Journal of the Eastern Asia Society for Transportation Studies, Vol. 6, pp. 1751 - 1765, 2005

MODELING OF HOUSEHOLD MOTORCYCLE OWNERSHIP BEHAVIOUR IN HANOI CITY

Vu Anh TUAN
Graduate Student
Department of Civil Engineering
The University of Tokyo
7-3-1 Hongo, Bunkyo-ku, Tokyo
113-8656 Japan
Fax: +81-03-5841-8507
E-mail: tuan@trip.t.u-tokyo.ac.jp

Tetsuo SHIMIZU
Associate Professor
Department of Civil Engineering
The University of Tokyo
7-3-1 Hongo, Bunkyo-ku, Tokyo
113-8656 Japan
Fax: +81-03-5841-8506
E-mail: sim@civil.t.u-tokyo.ac.jp

Abstract: The rapid increase of motorcycle ownership associated with inadequate public transport has largely contributed to increased traffic congestion, accidents and environmental pollution in Hanoi. A policy framework to improve public transport and control motorcycle ownership simultaneously has become necessary for solving the problems. Therefore, practitioners have shown interest in the household motorcycle ownership behavior and how households respond to transport policies. Objectives of this study are to develop dynamic discrete choice models expressing the ownership behavior and investigate household response to policy. First, a retrospective survey is conducted for collecting information of the household motorcycle transaction processes. Second, heterogeneity is analyzed using random coefficients logit model. State dependence is investigated using buy-smooth and lagged dependent variables. Finally, the results show the increases in number of workers or students, motorcycle price, income, and previous transactions significantly influence current transaction decisions. Sufficient high taxes imposed on motorcycle users could be effective in controlling the ownership.

Key Words: motorcycle ownership, transport policy, state dependence, transaction choice model.

1. INTRODUCTION

Motor vehicle ownership plays a vital role in determining travel behavior. Availability of a vehicle in one household encourages its utilization, and, the more cars in a household fleet, the more car travel in total occurs. On one hand, transportation practitioners are interested to know how many and what type of vehicles are being owned by households and how people adjust and utilize their vehicles. On the other hand, the government sees demand for transportation outpacing efficiencies so they support the promotion of new technologies (e.g. fuel cells) and is interested to start a "shift of consumer behavior". Understanding the behavioral responses of consumers to the actions of business and government is of interest to a wide spectrum of society. Therefore, there have been many studies on car or automobile ownership and usage at the household level. Unfortunately, very few researchers have carried out studies on motorcycle ownership behavior at the household level. Perhaps motorcycle has been considered as a "temporary" transport mode over the world. However, in some developing Asian cities such as in China, Thailand, Malaysia, Taiwan, and Vietnam, motorcycles play an important role in the daily travel pattern of the people. The significant role of motorcycles has been still remained in the urban transport systems even for decades in the future. Therefore, there is a great need to study the motorcycle ownership behavior in order to help policy makers propose effective policies to deal with the problems involving motorcycle.

Surprisingly, in Hanoi City, Vietnam, motorcycle ownership (hereafter, MCO) has been growing at very high rates, with an annual average of 14%. The MCO reached approximately 1.1 million over nearly a 3.2 million population and, particularly, grew at a rate of 25% per year in 2002. In terms of modal share, motorcycles share more than 60%, meanwhile bus service, the only public transport system in Hanoi, has only a 5% share. As a result, Hanoi City has been facing serious urban transport problems. These include heavy traffic congestion, a high rate of traffic accidents, and a polluted environment. To solve these problems, it is crucial to propose a policy framework, aiming at promoting public transport (e.g. bus service) and controlling the MCO and usage, simultaneously. However, proposing effective policies does require relevant information and effective tools for analyzing policy scenarios. Regarding the former, there is lack of necessary data on MCO and public responses to motorcycle-related policies. Regarding the latter, there is also a lack of analytical tools for simulating household response to transport-related policies, particularly, higher taxes on motorcycle users. Therefore, an understanding on household MCO behavior is very essential and useful since it could help evaluate the effects of motorcycle-related policies.

Previous studies on household vehicle ownership can be classified into discrete and non-discrete frameworks. Discrete choice models can further be divided into 2 model categories depending on the nature of the data used for model estimation, cross-sectional and panel data based models. Numerous empirical studies have been conducted in discrete choice frameworks using cross-sectional data. Golob et al. (1979) modeled household choice of fleet size using cross-sectional household interview data. In the study, household attributes, costs of holding and operating a car, household travel pattern, and transport system characteristics were explanatory variables. A number of researchers, e.g. Manski et al. (1980), Mannering et al. (1985), and Hensher et al. (1987), tried to bring two components of car ownership together by developing MNL or NL models for the number of vehicles owned and vehicle type choice. However, these studies are static so it is impossible to analyze the effect of past experience and household’s taste variations.

