an ultimate product of two probability column vectors as described by Equation (2), and then compared to a set of estimated ownership probabilities predicted by the Approach 1 model. The effect of household income on the model outputs can be investigated by presuming an increase in household income across the input dataset, re-running to the models and observing variations between model outputs. This test is based on a key assumption that household income is the only factor changing over the time while other factors, e.g. household size, level of education, occupation and physical conditions of the study area are unchanged. Rough approximation of income growth can be achieved by using recent annual growth and inflation rates in the study area. However, as there is no officially released information regarding growth rates and inflation available specifically for the study area, the average growth of income is reflected from the per capita Gross Domestic Product (GDP) and the inflation rate of the whole country of Thailand. These are therefore assumed to represent to the equivalent rates of the study area and are used in the approximation. According to IMF (2009), the average growth of GDP in Thailand in last ten years is 5.6 per cent per annum while the inflation rate over last ten years announced by DIP (2010) is on average 2.4 per cent annually. From this information, a rough approximation of average household income in the study area in the next 20 years is determined as presented in Table 5.

Table 5. Approximation of income in the study area for the next 20 years

Years after (n)	Avg. Annual Growth of GDP	Avg. Annual Inflation	Nominal Growth (i)	Future Income (FI)†	Percentage increase
2010	5.6%	2.4%	3.2%	$^{¥}$28,126	-
2015 (5)	5.6%	2.4%	3.2%	32,917	+17.0%
2020 (10)	5.6%	2.4%	3.2%	38,524	+37.0%
2025 (15)	5.6%	2.4%	3.2%	45,087	+60.3%
2030 (20)	5.6%	2.4%	3.2%	52,767	+87.6%

$^{¥}$ Average income in the study area in 2010 (PI)

† Future income can be calculated by: $FI = PI(1 + i)^n$ where i is nominal growth rate and n is time in years

The predictions in Table 5 are slightly different from growth projection models developed by Felipe *et al.* (2010) who suggested that the growth rate of Thailand could be between 4.14 and 4.99 per cent per annual over the next 20 years. Nevertheless, for model testing and income sensitivity examining purposes, the prediction in Table 5 might also be used. As a direct result of these base inputs, Tables 6 and 7 indicate the predicted ownership outputs from Approach 1 and Approach 2 models respectively. A total of 803 households are taken into the models as the input data source and the output is the estimated number of households for each ownership category. It is noted that only 803 of the total 811 observed households in the dataset are used because the other eight households are non-vehicle households, but the Approach 1 model does not support the non-vehicle household category. According to Table 6, there are eight ownership categories presented in the table as mentioned in the study methodology. The first output row of the table is the observed frequency for each ownership category while the rows beneath contain predicted outputs for the current and future years. The last four columns of the table illustrate sum of vehicles forecasted for the 803 households and average number of vehicles per household for each year correspondingly. Table 7 has a similar structure to Table 6, yet it contains nine ownership categories as Approach 2 model allows for the possibility of predicting the number of non-vehicle households. The average vehicles per household projected from both models are plotted in Figure 4.

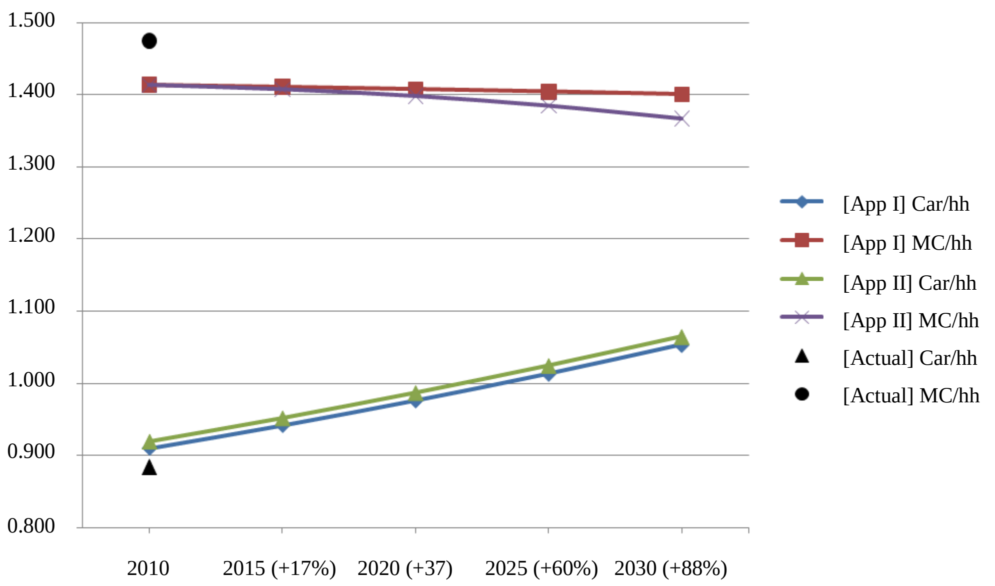

Figure 4. Average numbers of cars and motorcycles per household predicted by the Approach 1 and Approach 2 models

Figure 4 suggests that the predictions given by both models are somewhat identical. The degree of car ownership rises substantially if household income in the study area increases. In contrast, the degree of motorcycle ownership is almost constant for both approaches. Nevertheless, the Approach 1 model predicts a slightly lower degree of motorcycle ownership for increases in income exceeding 35 per cent. Although both approaches yield fairly identical results at an aggregate level, there are few discrepancies in the details of each ownership category.

