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A dynamic analysis of motorcycle ownership and usage: A panel data modeling approach

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ABSTRACT

This study aims to develop motorcycle ownership and usage models with consideration of the state dependence and heterogeneity effects based on a large-scale questionnaire panel survey on vehicle owners. To account for the independence among alternatives and heterogeneity among individuals, the modeling structure of motorcycle ownership adopts disaggregate choice models considering the multinomial, nested, and mixed logit formulations. Three types of panel data regression models – ordinary, fixed, and random effects – are developed and compared for motorcycle usage. The estimation results show that motorcycle ownership in the previous year does exercise a significantly positive effect on the number of motorcycles owned by households in the current year, suggesting that the state dependence effect does exist in motorcycle ownership decisions. In addition, the fixed effects model is the preferred specification for modeling motorcycle usage, indicating strong evidence for existence of heterogeneity. Among various management strategies evaluated under different scenarios, increasing gas prices and parking fees will lead to larger reductions in total kilometers traveled.

1. Introduction

In many Asian countries such as China, Indonesia, Malaysia, Taiwan, Thailand, and Vietnam, motorcycles are a primary mode of urban transportation. Due to low purchase and running costs and convenient parking, demand for motorcycles has continuously risen in these countries. Traffic congestion, accidents, parking disorder, and air pollution are the inevitable consequences of high rates of motorcycle ownership and usage. Especially, in the context of accident analysis, because of limited protection design of motorcycles in comparison to cars, motorcycles are the most dangerous form of motorized transport, with injury rates eight times, and fatality rates 35 times that of car occupants (per vehicle mile traveled) (NHTSA, 2007; Ranney et al., 2010). In most developed countries, motorcycle fatalities typically comprise around 5–18% of overall traffic fatalities (Mohan, 2002; Koornstra et al., 2003; WHO, 2006). This proportion reflects the relatively low ownership and usage of motorcycles in many developed countries. However, the ownership and usage of motorcycles and other two-wheelers is generally relatively high in many developing countries. Reflecting this difference, the levels of motorcyclist fatalities as a proportion of those injured on the roads are typically higher in developing countries than in developed countries. For example, in India, 69% of the total number of motor vehicles are motorized two-wheelers (Mohan, 2002) and 27% of road deaths in India are among users of motorized two-wheelers, while this figure is between 70% and 90% in Thailand, and about 60% in Malaysia (Mohan, 2002; Umar, 2002; Suriyawongpaisal and Kanchanusut, 2003). In China, motorcycles accounted for 23.4% of all registered motor vehicles in 1987, increasing to 63.2% in 2001. Motorcyclist fatalities and injuries increased 5.5-fold and 9.3-fold between 1987 and 2001, respectively. A total of 7.5% of all traffic fatalities and 8.8% of all traffic injuries were sustained by motorcyclists, with the corresponding proportions increasing to 18.9% and 22.8% in 1987 and 2001, respectively. The changing proportions of both traffic fatalities and injuries sustained by motorcyclists were positively correlated with the change in the proportion of motorcycles among all motor vehicles (Zhang et al., 2004). In Indonesia, the population of motorcycles has reached 78.3% of total motor vehicles and 75% fatality victims of traffic accidents were motorcyclists (Indriastuti and Sulistio, 2010). In Taiwan, the motorcycle ownership rate reaches 645 per thousand people (the highest motorcycle ownership rate in the world). In 2009, motorcyclist fatalities in Taiwan accounted for 56.69% of total traffic deaths (MOTC, 2010). To compare the fatalities and injuries of car and motorcycle crashes further, Tables 1 and 2, respectively give the statistics of car and motorcycle ownership, usage and crash victims of 23 counties/cities in Taiwan. Noted from Table 1, there are a total of 5.7 million registered passenger cars with 502 fatalities and 71,564 injuries in 2009, while the number of registered motorcycles reaches 14.6 million with 889 fatalities

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Table 1
Car ownership, usage and crash of 23 counties/cities in Taiwan.

County/city	Registered cars	Average kilometers traveled (km)	Total kilometers traveled (million veh-km)	Victims		Fatalities (million veh-km)	
				Victims	Fatalities (million veh-km)	Victims	Injuries (million veh-km)
Taipei city	637,354	9842	6273	28	0.005	5908	0.942
Kaohsiung city	367,265	9734	3575	17	0.005	8023	2.244
Taipei county	776,945	8694	6755	20	0.003	6093	0.902
Yilan county	111,717	8987	1004	19	0.019	1988	1.980
Taoyuan county	535,501	9636	5160	49	0.010	7437	1.441
Hsinchu county	152,342	9157	1395	16	0.011	2007	1.438
Miaoli county	159,682	7152	1142	26	0.023	1605	1.406
Taichung county	438,394	8908	3905	36	0.009	6668	1.708
Changhwa county	343,522	8978	3084	26	0.009	4509	1.462
Nantou county	147,459	10,035	1480	19	0.013	1644	1.111
Yunlin county	179,534	8901	1598	34	0.021	2006	1.255
Chiayi county	134,520	8437	1135	29	0.026	1242	1.094
Tainan county	287,513	8198	2357	31	0.013	3561	1.511
Kaohsiung county	298,871	7783	2326	41	0.018	4140	1.780
Pingtung county	194,016	7582	1471	25	0.017	2230	1.516
Taitung county	49,223	7354	362	13	0.035	710	1.963
Hualien county	84,012	9701	815	22	0.027	1379	1.692
Ponhu county	18,047	7702	139	3	0.023	141	1.016
Keelung city	77,898	8010	624	6	0.010	847	1.358
Hsinchu city	114,352	10,057	1150	11	0.009	1886	1.640
Taichung city	316,596	8936	2829	12	0.004	3969	1.403
Chiayi city	69,624	7900	550	8	0.015	1769	3.217
Tainan city	190,162	9744	1853	11	0.006	1799	0.971
Average	–	8758	–	–	0.014	–	1.524
Total	5,684,549	–	50,982	502	–	71,564	–