Fortunately, the demerits of static models can be overcome by using panel data models. Nobile et al. (1996) estimated a random effects multinomial probit model of car ownership choice utilizing panel data in the Netherlands. The effects of resistance in choice behavior and unobserved factors were investigated using the MNP model. The study revealed that the most number of variations in the observed choices could be attributed to between-household heterogeneity rather than to within-household random effects. Dargay et al. (1999) estimated a random effects plus first order auto-regressive model using pseudo-panel approach. The study found that the number of cars of an average household depends on the number in the previous year and there may be many dynamics involved in car ownership decisions. However, there are a few studies modeling auto ownership by explicitly considering household's vehicle transaction choices. The number of cars and fleet composition are obviously a result of serial transaction decisions made by the household: add a vehicle, replace one by another, and dispose one of them. For example, Hensher et al. (1992) described the dimensions of an auto demand project that was carried out in Sydney (1981-1991). De Jong et al. (1996) developed several sub-models, vehicle holding, vehicle choice, and vehicle usage.

A few studies have been carried out in non-discrete frameworks. Gilbert et al. (1992) developed a hazard duration model to estimate the distribution of auto ownership lengths and the effects of auto and socioeconomic characteristics on the length. Yamamoto et al. (1999) developed a competing risks duration model of household vehicle transactions. Although such kinds of models are powerful in explaining ownership choice behavior, extreme difficulties have been encountered in the collection of very detailed data over a specific time interval, thus, making them unpopular models.

Therefore, the discrete choice method using panel data is selectively applied to this study because of reasons mentioned above. Particularly, it will become easier to collect necessary information used for building the dataset for model estimation. Additionally, the discrete method has been mostly used by an increasing number of researchers and has been proven to be an advanced modeling technique. It is also more able to handle the model estimation based on the panel data collected.

Primary objectives of this study are to: 1) collect panel data on the history of household MCO in Hanoi City; 2) model the household MCO choice behavior as a dynamic decision-making process; 3) test the effects of tax policies aiming at controlling MCO. This paper is constructed in five sections. Section 2 describes the data used. Section 3 explains the modeling framework. Section 4 presents the estimation results. The last section gives the conclusion.

2. DATA COLLECTION

For modeling vehicle ownership behavior, single cross-sectional data is not enough to estimate the effects of time-variant factors. Since panel data can allow for capturing variations in vehicle ownership behavior and consumer responses to policy changes. It is desirable to utilize panel data in this study. Unfortunately, there are no such data available in Hanoi City. Therefore, we conducted a retrospective household survey in 2003, with total 299 sampled households, to build the dataset. Primary statistics from the survey are given in Table 1.

On average, one household has 3.6 people and is holding 1.75 motorcycles. Approximately, two people are holding one motorcycle, producing an extremely high rate of motorcycle ownership compared to other developing cities in Southeast Asia. It can be seen that more than 80% of the transactions observed are purchases, indicating that Hanoi people have been mainly purchasing motorcycles. Therefore, an important assumption can be made that every household only considers whether to add a motorcycle or not, annually. This point is very important in specifying the number of alternatives in the choice set.

Table 1. Main Statistics from the Retrospective Household Interview Survey

Item	Observed value
Total number of interviewed households	299
Total number of household individuals	1,066
Total number of motorcycle transactions during period 1990-2002 (100%)	626
• Purchase (83.9%)	525
• Replace (13.6%)	85
• Dispose (2.5%)	16
Total number of motorcycles being owned by the households	542
Average household size	3.6
Average motorcycle transactions per household	2.1
Average number of motorcycles being owned by a household	1.75

3. MODELLING FRAMEWORK

A decision to buy a motorcycle is one of the most important decisions made by a household. MCO represents a dramatic increase in mobility and access to employment. The way households make decisions with respect to vehicle ownership has been the subject of numerous studies across many disciplines. In general, a market-based decision can be described as three-stage process of “becoming active in the market”, “searching for the best alternative”, and “bidding or accepting an alternative”. The decision-making process and transaction approach can be applied to this study due to the fact that they show consistency with the actual process made by the decision maker. This allows us to model any size of vehicle fleet within the proposed framework. The framework is a two-stage modeling system. The first stage is a "Motorcycle Transaction Choice Model" simulating the motorcycle acquisition process. The second one is a "Motorcycle Type Choice Model" simulating the decision to buy a specific motorcycle type. The models recognize fundamentally that the processes of buying and selling motorcycles are different and are perceived differently by households. From a utility maximizing perspective, when the household’s net utility gain of transacting exceeds a threshold, a transaction is triggered. The condition of current fleet, changes in household demographic and socioeconomic conditions might also trigger a transaction.