Table 6. Prediction results from Approach 1 model

Approach 1	Households predicted by model for each choice set (eight ownership categories)									Total vehicles predicted by model		Average vehicles per household	
	[0Cr/0MC]	[0Cr/1MC]	[0Cr/2$^+$MC]	[1Cr/0MC]	[1Cr/1MC]	[1Cr/2$^+$MC]	[2$^+$Cr/0MC]	[2$^+$Cr/1MC]	[2$^+$Cr/2$^+$MC]	Car	MC	Car/hh	MC/hh
2010 (observed)	-	149	135	42	183	147	26	55	66	717	1196	0.884	1.475
2010 (by model)	-	143	136	52	179	129	42	57	65	738	1146	0.910	1.413
2015 (inc +17%)	-	130	138	50	181	127	50	60	66	764	1144	0.942	1.411
2020 (inc +37%)	-	118	140	49	183	124	60	62	67	792	1142	0.976	1.408
2025 (inc +60%)	-	105	142	47	184	121	71	65	68	822	1139	1.013	1.404
2030 (inc +88%)	-	93	143	45	184	117	85	67	68	854	1136	1.053	1.400

Table 7. Prediction results from Approach 2 model

Approach 2	Households predicted by model for each choice set (nine ownership categories)									Total vehicles predicted by model		Average vehicle per household	
	[0Cr/0MC]	[0Cr/1MC]	[0Cr/2$^+$MC]	[1Cr/0MC]	[1Cr/1MC]	[1Cr/2$^+$MC]	[2$^+$Cr/0MC]	[2$^+$Cr/1MC]	[2$^+$Cr/2$^+$MC]	Car	MC	Car/hh	MC/hh
2010 (observed)	0	149	135	42	183	147	26	55	66	717	1196	0.884	1.475
2010 (by model)	9	143	129	47	177	138	35	63	62	745	1146	0.919	1.413
2015 (inc +17%)	9	137	124	47	176	138	38	67	66	772	1141	0.952	1.407
2020 (inc +37%)	8	132	119	47	174	138	41	72	71	800	1134	0.987	1.398
2025 (inc +60%)	8	126	115	47	172	138	45	77	76	831	1123	1.025	1.385
2030 (inc +88%)	8	120	109	46	168	137	49	83	82	864	1108	1.065	1.367

Considering the differences between the 2030 predicted results relative to the 2010 predicted results from both approaches; in the Approach 1 model, there are slight variations in most ownership categories except the category of ‘0 car 1 motorcycle’ which declines by half and the category of ‘2+ cars 0 motorcycle’ which doubles by 2030. In contrast, the Approach 2 model estimates all ‘2+ cars’ categories to increase by 25 per cent while the categories of no car but at least one motorcycle drop by 16 per cent in 2030. Regarding the discrepancies between both approaches, it seems that the different models permit income to impact household vehicle ownership in different ways. It also implies that the Approach 2 seems to overestimates those who own more than two vehicles, and that might be the result of substitution between car and motorcycle which cannot be represented by the Approach 2. Nevertheless, this test has proved that in the study area there should be a strong positive relationship between household income and number of cars in household. Besides this, income may also have a negative impact on the number of motorcycles in household, but the impact is not as large nor as clear.

6. DISCUSSION AND CONCLUSIONS

This paper has investigated the effect of income on household car and motorcycle ownership within a motorcycle dominant environment, focusing on a mid-sized city in Thailand. Two different modelling approaches are established and compared. The data used in this study comes from a household vehicle ownership survey recently undertaken in Khon Kaen City, Thailand. A multinomial logit model is used for the generic modelling structures in the study and all explanatory variables are extracted from household socio-demographic and economic characteristics.

The two different models developed in this study have suggested some similarities and discrepancies between the situation of car and motorcycle ownership in the study area, as a mid-sized city of Thailand, and other million-population cities in Southeast Asia that previous studies have investigated. From the modelling results it can be observed that the degree of car ownership will grow if household income in the study area increases, similar to other urbanized environments around the world. In contrast, the degree of motorcycle ownership is nearly constant with increasing income until the income reaches a critical level then starts to decline. This means that an increase in income alone might not be enough to reduce the degree of motorcycle ownership in an obvious manner. Thus, if the general socio-economic conditions in the study remain constant except for income increases, it might be possible that the degree of household motorcycle ownership will remain at a constant level into the near future, a conclusion that differs from suggestions in some previous studies.