and 129,200 injuries in Table 2. Even in terms of accident rates (i.e., number of victims per million kilometers traveled), motorcycle usage (in terms of total kilometers traveled) still exhibits higher rates of fatal and injured victims than car usage. On an average, there are 0.017 fatalities and 2.038 injuries per million kilometers traveled by motorcycles in comparison to 0.014 fatalities and 1.524 injuries per million kilometers traveled by cars. To further examine the relationship between motorcycle usage and numbers of victims of two severity levels, the Pearson correlation test is performed. Results show that correlation coefficients of motorcycle usage with fatalities and injuries are 0.586 (p-value = 0.003) and 0.886 (p-value < 0.0001), respectively, indicating a significant and positive correlation between motorcycle usage and crash victims. Compared with the relationship between motorcycle usage and

Table 2
Motorcycle ownership, usage, and crashes of 23 counties/cities in Taiwan.

County/city	Registered motorcycles	Average kilometers traveled (km)	Total kilometers traveled (million veh-km)	Fatalities		Injuries	
				Victims	Fatalities (million veh-km)	Victims	Injuries (million veh-km)
Taipei city	1,092,788	4438	4850	24	0.005	9513	1.962
Kaohsiung city	1,207,026	4778	5768	41	0.007	14,950	2.592
Taipei county	2,259,828	4912	11,099	66	0.006	13,600	1.225
Yilan county	292,879	4730	1385	34	0.024	3064	2.212
Taoyuan county	1,081,978	4665	5047	47	0.009	9919	1.965
Hsinchu county	271,233	4769	1293	35	0.027	2844	2.200
Miaoli county	350,202	3800	1331	23	0.018	2117	1.591
Taichung county	1,008,400	4199	4234	59	0.014	12,121	2.863
Changhwa county	902,353	4220	3807	62	0.016	8245	2.166
Nantou county	349,862	3883	1359	34	0.025	2888	2.125
Yunlin county	486,157	4308	2094	58	0.028	3384	1.616
Chiayi county	365,747	4597	1681	43	0.025	2123	1.263
Tainan county	805,813	4580	3691	57	0.015	7594	2.058
Kaohsiung county	1,014,396	5119	5192	79	0.015	9968	1.920
Pingtung county	697,431	4697	3276	86	0.026	5462	1.667
Taitung county	177,999	4006	713	30	0.042	1579	2.215
Hualien county	241,958	4472	1082	28	0.025	2435	2.251
Ponhu county	68,426	4125	282	4	0.014	585	2.074
Keelung city	190,771	4569	872	11	0.013	1653	1.895
Hsinchu city	262,338	4307	1130	16	0.014	3507	3.103
Taichung city	646,739	3813	2466	23	0.010	6127	2.484
Chiayi city	202,586	4961	1005	11	0.011	2312	2.300
Tainan city	583,436	4885	2850	17	0.006	3210	1.126
Average	–	4471	–	–	0.017	–	2.038
Total	14,560,346	–	66,509	889	–	129,200	–

crash victims, the correlation coefficients of car usage with fatalities and injuries are also significantly tested with slightly lower coefficients of 0.475 (p-value = 0.022) and 0.876 (p-value < 0.0001), respectively. Thus, effective management strategies for decreasing the ownership and usage of motorcycles and cars are urgently required.

In the past, substantial research has been devoted to the development of car ownership and usage models, which has contributed to enhance our understanding of choice behaviors (De Jong et al., 2004). These studies have been mostly conducted in the developed countries because people rely heavily on private cars for urban travel in these areas, and motorcycles play a secondary role as a mode of transportation. As a result, few studies have been done in the context of motorcycle ownership and use. In addition, previous works on ownership and usage of motor vehicles often used either cross-sectional or time-series data. Data sets that pool cross sections and time series (called panel or longitudinal data) have become increasingly common in transportation and other fields. Panel data analyses have many advantages, such as controlling for individual heterogeneity, less collinearity among the variables, more degrees of freedom, and more efficiency, over analyses only based on either cross-sectional or time-series data alone (Baltagi, 2005). Moreover, the panel data models allow for analyzing the repeated choices over time and can capture the state dependence effect by incorporating past choices.

The current literature lacks the analysis of motorcycle ownership and usage using panel data. To examine dynamic choice behaviors associated with motorcycle ownership and usage, this study conducted a large-scale, nationwide two-wave panel survey on owners of motorcycles in Taiwan. Thus, disaggregate models of motorcycle ownership and usage using panel data are proposed. The discrete choice model has been widely used as an appropriate methodology for examining vehicle ownership. Compared with the ordered choice model, the unordered discrete choice model derived from random utility theory provides a theoretical base for modeling the number of vehicles owned in the household (Bhat and Pulugurta, 1998). In addition to the use of a standard discrete choice model, i.e., the multinomial logit model (MNL), this study also adopts nested logit (NL) and mixed logit (MXL) models to accommodate the possible independence among alternatives and parameter heterogeneity among individuals. For modeling the usage of motorcycles, panel data regression models involving fixed and random effects approaches accounting for heterogeneity are developed and compared. These models can be used to identify factors influencing motorcycle ownership and usage, such as household structure, residential location, transportation system performance, driver's travel patterns, and vehicle characteristics. Our proposed panel data models provide reliable parameter estimates to evaluate the effects of management strategies in reducing motorcycle ownership and usage. Due to a significant relationship between motorcycle usage and crash victims, these strategies will also lead to reductions in traffic accidents by motorcycles.