3.1 Structure of Household Motorcycle Ownership Decision-making Process

In reality, the transaction choice set consists of “*add*”, “*replace*”, “*dispose*”, and “*do-nothing*” options. However, as seen in Table 1, more than 80% of the transactions observed are purchases. To simplify the transaction model, it is assumed that a household annually considers whether to add a motorcycle to the current fleet or not. Therefore, there are two alternatives in the choice-set, “*add a motorcycle*” or “*not add motorcycle*” (see Fig. 1). If the household decides to add a motorcycle to the current fleet, the number of motorcycles owned will increase.

Otherwise, the fleet is unchanged and the likelihood of adding a motorcycle will continuously increase until the adding occurs.

Household motorcycle holdings have evolved over time in response to such yearly decisions. At first, whether the household adds a motorcycle or not depends on their evaluation of the current holdings, in terms of the number, type, and age of motorcycles being held. In addition, the decision is also dependent on the choices in the past, changes in household characteristics (e.g. household size, number of workers/students, income, and market price of motorcycle). Subsequently, given that the purchase transaction has occurred, the household decides what brand (Japanese/Thai, Vietnamese, Chinese, or others), vintage (brand-new or used), and engine capacity (50cc, 70cc to 100cc, or more than 100cc) of the motorcycle to be selected. To represent this behavior, we propose several models, such as MNL and NL models. However, since estimation using NL model failed, it is assumed that households make decision on brand, vintage, and engine capacity jointly. Furthermore, to analyze motorcycle type simultaneously with the effects of motorcycle transaction is required. To integrate these two models, several different decision-making structures are tested. However, the structure, as illustrated in Fig. (1), seems to be the most consistent.

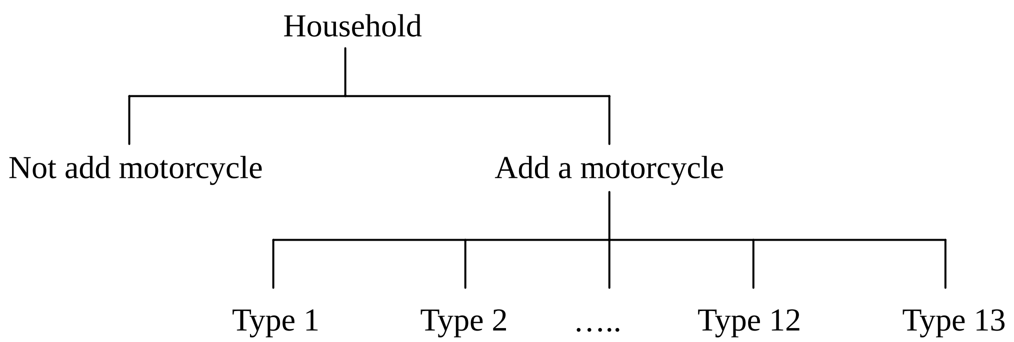

Figure 1. Structure of Household Motorcycle Ownership Decision-making Process

3.2 Models of Motorcycle Transaction Choice Considering State Dependence

While analyzing repeated choice behavior in labor force participation, Hyslop et al. (1999) finds that a predominant characteristic of annual participation behavior is the high degree of persistence in individual participation decisions. Several sources of the serial persistence have been identified, such as state dependence, individual unobserved heterogeneity, and serial correlation in the time-varying error component of the latent regression model. In this study, an investigation of state dependence and heterogeneity is conducted to explain the observed persistence in MCO choice. It is revealed that there can be a high dependence of the current choice on the previous choices in terms of transaction timing and type of motorcycle. We find many of the sampled households, whose first motorcycles were Japan-made, delayed their decisions to buy a motorcycle for several years in order to save enough money to buy second ones of the same type. Thus, the time duration between buying these ordered motorcycles and the number of motorcycles in the household could be affected by such behavior. To analyze the behavior, we employ both dynamic random coefficients model (Model 1) and structural state dependence logit model (Model 2).