However, considering the signs of the parameters contained in Approach 2’s sub-models, only a few parameters are found to negatively impact on household car ownership while there is a greater number of parameters that negatively interact to influence the degree of motorcycle ownership in the study area. According to the Thailand nationwide statistics officially provided by NSO (2011), it is found that those negatively signed parameters in the motorcycle ownership model all seem to be growing over time. If this situation continues in the future, it is quite possible that the degree of household car ownership will grow even faster while the degree of household motorcycle ownership might decrease quicker than demonstrated in Figure 4, where those parameters are assumed to remain constant over time.

By this projection it seems clear that if the current situation continues into the future (‘business as usual’), the number of cars in the study area will dramatically increase while the number of motorcycles will remain high. This situation might be somewhat similar to Taiwan where the income is high but the massive demand for motorcycles still exists. A combination of vast amount of private car and motorcycle use on the road could subsequently cause many more serious problems for the study area in next few years related to the negative impacts of transport, especially for road safety and environmental impact. To prevent this happening, household vehicle ownership may need to be restrained; vehicle ownership control policies would then play an important role for this issue. From several previous studies including ADB (2003), Koh (2004), Kockelman and Kalmanje (2005), Tuan and Shimizu (2005), Lai and Lu (2007) and Ed-Pike (2010), there have been many types of policy instruments introduced in order to deal with the issue, and one that is most widely suggested and can be related to the findings of this study is the price mechanism, e.g. increase of vehicle expenditures and road pricing.

Considering the results from the developed models, it has been demonstrated that in the study area the household car ownership is sensitive to changes in income while the motorcycle ownership is not. The level of responsiveness to the change of income has deep implications for the vehicle ownership control price mechanism design; the higher the level of responsiveness indicating the greater likelihood of policy success in that area. Thus, the model results imply that a price mechanism might be an effective policy for controlling the household car ownership in the study area. However, they are not recommended for the case of the motorcycle ownership, as the model has proven that household motorcycle ownership is insensitive to changes in income.

Although the price mechanism seems to be an effective means of influencing car ownership in this study area and other environments, to implement such a mechanism for motorcycle dominant environments, including the study region, one aspect that must be given due consideration is the trade-off between car and motorcycle ownership. It is quite possible that if a pricing policy is implemented in the study area, the growth of car ownership and use might slow down or even regress, but motorcycle ownership and use might increase in compensation for the reduced car demand. That ultimate result of this would be to merely shift the problems of household vehicle ownership from vehicle type to another.

Introducing a high quality public transit service might also be a potential solution for the study area as it has been suggested in metropolitan motorcycle dominant environments, e.g. Bangkok, Taipei and Jakarta (Rujopakarn, 2003; Hossain, 2006; Lai and Lu, 2007; Hsu *et al.*, 2007; Acharya and Morichi 2007). However, there are a few essential differences that could lead to a greater difficulty for introducing the services in the mid-sized cities as the study area. Firstly, although the motorcycle is not appropriate for many long-distance trips, the trip distance in mid-sized cities is much shorter than in those large cities and typically does not exceed the suitable range for motorcycle use, about ten kilometres for a journey (Hsu *et al.*, 2003). Secondly, the income levels of people in mid-sized cities are usually low, relative to larger metropolises in the same country; this limits the maximum fares for services if they are to remain socially equitable. Hence, in establishing a high quality public transport service in a mid-sized city, the fare must be low enough to compete with the cost of using a motorcycle. Simultaneously, the service quality must be superior in order to negotiate the other two major advantages of motorcycle (i.e. on-demand and door-to-door service). Since the quality of service is certainly associated with the cost of operation, serious attention to the service provision from the federal and local government authorities is required, including a significant amount of fare subsidy that may be required.

Since the city of Khon Kaen is of an average size when compared to other regional major cities of Thailand, the forecast vehicle ownership situations estimated by these models might also occur in similar cities, including Chiang Mai, Phuket, Surat Thani, Udon Thani etc. Therefore, all recommendations including those related to the problem of restraining household vehicle ownership might also be applicable for other major regional cities in Thailand. Suggested further research may include obtaining model input data from the other mid-sized cities in Thailand and beyond to further test the validity of models developed in this study and provide greater confidence in the model findings and structures. For the concept developed for the Approach 2 model; although it can give somewhat similar prediction to a common joint model used in the Approach 1, it is yet questionable regarding the lack of representing the pattern of substitution between car and motorcycle ownerships. Thus, if available sample size is sufficient (approximately 800 samples or more), a joint model as demonstrated in the Approach 1 may be more appropriate. Incidentally, this paper details only with the effect of income on the model prediction scenarios. It may be useful for subsequent research to account for variations in other potentially influential factors, such as household size, household activities and land-use and geographical conditions of the community, to expand the applicability of the model to other cities and regions.

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