The remainder of this paper is structured as follows. Section 2 provides a brief overview of previous literature. Section 3 presents the framework of the motorcycle ownership and usage models. Section 4 describes the data sources and estimation results of motorcycle ownership and usage models as well as scenarios and analyses of management strategies. Finally, this paper concludes with the research findings, and gives directions for further research.

2. Literature review

Studies on vehicle ownership often use either aggregate model (e.g., Jansson, 1989; Button et al., 1993) or disaggregate model (e.g., Train, 1980; Mannering, 1983). The aggregate models may suffer the shortcomings of aggregation bias and multicollinearity between explanatory variables (Potoglou and Kanaroglou, 2008). On the contrary, the disaggregate modeling approach overcomes the weaknesses of aggregate models by capturing individual choice behavior and explanatory variables at an individual level, with the ability to obtain more reliable estimates, and therefore, it has received greater attention in recent vehicle ownership research. The number of vehicles in a household, which is a categorical dependent variable, is typically analyzed by using either the ordered- or unordered-response choice models (Bhat and Pulugurta, 1998). Conditional on the household's decision to own vehicles, individual's vehicle usage measured as miles (or kilometers) per year and vehicle type can be modeled simultaneously to examine the relationship between these two variables (Mannering and Winston, 1985).

The recent development of vehicle ownership models has moved from static to dynamic modeling by collecting panel data that contain households' vehicle information for consecutive years. Studies of household vehicle ownership with panel data often adopted ordered-response models accounting for state dependence and heterogeneity (Kitamura and Bunch, 1990; Hanly and Dargay, 2000; Giuliano and Dargay, 2006; Dargay and Hanly, 2007). The panel data analysis of vehicle usage commonly employed random- and fixed-effects specifications allowing for unobserved heterogeneity (e.g., Dargay, 2007; Woldeamanuel et al., 2009). A substantial body of research documents modeling and empirical findings of car ownership and usage worldwide. However, there has been relatively little research into motorcycle ownership and usage. For example, Senbil et al. (2007) applied ordered probit models and tobit/probit regression models with sample selection to explore motorcycle usage in the metropolitan area of Jabotabek, Indonesia; these models have identified key explanatory variables (e.g., residential location, land use, transportation system performance, and socioeconomic/demographic characteristics). Burge et al. (2007) presented a two-level NL model containing the household's decision to own motorcycles at the upper level and the choice of engine sizes at the lower level. Lai and Lu (2007) applied a three-level NL model to analyze household joint choices of the number of cars, the number of motorcycles, and work mode of transportation. More recently, Chiou et al. (2009) proposed an integrated model that analyzes choice behaviors associated with ownership, type, and usage of cars and motorcycles in Taiwan. The existing literature still lacks dynamic analysis of motorcycle ownership and usage, which allows for incorporating household preferences over time and identifying factors that influence ownership and usage behavior.

3. Methodological framework

3.1. Motorcycle ownership model

Motorcycle ownership model examines the number of motorcycles (i.e., 0, 1,. . .) owned by households in each year. Households may alter or maintain the number of motorcycles next year. The existing methods for modeling this type of dependent variable typically used discrete choice model, ordered logit or probit model, and count data model (Karlaftis and Golias, 2002), but the unordered discrete choice model is preferred because it provides a theoretical framework on a basis of random utility theory that is widely used to explain human behavior. Under the framework of discrete choice analysis, a decision-maker (i.e., a household) is assumed to choose the alternative (i.e., number of motorcycles owned by a household) with the highest utility under the principle of utility maximization. The attractiveness (in terms of utility) of each alternative can be represented by the sum of systematic (observable) and random-error (unobservable) components. The total utility of an alternative i for household n at year t is specified as

$$U_{itn} = V_{itn} + \varepsilon_{itn} = \alpha_i + \beta S_{tn} + \gamma L_{tn} + \delta C_{itn} + \lambda D_{itn} + \varepsilon_{itn} \tag{1}$$

where V_{itn} is the observed component of utility; S_{tn} (household's characteristics) and L_{tn} (location characteristics and transportation system performance) are vectors of alternative specific variables that do not vary over alternatives; C_{itn} is a vector of generic variables including fixed and variable costs of their own motorcycles; these are varied by alternatives and allow the same marginal effect on each alternative's utility; α_i (alternative specific constant), β, γ, δ, and λ are the unknown parameters to be estimated; ε_{itn} is the random error term.

In Eq. (1), lagged dummy variables were used to account for state dependence. For each alternative, if the number of motorcycles owned by the household n in year t is the same as the number of motorcycles owned by the household n in the previous year $(t-1)$, $D_{itn} = 1$, and 0 otherwise. If the state dependence parameter is statistically significant, it indicates that motorcycle ownership in the current year is affected by motorcycle ownership in the previous year.