In Model 1, which takes a form as given in Eq. (1), heterogeneity is accounted for by letting certain coefficients normally distribute. Accounting for state dependence can be performed through allowing past choices have an impact on current period utility evaluation. In terms of functional forms for dependence of current utility evaluations on past choices, a dummy variable for lagged choices can be used in current utility functions as being applied in Model 2. Another functional form used in Model 1 is a buy smooth variable, which was proposed by Guadagni et al. (1983). Mathematically, buy smooth is an exponentially smoothed weighted average of past choices, which takes a form as given in Eq. (2).

$$P_{in} = \int \left(\frac{e^{\beta' x_{in}}}{\sum_j e^{\beta' x_{jn}}} \right) f(\beta) d\beta \tag{1}$$

Where, P_{in} is the probability of household n choosing transaction alternative i; x_{in} is a vector of explanatory variables, including the buy smooth variable; β is a vector of coefficients assumed to be normally distributed;

$$Buysmooth_{n,t}(i) = (1-\lambda) Buysmooth_{n,t-1}(i) + \lambda Y_{n,t-1}(i) \tag{2}$$

Where, $Y_{n,t}(i)$ is given value of 1 if household n chooses alternative i on choice situation t and 0, otherwise; λ is a smoothing parameter assumed to be constant over time and across households. The idea is that a motorcycle transaction itself may have an effect on household needs and motivation for MCO level. Therefore, each transaction can potentially affect the timing and type of the transaction that follows. To calculate the value of buy smooth variable, it is required to estimate λ value. The value can be either directly estimated during the model estimation process or obtained through a search procedure over the range [0, 1]. In this study, we applied the latter method by testing different values of λ (for example, 0, 0.1, 0.2,.., 0.9, and 1) and finally selecting the one that best fits the survey data. If value of λ closes to one, it means the chosen alternative in the most recent choice drives the choice in the current choice procedure. In contrast, if the value closes to zero, it indicates that historical choices play much more important role in accounting for the effects on the current choice.

In Model 2, which takes a form as given in Eq. (3), a lagged dependent variable is developed to investigate state dependence.

$$P_{add-a-MC,i,t}(Y_{i,t} = 1) = \Pr(U_{i,t} > 0) \qquad (i = 1..N;\ t = 1..\ T\text{-}1) \tag{3}$$

where, $P_{add\text{-}a\text{-}MC,i,t}(Y_{i,t}=1)$ is the probability that household i adds a motorcycle in year t; $U_{i,t}=\beta' x_{i,t}+\gamma Y_{i,t-1}+\varepsilon_{i,t}$ is the utility function of the alternative of adding a motorcycle at year t; x_{it} is a vector of explanatory variables; β, γ are coefficients to be estimated; ε_{it} is error term; $Y_{i,t-1}$ is a lagged dependent variable in year t-1. The initial condition is specified as follows:

$$Y_{i,0} = 1(\beta_0' x_{i,0} + \varepsilon_{i,0} > 0), \qquad \varepsilon_{i,0} \sim i.i.d.Gumbel(0,1) \tag{4}$$

In addition, a standard binary logit model (Model 3) is estimated for the purpose of model comparison.

3.3 Model of Motorcycle Type Choice

Table 2. Choice Sets of Motorcycle Type Choice Models

Type	Vintage	Make	Engine Capacity	Av. Price (VND)	Note
1	Brand-new	Japan/ Thailand	Up to 100cc	21000000	
2	Brand-new	Japan/ Thailand	Over 100 cc	28000000	
3	Brand-new	Others	Up to 100cc	11000000	
4	Used	Japan/ Thailand	Up to 100cc	15000000	
5	Used	Japan/ Thailand	Over 100 cc	22000000	
6	Used	Others	Up to 100cc	7000000	
7	Brand-new	Vietnam	Up to 100cc	16000000	First introduced in 1996
8	Brand-new	Vietnam	Over 100 cc	19000000	First introduced in 1996
9	Brand-new	China	Up to 100cc	10000000	First introduced in 1996
10	Brand-new	China	Over 100 cc	12000000	First introduced in 1996
11	Brand-new	Others	Over 100cc	30000000	First introduced in 1996
12	Used	Vietnam	Up to 100cc	13000000	First introduced in 1996
13	Used	China	Up to 100cc	7000000	First introduced in 1996

Note: US$1=VND15000

Since household tastes could be time invariant, it could be assumed that the decision-making process made by a household on motorcycle type is static. Initially, several decision-making structures are tested, including MNL and NL models. Finally, only the MNL model successfully estimated the process. The choice set from which households make choices is defined by alternatives available in the dataset. There are initially 24 different motorcycle types. However, some types are by far the least common types of motorcycles owned and many types are almost similar. The 24 types are then aggregated into 13 common types. In addition, due to the fact that Vietnamese and Chinese motorcycles were first introduced to the market in 1996, the number of choices dramatically increased since 1996. To avoid the impact of the fact, we estimate two models for two periods, before 1996 and since 1996. As seen in Table 2, there are 6 alternatives {1,2,3,4,5,6} and 13 alternatives {1,2,3,..,13} in the before-1996 model and the since-1996 model, respectively.