The discrete choice model can be derived under distributional assumptions with respect to the error term. The MNL is the most used model due to its simplified probability formulation and tractable computation. The probability form of the MNL is given by:

$$P_{itn} = \frac{\exp(V_{itn})}{\sum_j \exp(V_{jtn})} \tag{2}$$

The panel MNL model assumes that the error term has an independent and identical Gumbel distribution across individuals, alternatives, and years, and thus it exhibits the independence of irrelevant alternatives (IIA) property that imposes restrictions on the relative probabilities of each pair of alternatives. The NL model, which has been widely used to relax the IIA property, allows for correlation between the utilities of pairs of alternatives in a common nest and accommodates similarities among alternatives in the same nest. Theoretically, any alternative can be grouped into a nest. However, the number of motorcycles has the characteristics of ordered nature. This study only considers behavioral interpretable nested structure. For example, the adjacent alternatives (e.g., households owning 1 and 2 motorcycles) can be grouped into a nest, and alternatives of 3 and 4 motorcycles have single alternative nests. For the NL model, the probability that an alternative i will be chosen by household n at year t can be written as:

$$P_{itn} = \frac{\exp(V_{itn}/\mu_m) \times \left[\sum_{j \in N_m} \exp(V_{jtn}/\mu_m)\right]^{\mu_m - 1}}{\sum_m \left[\sum_{j \in N_m} \exp(V_{jtn}/\mu_m)\right]^{\mu_m}} \tag{3}$$

where the logsum parameter for the nest m, μ_m, indicates the degree of correlation between alternatives' utilities in the nest. N_m is a set of alternatives in the nest m.

The value of logsum parameter must lie within the range of 0–1 for consistency with utility maximization. If the NL model cannot outperform the MNL model, the MNL is the appropriate specification. The likelihood ratio test can be used to compare the MNL and various NL models to verify whether the IIA assumption does or does not hold (Hausman and McFadden, 1984).

Although more recent developed discrete choice models, such as the generalized nested logit model (Wen and Koppelman, 2001), have more flexible correlation structures than the NL model, the NL model remains popular. However, either the standard MNL or NL model does not allow for individual preference heterogeneity and may not adequately describe the behavior of all users. On the contrary, the MXL model allows the estimation of each parameter by assuming a distribution over the population instead of a single fixed value imposed in the standard MNL or NL model. The MXL model has been applied in analyzing households' preferences for automobiles to capture the systematic heterogeneity in decision makers' preferences (Brownstone et al., 2000). The present study applies the MNL, NL, and MXL models for motorcycle ownership.

3.2. Motorcycle usage model

The continuous dependent variable used for representation of motorcycle usage is annual mileage traveled across three years. Most panel data applications use fixed and random effects models to control individual effects (heterogeneity). Due to the unobserved individual effects that may be correlated with the included variables, the fixed effects model allows each observation to have its own intercept, by creating a set of dummy (either 0 or 1) variables included as regressors. This model is also called the least squares dummy variable and can be estimated by standard least squares. The formulation of fixed effects model in this study is

$$\ln y_{tn} = \sum_{n=1}^{N} \tau_n D_{tn} + \lambda R_{tn} + \pi H_{tn} + \theta C_{tn} + \omega W_{tn} + \varepsilon_{tn} \tag{4}$$

where $\ln y_{tn}$ is annual kilometers traveled by principal driver n at year t, taking the natural logarithm. R_{tn} (principal driver's characteristics), H_{tn} (principal driver's household characteristics), C_{tn} (fixed and variable costs at year t), and W_{tn} (principal driver's vehicle characteristics) are vectors of explanatory variables. D_{tn} is a set of intercept dummies; each observation (principal driver) has its own intercept. τ_n, λ, π, θ, and ω are the unknown parameters to be estimated. ε_{tn} is the normally distributed error term.

Under the null hypothesis that the pooled regression model with a single constant term using ordinary least squares estimation is the proper specification for the data, the F test is applied to test the significance of the fixed effects parameters. Rejection of the null hypothesis indicates that the fixed effects model is preferred.

Alternatively, the unobserved effects can be captured by a randomly distributed parameter, if the individual effects are uncorrelated with the regressors. This type of panel data model is referred to the random effects model and can be estimated by the generalized least squares procedure. The random effect model is written as

$$\ln y_{tn} = (\tau + \upsilon_n) + \lambda R_{tn} + \pi H_{tn} + \theta C_{tn} + \omega W_{tn} + \varepsilon_{tn} \tag{5}$$

where τ is the single constant term; υ_n is the unobservable random component only specific to the nth observation, and ε_{tn} the element of the error that varies over observation and year.

The random effects model reduces the number of parameters to be estimated. However, if the assumption of random effects specification is not held, the random effect estimator is inconsistent. The Lagrange multiplier (LM) test, proposed by Breusch and Pagan (1980), is used to justify appropriateness of the random effects model versus the pooled regression model. Under the null hypothesis that the pooled regression model has a correct model specification, rejection of the null hypothesis indicates that the random effects model is favored. The selection between fixed and random effects specifications is based on the Hausman test (Hausman, 1978). The null hypothesis is that the random effects model is the preferred specification. Rejecting null hypothesis indicates the fixed effects specification is the preferred one.

4. Empirical analysis

4.1. The data

The survey questionnaire contains three main components. The first part includes household characteristics, such as household

Table 3
Distribution of household characteristics under various numbers of motorcycles owned in the second-wave survey.

Item	Level	Motorcycle ownership (in number)					Motorcycle ownership (in percentage)			
		1	2	3	4	Subtotal	1	2	3	4
Household size	1	12	4	1	1	18	65.94	22.05	6.03	5.99
	2	39	77	16	11	143	27.17	53.97	11.32	7.54
	3	65	89	45	22	221	29.54	40.14	20.52	9.80
	4	77	133	100	52	362	21.18	36.84	27.58	14.40
	5	29	77	64	43	213	13.40	36.16	30.08	20.36
	≥6	22	73	52	29	177	12.69	41.27	29.47	16.56
Number of motorcycle licenses	1	108	27	2	2	140	77.39	19.43	1.59	1.58
	2	91	255	34	5	385	23.60	66.23	8.77	1.40
	3	26	106	107	28	267	9.59	39.70	40.16	10.55
	4	14	49	103	87	253	5.68	19.33	40.72	34.26
	≥5	5	16	32	36	89	5.46	18.27	36.20	40.07
Household monthly income	0–5	93	176	88	52	409	22.74	43.03	21.48	12.74
	5–10	99	202	123	69	493	20.10	40.94	24.89	14.07
	10–15	28	45	43	28	145	19.07	31.36	30.08	19.50
	15–20	10	11	9	5	35	29.15	30.95	24.58	15.31
	20–25	6	5	2	1	14	43.66	32.45	15.96	7.93
	25–30	0	6	4	1	12	0.00	54.54	35.93	9.53
	≥30	8	9	10	1	28	29.25	31.29	35.44	4.03
Car ownership	0	78	91	51	31	251	30.89	36.27	20.30	12.54
	1	132	266	157	87	641	20.55	41.43	24.52	13.51
	2	27	77	56	34	193	13.74	39.82	29.09	17.34
	3	8	17	13	2	41	19.84	42.43	32.27	5.46
	≥4	0	2	1	4	8	0.00	29.00	14.27	56.73
Yearly kilometers traveled	0–2500	106	159	74	38	377	28.08	42.07	19.66	10.20
	2500–5000	63	141	101	58	363	17.25	38.90	27.83	16.03
	5000–7500	30	58	44	14	146	20.68	39.66	29.91	9.74
	7500–10,000	24	60	37	29	150	15.81	40.28	24.76	19.15
	≥10,000	21	35	23	19	98	21.99	35.75	23.12	19.14
Subtotal		244	453	279	158	1134	–	–	–	–

Table 4
Estimation result of motorcycle ownership model.

Variables	MNL Model 1		MNL Model 2	
	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic
Alternative specific constants				
One vehicle	1.408	3.869***	−0.750	−1.611
Two vehicles	0.674	1.315***	−0.883	−1.348
Three vehicles	−3.542	−5.511	−3.284	−4.044***
Four vehicles	−6.232	−8.121***	−5.706	−5.754***
Lagged dummies				
Zero vehicle	–	–	4.237	5.883***
One vehicle	–	–	3.239	17.899***
Two vehicles	–	–	3.002	19.200***
Three vehicles	–	–	2.659	15.594***
Four vehicles	–	–	4.460	14.082***
Number of household members				
Two vehicles	0.216	6.375***	0.149	2.505*
Three vehicles	1.480	22.844***	0.923	9.452***
Four vehicles	2.022	23.150***	1.463	11.248***
Members without motorcycle license				
Three vehicles	−1.256	−22.608***	−0.785	−9.602***
Four vehicles	−1.806	−22.051***	−1.410	−11.308***
Number of cars in the household				
Three vehicles	−0.372	−5.299***	−0.228	−2.059**
Four vehicles	−0.527	−5.724***	−0.574	−3.750***
Transit density				
Two vehicles	−0.006	−4.349***	−0.008	−2.919***
Three vehicles	−0.004	−2.215**	−0.007	−2.272**
Four vehicles	−0.008	−2.951***	−0.007	−1.412
(Annual insurance fee)$^{0.5}$	−0.008	−3.612***	−0.006	−1.789*
(Annual license tax and fuel fee)$^{0.5}$	−0.043	−2.657***	−0.044	−2.235**
(Maintenance cost per km)^{2}	−0.001	−2.795***	−0.001	−1.686*
Final log-likelihood value		−3731.604		−1542.354
Likelihood ratio ρ^2		0.282		0.703
Adjusted likelihood ratio $\bar{\rho}^2$		0.278		0.699
Sample size		3228		3228

[*] Significance of *t*-statistics at 10%.
[**] Significance of *t*-statistics at 5%.
[***] Significance of *t*-statistics at 1%.

location, age, and gender of household heads, family size and structure, household income, number of workers in the household, number of vehicles in the household, distance from home to nearest public transit stop, and purchases or sales of motorcycles. The second part includes principal driver/rider demographics, such as gender, age, occupation, educational level, income, driving experience, commuting mode, and travel time to work. The third part includes vehicle characteristics, such as year of production, year of acquisition, brand-new or second-hand, brand name, purchase price, engine size, gas mileage, annual kilometers traveled, cumulated kilometers traveled, major areas in use, weekly commuting days, weekly recreational days, total annual usage costs (e.g., fuel, maintenance, parking, road toll, and insurance).