4. ESTIMATION RESULTS

The expected utility from the motorcycle type choice model, which has been estimated in the lower level nest, is added to the utility function of adding alternative in the transaction model. This is in the form of an inclusive value (log-sum), which is interpreted as the expected value of the attributes that determine the type of the motorcycle chosen in the lower level nest. The parameter of inclusive value is a coefficient with a value between zero and one to be consistent with the model derivation. The estimation approach in this study is a sequential estimation procedure. First, at the lower nest, MNL models are estimated using the standard maximum likelihood method. The estimated coefficients are then used to calculate the inclusive values. The final step is to estimate the upper level nest using the maximum simulated likelihood method. We write estimation programs in GAUUS to perform the estimation tasks. Estimation results are presented and discussed hereafter.

4.1 Motorcycle Transaction Choice Models

Table 3. Parameter Estimates for Motorcycle Transaction Models

Explanatory variable	Model 1		Model 2		Model 3	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
-There is a household member who is going to start or has recently started working (dummy)	0.9159	5.525	0.8539	4.656	0.7836	4.357
Standard deviation	0.607	2.630				
-There is a household member who is going to enter or has recently entered university (dummy)	0.4537	3.030	0.3919	2.578	0.3589	2.364
-Natural logarithm of [average price of fleet (VND million)]+1 {plus 1 if non-motorcycle household}	-1.0386	-16.507	-0.4065	-7.275	-0.4498	-8.127
-INDEX = Motorcycle cost (VND million) is divided by annually average income per household member (VND million/year)	-0.2566	-8.932	-0.2297	-8.712	-0.2122	-8.342
Standard deviation	0.0932	1.724				
-Buy smooth (with λ=0.7) (Model 1)	-2.1662	-3.902				
-Lagged dependent variable (Model 2)			-0.6232	-3.203		
-Inclusive value (from the type choice model)	0.4169	13.233	0.2798	9.520	0.2633	9.222
Log likelihood ratio	0.5316		0.2412		0.2336	
Hitting ratio	0.8385		0.7724		0.7692	
Observations	3296		2496		2496	

Estimation results of the three transaction models are presented in Table 3. Model 1 is dynamic random coefficients logit model. Model 2 is (dynamic) structural state dependence logit model. Model 1 utilizes buy smooth to capture state dependence, while Model 2 uses a lagged dependent variable to do so. And Model 3 is a (static) standard binary logit model, without state dependence.

In Model 1, statistically significant coefficients are obtained for the model and the effects of previous transactions are also effectively captured in the process. The coefficient of inclusive value is 0.4169 with a strong t-statistic (13.233), significantly different from zero and one. This provides support for the nested structure presented in Fig (1). Initially, changes in the number of jobs in the household have produced a significant positive coefficient. It suggests that a household, whose members recently became or is to be employed, is more likely to acquire a motorcycle. Its standard deviation, 0.607, shows that there is small variation in the factor's effect across the population. Rich households are much more likely to add a motorcycle when the changes occur while poor households are less likely to do so. Similarly, the change in which there is a household member, who recently entered university or is planning to do so, results in a significant and positive coefficient. This suggests that a household with this characteristic is more likely to purchase a motorcycle for that person. There is no taste variation for the attribute, indicating that every household is likely to add a motorcycle when this change occurs.

Secondly, the natural logarithm of the average price of the motorcycle fleet plus one (to account for households without motorcycle) has a highly significant coefficient estimate with a t-statistic of –16.507. Its negative sign (-1.038) suggests that households with more valuable fleet are less likely to make transaction. A fleet with a higher market value means a younger fleet with better motorcycles in it, which makes the owner less likely to decide to change it.

Thirdly, to capture joint effects of motorcycle price and annually average income per household member, we introduce an index variable that is a ratio between these two factors. The coefficient is significantly estimated with a negative sign (-0.2566). The results imply that a household is less likely to buy a motorcycle when the costs of holding a motorcycle are much higher than its annual income or savings. The costs include purchase cost, VAT (5 %), and registration tax (5% at the present). Therefore, if some tax related policies target on raising the costs, annual growth rate of MCO would decline. How MCO is affected will depend largely on the nature of taxes and, of course, on people's perception.

Fourthly, the buy smooth factor is employed to capture the effects of previous transactions and to account for state dependence. A searching procedure yields a value of 0.7, meaning that the relative importance of the most recent transaction (0.7) is larger than the importance of all preceding years' transactions (0.3). The coefficient -2.1662 means that if a household recently bought a motorcycle, it has lower probability of adding a motorcycle in the following year. However, the use of buy smooth variable is purely an *ad hoc* approach to capture state dependence. Therefore, Model 2 is developed to compare with Model 1 in terms of consistency and fitness. Finally, all coefficients return very strong t-statistics and correct signs (See Table 3). The likelihood ratio (0.5316) is excellent for this model type, the reason is due to the dominant not add alternative accounts for 86% of the observed behavior. The percentage predicted correct for the model is 83.85%.