The questionnaires were disseminated by post to owners in 23 cities/counties in Taiwan proportionally to the numbers of motorcycles registered in those jurisdictions according to the stratified randomization sampling method. The first-wave survey randomly selected a total of 45,000 drivers from Taiwan's Vehicle Registration (VR) Database from October 1 to November 30, 2007. A total of 2536 valid questionnaires were returned, with an effective response rate of 5.6%. In 2008, the second-wave survey sent the questionnaire to the responded drivers in the first wave and returned 1134 valid questionnaires, with an effective response rate of 44.7%.

Table 3 presents the distribution of household characteristics under various numbers of motorcycles owned. Noted from Table 3, the households with a larger size tend to own more motorcycles. The same distribution also exists for the number of motorcycle licenses. However, the number of motorcycles will decrease as the household income increases, suggesting that motorcycles are considered as inferior goods. In addition, car usage is usually considered as a substitute of motorcycle usage. However, from the cross-tabulation of car and motorcycle ownership, the substitution effect between the ownership of these two models is not significant. One of the reasons for the insignificant substitution effect may be because people in Taiwan treat motorcycles as a short-range transport mode even for those who have already owned cars. As to the effect of motorcycle usage, there is still no obvious distribution that can be identified for the relationship between motorcycle usage and ownership. Furthermore, as to the distribution of households with various numbers of motorcycles, the largest percentage of sampled households (39.96% and 453 households) own two motorcycles, followed by the households that own three motorcycles (24.57% and 279 households). The demographic breakdowns of motorcycle owners and characteristics of sampled motorcycles of the first-wave survey can refer to Chiou et al. (2009) for more details.

4.2. *Estimation result of motorcycle ownership model*

For motorcycle ownership, the estimation results of MNL models with and without state dependence variables are reported in Table 4. The questionnaire survey revealed few households possessing more than four motorcycles or replacing more than one motorcycle annually, and thus the motorcycle ownership model considers five alternatives (zero to four-vehicle households). The alternative of zero motorcycles in the household was selected as the reference that its constant is zero. The explanatory variables used in the models are mainly obtained from our survey, except for one variable: transit density (defined as transit vehicle-kilometer per capita), which was calculated for each city/county. This variable reflects differences in public transportation environment among counties/cities, and respondents living in the same residential areas share the same value. Comparing two MNL models in terms of likelihood ratio index indicates that the MNL model 2 performs best with $\rho^2 = 0.703$. The coefficients of state dependence variables (lagged dummies) are positive and statistically significant, suggesting that the state dependence effect plays an important role in households' decision to own a motorcycle. Ignoring state dependence as the MNL model 1 specification may lead to based estimates and inferior model fit. Our finding is consistent with the results reported in Kitamura and Bunch (1990) and Hanly and Dargay (2000) and further indicates the importance of state dependence in modeling vehicle ownership with panel data.

The parameter coefficients of explanatory variables are significantly different from zero at the 10% level, except for some alternative specific constants. The generic variables, namely, annual license tax plus fuel fee, annual maintenance and insurance costs per kilometer in owning and using motorcycles have negative parameter coefficients, indicating that increasing the value of each variable will reduce the utility of the alternative, and thus the probability of the alternative being selected, provided all else remains unchanged. Negative coefficients, as expected, were related to these costs, suggesting car ownership reduces with increasing fixed or variable costs. Judging from a relative magnitude of coefficient estimates, license tax plus fuel fee shows the largest and most significant effect on motorcycle ownership, followed by insurance cost. Maintenance cost has the smallest coefficient.

The remaining explanatory variables are alternative specific to the number of motorcycles. The transit density variable reveals three negative coefficients related to three alternatives (two, three, and four motorcycles in the household), indicating that more convenient transit service reduces motorcycle ownership. The household size estimates specific to three alternatives (two, three, and four motorcycles in the household) are all positive and significant; the value of coefficient becomes large as the household size increases, suggesting that as there are more members in the household, more motorcycles are needed to satisfy their travel requirements. Numbers of cars in the household show significant and negative effects on two alternatives (three and four motorcycle households), indicating high substitution relationships between cars and motorcycles. As the number of household members without motorcycle licenses increases, the households are inclined not to own too many motorcycles, particularly three and four motorcycles. Household income is an important explanatory variable in the car ownership study. It is a surprise that household income is not associated with motorcycle ownership in the current study. This may be due to low purchase cost of motorcycles. Most low-income households can afford to buy inexpensive motorcycles as they need, and high-income households prefer more cars than motorcycles.

To capture the possible correlation structure between alternatives, this study estimated a variety of NL models. The estimation results of all NL models showed that the logsum parameters fell outside the reasonable range or were not significantly different from one. In addition, the NL models do not outperform the MNL model using likelihood ratio test, indicating that the standard MNL model, a more parsimonious model than the NL, would be appropriate. The MXL model was further used to determine if individual heterogeneity exists in the standard MNL specification. Random coefficients were applied to all explanatory variables with the exception of the alternative specific constants, but none of the standard deviation estimates were statistically significant. Additionally, the result of likelihood ratio test does not support the use of the MXL specification. The IIA assumption of the MNL model holds, indicating that the use of either NL or MXL model is not required. Consequently, the standard MNL specification is chosen as the preferred motorcycle ownership model.

Table 5
Results of goodness-of-fit assessment for fixed- and random-effects models of motorcycle usage.

Tests	Statistics
F test[a]	$F(1133, 1088) = 4.04$, p-value < 0.001
LM test[b]	$\chi^2 = 73.58$, p-value < 0.001
Hausman test[c]	$\chi^2 = 28.18$, p-value < 0.001

[a] The pooled regression model is rejected by the fixed effects model.
[b] The pooled regression model is rejected by the random effects model.
[c] The random effects model is rejected by the fixed effects model.

4.3. Estimation result of motorcycle usage model

This study estimated the parameters of motorcycle usage model in a stepwise manner. The dependent variable is ln (annual kilometers traveled), and explanatory variables consist of household and principal driver's characteristics, vehicle characteristics, ownership and usage costs, and travel patterns of principal driver. Pooled regression model using ordinary least squares estimation was initially estimated and used to identify important explanatory variables. Subsequently, the random and fixed effects models were estimated. The *F*, LM, and Hausman tests were used to determine the preferred motorcycle usage model. Test results of pooled, fixed, and random effects models are presented in Table 5.

The *F* test concludes rejection of the null hypothesis, indicating that the fixed effects model is the preferred specification. Moreover, the LM test suggests the random effects model is an appropriate specification over the pooled regression model. Finally, the Hausman test was applied to select between fixed and random effects specifications. The test result rejects the random effects specification, which indicates the fixed effects specification is the preferred one.

Table 6 lists the estimation result of the preferred fixed effects model. The coefficient of determination $R^2 = 0.809$ indicates good model fit. The principal driver income negatively influences motorcycle vehicle miles traveled because high income drivers prefer to use cars more frequently than motorcycles; the coefficient estimate also indicates low income elasticity of −0.236. The negative coefficient estimate of the squared number of motorcycles in households indicates that the existence of high substitution effects among motorcycles within households would lead to a reduction of each motorcycle's usage. The positive coefficient of principal driver's gender variable provides evidence that males use motorcycles for travel more than females. More commuting and recreational days

Table 6
Estimation result of motorcycle usage model.

Variables	Coefficient	*t*-Statistic
Gender of principal user (male = 1; female = 0)	1.068	1.788^{*}
ln(monthly income of principal user)	−0.236	-1.729^{*}
Daily commuting time	0.002	2.387^{**}
Engine size (c.c.)	2.347	2.808^{***}
Age of vehicle	−0.011	-2.178^{**}
Number of household members	0.001	2.188^{**}
Number of workers in household	0.028	2.159^{**}
(Number of motorcycles)^2	−0.014	-2.043^{**}
ln(maintenance cost per km)	−0.116	-4.256^{***}
ln(fuel cost per km)	−0.232	-24.627^{***}
ln(parking cost per km)	−0.212	-7.813^{***}
Weekly commuting days	0.031	3.071^{***}
Weekly recreational days	0.001	2.343^{**}
R^2	0.809	
Sample size	2196	

The constants are not shown due to a large number of estimates produced by the fixed effects model.
[*] Significance of *t*-statistics at 10%.
[**] Significance of *t*-statistics at 5%.
[***] Significance of *t*-statistics at 1%.

Table 7
Changes in number of motorcycles for management strategies under various scenarios.

Strategies	Number of motorcycles	Base value	10%	30%	50%
Increasing license tax and fuel fee	Total	14,281,206	14,251,215	14,171,241	14,072,700
	Number change	–	−29,991	−109,965	−208,506
	Percent change	–	−0.21	−0.77	−1.46
Increasing insurance cost	Total	14,281,206	14,275,494	14,249,787	14,225,509
	Number change	–	−5712	−31,419	−55,697
	Percent change	–	−0.04	−0.21	−0.39

per week tend to increase annual kilometers traveled. The engine size variable is positively associated with annual kilometers traveled, indicating that larger motorcycles are more intensively used by the driver. However, age of motorcycle has a negative impact on annual kilometers traveled. The coefficients of gas price, maintenance cost, and parking cost are all negative, indicating that the lower usage cost of motorcycles increases usage intensity with elasticities of 0.232, 0.116, and 0.212, respectively.

4.4. Strategy analysis results

The predicted choice probabilities for the number of motorcycles owned by households were calculated using the ownership model. The total number of motorcycles in Taiwan was estimated as 14,281,206 by multiplying the average number of motorcycles owned by a household (the predicted choice probabilities × corresponding number of motorcycles) and total number of households. Using the average annual kilometers traveled obtained from the usage model, the estimated total kilometers traveled (in thousands) is 72,505,683. Based on the parameter estimates obtained in motorcycle ownership and usage models, changes in the number of motorcycles and total kilometers traveled under various management strategies can be calculated to evaluate the effectiveness of management strategies in reducing motorcycle ownership and usage. Two management strategies (increasing license tax/fuel fee and increasing insurance cost) influence both motorcycle ownership and usage, while gas prices and parking fees mainly affect the usage of motorcycles.

Table 7 reports the simulation results for the changes in the number of motorcycles with respect to two management strategies (license tax/fuel fee and insurance cost) under the base case (unchanged) and three scenarios of 10%, 30%, and 50% increase. Total number of motorcycles for the base scenario is 14,281,206 in Table 7. Under scenario of 10% increase in license fax/fuel fee and insurance cost, the total number of motorcycles decreases by 0.21% and 0.04%, respectively. Despite a small percentage of change in both strategies, increasing license fax/fuel fee is more effective in reduction of motorcycle ownership.