Unfortunately, the dataset used for estimating Model 1 is different from the dataset of the last two models. In this study, the results of Model 1 are just used as a reference and it can be stated that the buy smooth variable can be utilized for investigating state dependence. Therefore, at the moment it is impossible to compare Model 1 with Model 2 and Model 3. In the next step of the study, further effort will be made to estimate Model 1 based on the same dataset, which was used to estimate Model 2 and Model 3. Subsequently, detailed model comparison can be performed sufficiently.

In Model 2, a lagged dependent variable is added in the utility function to capture the effect of the previous transaction choice. This method is seen to be more effective than the use of buy smooth variable in Model 1. First, it can be seen that the model successfully estimated significant and correct coefficients. Signs and magnitudes of the coefficients are almost the same as the corresponding coefficients in Model 1. These imply the use of lagged dependent variable to capture state dependence is successful in the process. However, the coefficients in Model 2 declined in magnitude, approximating to 90% of the equivalent coefficients in Model 1. Finally, the likelihood ratio is acceptable even though its value is not as high as expected since a value of 0.2412 is acceptable when using a quite complicated econometric model. The percentage predicted correct for the model is 77.2%.

The third model, a static transaction model, is additionally estimated in order to compare with Model 2 in terms of model based estimates. The coefficients are obtained with significantly high t-statistics and correct signs, saying the same as two previous models. The results are relatively similar to Model 2 in terms of coefficient estimates, log-likelihood and hitting ratios. However, the results find high correlations between the variable, natural logarithm of average price of motorcycle fleet, and all other variables in the model. Therefore, it should be better to use this model for short-term effects prediction. At the moment, the results show there are no significant improvements in the dynamic models. However, we still believe that Model 2 is the best model among the three models. How to improve Model 2 to be the best with respect to data collection and model reconstruction remains a future work.

4.2 Motorcycle Type Choice Models

Table 4 presents estimation results of the type choice models. Generally, all coefficients have t-statistics greater than 1.64 (95% confidence level) and the models have ρ^2 of 0.368 and 0.177, respectively. First, the signs of all model coefficients are correct and unambiguous. Analysts would expect that a negative sign would be associated with motorcycle price and income that cause negative utility. It is obvious that a household's relative utility would increase when the price decreases and/or the income increases. This should justify negative signs for "Market motorcycle price divided by natural logarithm of annual income per household member". Second, if a household has low income, it is more likely to choose cheaper motorcycles (e.g. types 3, 4, 6, 9, 10, 12, and 13, see Table 2). This dummy is not included in the before-1996 model because there were no such cheap motorcycles before 1996. Third, if the main user of the motorcycle is an office worker or university student, they are more likely to choose an expensive one. This factor has more effect on the utility function of the before-1996 model than the since-1996 model, with a higher coefficient estimate and t-statistic. Similarly, if the main user is male, the household is likely to choose a brand-new model. Finally, two additional factors are added in the since-1996 model to address the effects of current fleet's characteristics on type choice. If the household has never owned a Japanese or Thai motorcycle, they are more likely to choose the same motorcycles to own. If the household owned a second-hand motorcycle, they are more likely to choose a second-hand one because they have experienced using it and could accept adding the same kind due to budget constraints.

Table 4. Parameter Estimates for Motorcycle Type Choice Models

Explanatory variable	Alternative	Before-1996 model		Since-1996 model	
		Coeff.	*t-stat*	*Coeff.*	*t-stat*
-Motorcycle price (VND million) divided by natural logarithm of annual income per household member (VND thousand)	All	-1.877	-12.060	-0.562	-3.237
-If the main user is office worker/student (*dummy*)	1,2,6,7,9,8,9	3.314	11.726	2.032	4.082
-If the main user is male (*dummy*)	1,2,3,4,7,9, 10,13	2.041	16.076	3.549	2.550
-If the household is of low income level *(dummy)*	3,5,8,10,11, 12,13			1.740	2.736
-If the household has never owned Japanese/Thai motorcycle (*dummy*)	1,2,5,6			1.842	11.948
-If the household has ever owned used motorcycle (*dummy*)	5,6,8,11,12			3.340	2.197
Log likelihood ratio		0.3682		0.1770	
Hitting ratio		0.5036		0.2670	
Observations		137		315	