Table 8 reports the simulation results for the changes in total kilometers traveled with respect to four strategies under three scenarios. Total annual kilometers traveled (in thousands) by all motorcycles for the base scenario is 72,505,683. Total kilometers traveled by motorcycles decrease by 2.28%, 6.15%, and 9.34%, respectively, under scenarios of 10%, 30%, and 50% gas price increases. Total kilometers traveled by motorcycles decrease by 2.01%, 5.42%, and 8.25%, respectively, under scenarios of 10%, 30%, and 50% parking fee increases. These two management strategies will lead to greater reductions in total kilometers traveled by motorcycles. In addition, these strategies are effective in alleviating motorcycle fatalities and injuries. For example, fatalities decrease by 28, 76, and 115, respectively, under scenarios of 10%, 30%, and 50% gas price increases.

5. Discussion and conclusions

A nationwide panel survey of motorcycle owners was conducted to examine the dynamic choices of the number of motorcycles as well as usage. For modeling ownership, this study uses the MNL, NL, and MXL models to accommodate the possible existence of independence among alternatives and individual heterogeneity. Panel data regression models considering fixed and random effects were developed for the usage. To demonstrate the applicability of the ownership and usage models, the effects of various management strategies in decreasing number of motorcycles and total kilometers traveled were then evaluated.

Table 8
Changes in kilometers traveled and number of victims for management strategies under various scenarios.

Strategies	Kilometers traveled (in thousands)	Base value	10%	30%	50%
Increasing license tax and fuel fee	Total	72,505,683	72,475,692	72,395,718	72,297,177
	Number change	–	−29,991	−109,965	−208,506
	Percent change	–	−0.21	−0.77	−1.46
	Fatalities change		−1	−2	−4
	Injuries change		−61	−224	−425
Increasing insurance cost	Total	72,505,683	72,476,681	72,346,170	72,222,911
	Number change	–	−29,002	−159,513	−282,772
	Percent change	–	−0.04	−0.22	−0.39
	Fatalities change		−1	−3	−5
	Injuries change		−59	−325	−576
Increasing gas price	Total	72,505,683	70,849,063	68,049,947	65,736,391
	Number change	–	−1,656,620	−4,455,736	−6,769,292
	Percent change	–	−2.28	−6.15	−9.34
	Fatalities change		−28	−76	−115
	Injuries change		−3376	−9081	−13,796
Increasing parking fee	Total	72,505,683	71,049,000	68,578,351	66,521,858
	Number change	–	−1,456,683	−3,927,332	−5,983,825
	Percent change	–	−2.01	−5.42	−8.25
	Fatalities change		−25	−67	−102
	Injuries change		−2969	−8004	−12,195

Motorcycle ownership and usage models identify factors influencing motorcycle ownership and usage, such as household structure, residential location, transportation system performance, driver's travel patterns, and vehicle characteristics. Previous studies on car ownership showed that high-income households prefer more vehicles. On the contrary, household income is not associated with motorcycle ownership in the present study because low-income households can afford to buy inexpensive motorcycles as they need, and high-income households prefer more cars than motorcycles. In addition, our result indicates that the state dependence effect (previous choices) plays an important role in households' decision to own motorcycles.

The simulation results indicate that the changes in total number of motorcycles are insensitive to management strategies of both increasing license fax/fuel fee and insurance cost. However, raising gas prices and parking fees show effectiveness in reduction of total kilometers traveled. In Taiwan, except for a metropolitan area like Taipei, which has a metro system and an extensive bus-transit network, people in other cities and counties rely heavily on private modes for mobility. Thus, controlling for motorcycle ownership is unlikely to be successful. In contrast, curtailing the usage of motorcycles can be achieved using some management strategies. Our finding suggests that in addition to the use of high gas price policy, effective parking demand management should be exercised. In Taiwan, motorcycles are ubiquitous in urban and suburban areas where parking is convenient and free in many regions. For sustainable transportation and development, motorcycle parking charge scheme, such as an hourly or flat rate charge to on-street parking, can be implemented in urban areas, particularly where public transportation system has been sufficiently provided. Because a significant and positive relationship between motorcycle usage and crash victims is identified, these management strategies could be effective in alleviating motorcycle accidents and crash victims.

The result of motorcycle ownership model indicates that good transit services decrease the tendency of households to own more motorcycles. The finding suggests that improving transit services can be effective in reduction of the number of motorcycles. For example, Taipei City with the best public transit services among 23 counties/cities has the lowest rate of motorcycles per household (Institute of Transportation, 2010). As a result, Taipei City has the lowest fatal crash rate for motorcycles. Currently, only two cities in Taiwan have rapid transit systems, and bus mode shares are relatively low for the rest. To reduce motorcycle ownership and usage, other cities could improve the level of bus transit services by extending the bus network or increasing bus frequency.

There were several limitations to this study, many of which highlight directions that could be considered in future research. This study only developed motorcycle ownership and usage models. Due to the high substitution between motorcycles and cars, an integrated model with panel data including owners of motorcycles and cars can be further developed. This study conducted a large-scale panel survey on owners of motorcycles in Taiwan, and therefore, the findings cannot be generalized to other countries with diverse characteristics. Consequently, it may be worthwhile to validate our proposed models and results using data from different countries. The data sets in this study comprise two waves of surveys. The third or more waves of follow-up surveys should be continuously conducted to enrich the data sets for a comprehensive analysis of the dynamic choice behaviors. The motorcycle ownership and usage models developed in this study consist of two separate components. It is likely that the choices of ownership and usage are interrelated. Future research could examine a joint choice of motorcycle ownership (discrete) and usage (continuous) by using discrete/continuous modeling structures.

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