4.3 Sensitive Analysis of Motorcycle related Tax Policies

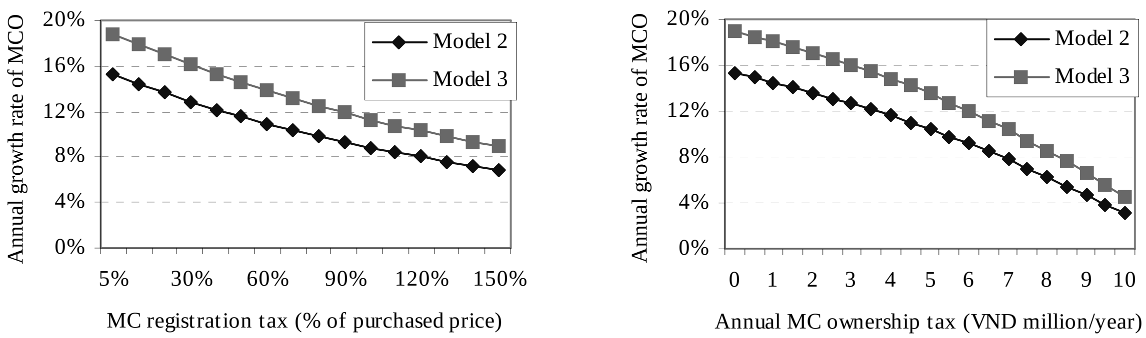

Figure 2. Changes in the Annual Growth Rate of MCO by Motorcycle Ownership Taxes

Transport pricing measures, in general, have been seen as policy instruments to control traffic. One of the greatest advantages of such policies, compared to physical restriction measures, is they provide considerable revenues. The revenues then can be used for making whatever other improvements. In the case of Hanoi City, it can be possible to apply taxation systems as effective tools for controlling ownership and usage of private vehicles, especially motorcycles. If the motorcycle users or holders have to pay much more for holding and using motorcycles relatively compared to income, given the sufficiently good public transport systems, they will consider giving up using motorcycle and/or may shift to public transport services. Therefore, analytical tools for predicting policy response have been very much critical and valuable.

The purpose of developing a behavioral model is to forecast the effects of policy changes. In this study, it is assumed that there are no changes in market price of motorcycles, household income, etc. Firstly, changes in MCO rate due to different levels of motorcycle registration tax can be seen in the left part of Fig (2). At present, the tax is 5% of the purchased price of the motorcycle so the growth rate is about 16% per year. Unbelievably, it may be necessary to raise the tax up to 150% in order to keep the rate at 7% per year. It seems that only charging motorcycle users at the time of motorcycle registration cannot sufficiently impact their desire to add motorcycle.

Secondly, an effort is made to simulate household response to annual ownership tax, which has not been implemented in Vietnam yet. Such kind of tax, however, has been already applied in many countries and has shown effectiveness in controlling the automobile ownership growth rate. The changes in MCO rate corresponding to various levels of the tax are illustrated in the right part of Fig (2). It suggests that to keep MCO growing at 3% per year, it is necessary to charge motorcycle user a VND 10 million annually, regardless of the type and the price of motorcycles. This level of the tax seems to be much higher than the average price of a motorcycle purchased at around VND 20 million by a household of annual average income from VND 24 to 30 million. But it would be effective in controlling MCO if a significant and reasonable level of the tax is well defined. Therefore, it is strongly recommended that such a policy be introduced and implemented in Hanoi City. In addition, such policies can generate much revenue, which can be then alternatively utilized as a subsidy in improving the public transport system.

Lastly, it is easily realized there exist significant differences between the growth rates estimated by Model 2 and Model 3. In both cases of simulation, estimates of Model 3 are significantly higher than the same ones of Model 2. Moreover, the slopes of the growth rate lines based on Model 3 are slightly higher than the same things based on Model 2. The reasons behind the differences can be explained by the effects of state dependence in Model 2 on the probability of adding a motorcycle. Specifically, in a household the purchases of motorcycle in previous years generally help lower the likelihood of purchasing one more motorcycle this year. This negative impact can be seen as the saturation phenomenon in transactions.

5. CONCLUSIONS

This paper has presented an overview of a process aiming at developing a comprehensive dynamic model of household motorcycle ownership. It is a two-stage modeling system, the first stage is a “Dynamic Motorcycle Transaction Choice Model” to simulate the motorcycle acquisition process, and the second stage is a “Motorcycle Type Choice Model” to simulate the decision to buy a specific motorcycle type.

In the transaction choice model, an effort was made to investigate the effects of heterogeneity and state dependence in the household MCO decision and to distinguish between heterogeneity- and state dependence-based explanations for the observed persistence in choice behavior. Model 1 with the buy smooth variable proved that heterogeneity is not an important issue and the estimated buy smooth factor could be effective in capturing the occurrence of state dependence correctly. Model 2 with a lagged dependent variable showed that the endogenously lagged dependent variable could be more effective in analyzing state dependence. It was also determined that using both a lagged dependent variable and a structure of serially correlated error component could only be effective in investigating “true” and “spurious” state dependence. However, we failed to develop such model due to lack of information and it remains a task for further investigation.

The type choice model has well reproduced the aggregate market shares even though the overall percentage predicted a correct share for the models at 50% and 27%, respectively. It implies that the predicted choice for a household is unlikely to match the actual choice. However, it should be kept in mind that many of the actual motorcycle types were aggregated into 13 types and modeling a choice problem with such diversity in the choice set is a difficult task, given the limited observations. Therefore, the obtained results seem to be the best achievable outputs for a complex behavioral problem with many alternatives and an unknown decision hierarchy.

The policy sensitive analysis gave suggestions to adopt effective and feasible transport policies for controlling the rapid increase of MCO in Hanoi City. Among many applicable policies, the imposition of sufficiently high taxes (e.g. registration and annual ownership tax) on motorcycle users could be a promisingly applicable measure in the context of Hanoi, Vietnam. Especially, the introduction of the annual ownership tax could be considered by policy makers in order to effectively manage the rapidly increased motorcycle ownership.

Finally, it should be realized that state dependence could be present not only in the motorcycle transaction choice behavior but also in the motorcycle type choice behavior. In this case, experiences achieved by the household, brand loyalty, and economic conditions could drive the observed persistence in type choice behavior. Exploring this issue also remains a task for our future work.

REFERENCES

Ben-Akiva, M. and Lerman, R. (1985) Discrete Choice Analysis-Theory and Application to Travel Demand, **MIT Press**, pp. 59-129 and pp. 323-357.

Bhat, C., and Pulugurta, V. (1998) A Comparison of Two Alternative Behavioral Choice Mechanisms for Household Auto Ownership Decisions, **Transportation Research B, Vol. 32 (1)**, pp. 61-75.

Chia, N., Tsui, Albert, K., and Whalley, J. (2004) Taxes and Traffic in Asian Cities: Ownership and Use Taxes on Autos in Singapore, **Working Paper**.

De Jong, G. (1997) A Micro-economic Model of the Joint Decision on Car Ownership and Car Use, Stopher, P. and Lee-Gosseline, M. **Understanding travel behavior of an Era of Change, Pergamon**.

Dargay, J. and Vythoulka, P. (1999) Estimation of a Dynamic Car Ownership Model: A Pseudo-panel approach, **Transport Economics and Policy, Vol. 33(3)**, pp. 287-302.

Golob, T. and Burns, D. (1979) Effects of Transportation Service on Automobile Ownership in an Urban Area, **Transportation Research Record, No. 673**.

Guadagni, P. and Little, J. (1983) A Logit Model of Brand Choice Calibrated on Scanner Data, **Marketing Science, No. 2**, pp. 203-238.

Gilbert, S. (1992) A Duration Model of Automobile Ownership, **Transportation Research B, Vol. 26(2)**, pp. 97-114.

Hensher, D., Smith, N., Milthorpe, F., and Barnard, P. (1992) Dimensions of Automobile Demand-A Longitudinal Study of Household Motorcycle Ownership and Use, **Studies in Regional Science and Urban Economics**. Amsterdam: North Holland.

Hensher, D. (1987) Modeling Dynamics of Car Ownership and Use: A Methodology and Empirical Synthesis, **Fifth International Conference on Travel Behavior, France**.

Hyslop, D.R. (1999) State Dependence, Serial Correlation and Heterogeneity in Intertemporal Labor Force Participation of Married Women, **Econometrica, Vol. 67(6)**, pp. 1255-1294.

Manski, Charles, F., and McFadden, D. (1981) Structural Analysis of Discrete Data with Econometric Application, **MIT Press**, pp. 114-195.

Manski, Charles, F., and Sherman, L. (1980) An Empirical Analysis of Household Choice Among Motor Vehicle, **Transportation Research A, Vol. 14A**, pp. 349-366.

Mannering, F., and Wilson, C. (1985) A Dynamic Empirical Analysis of Household Vehicle

Ownership and Utilization, **RAND Journal of Economics, Vol. 16**, pp. 215-236.

Train, K. (2003) Discrete Choice Methods with Simulation, **Cambridge University Press**, pp. 38-217.

Train, K., Revelt, D., and Ruud, P. (1999) Mixed Logit Estimation Routine for Panel Data, **http://elsa.berkeley.edu/Software/abstracts/train0296.html,** Accessed August 2004.

Willoughby, C. (2001) Singapore's motorization policies 1960-2000, **Transport Policy 8**, pp. 25-139.

Yamamoto, T., Kitamura, R., and Kimura, S. (1999) A Competing Risk Duration Model of Household Vehicle Transactions, **Transportation Research Records, No. 1676**, pp. 116-123.