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Direct and indirect factors affecting emissions of cars and motorcycles in Taiwan

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This article proposes Direct Correlation (DC) models and Integrated Correlation (IC) models for cars and motorcycles emissions, respectively. The DC models regress emissions on vehicle-related variables (i.e. direct factors), while the IC models further account for such variables (i.e. indirect factors) as driver/rider demographics, vehicle mileages travelled and regional types by using structural equation modelling. Results show that vehicle characteristics are the most influencing factors affecting hydrocarbon and carbon monoxide emissions. The old vehicles with small engine, manual transmission, high cumulative mileages travelled, using unleaded gasoline #92 and 2-stroke engine (for motorcycle) can be identified as 'high-emitting' vehicles. The second most influencing construct is the driver/rider demographics. The aged, male, low-educated car drivers and motorcyclists with high income and long driving/riding experience tend to use high-emitting vehicles.

Keywords: emissions; structural equation modelling; car; motorcycle

1. Introduction

The buoyant economic growth associated with the constant construction of highway infrastructures for convenient movements of people and freights in Taiwan has inevitably brought into a rapid growth of private vehicles over the past decades. In 1990, for instance, there were only 2.3 million cars and 7.1 million motorcycles registered; in 2008, these figures have increased to 6.7 and 14.3 millions, respectively, almost tripled and doubled the 1990 figures. The trend toward greater usage of private vehicles has not only created ubiquitous congestion on urban roadways and intercity highways, but also resulted in the excessive consumption of gasoline along with emissions. The poor air quality in urban areas particularly has been due to the mobile polluting sources (Ghose *et al*. 2004, Nesamania *et al*. 2007). It is imperative to identify the high-emitting vehicles and to scrutinise the key direct and indirect factors affecting the use of the high-emitting vehicles so as to exercise more effective inspection and management (I/M) programs to restrain the air pollution from these vehicles.

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To identify the contributing factors affecting vehicle emissions and then propose effective countermeasures accordingly, numerous studies have been conducted. In general, they can be divided into three approaches: the estimation model approach, the laboratory investigation approach and the statistical model approach. The estimation model approach aims to estimate vehicular emissions based on vehicle inventory and determine pollutants concentration levels in various zones of an urban area by various models, such as MOBILE5, COPERT III, CALINE3, IITLS and so on (e.g. Goyal and Rama Krishna 1998, Sharma and Khare 2001, Skiba and Davydova-Belitskaya 2003, Cai and Xie 2007, Nesamania *et al.* 2007, Coelho *et al.* 2009, Das *et al.* 2009). The laboratory investigation approach is to examine variations of vehicular emissions under various driving patterns, i.e. testing cycles (e.g. Tzeng and Chen 1998, Tsai *et al.* 2000, Szwarcfiter *et al.* 2005, Jia *et al.* 2006, Ntziachristos *et al.* 2006, Vasic and Weilenmann 2006). The statistical model approach attempts to identify key factors affecting emissions of in-use vehicles based on vehicle I/M database or on-road remote sensing database by employing various statistical methods. The statistical methods employed include regression analysis (e.g. Muncaster *et al.* 1996, Harrington 1997, Chan *et al.* 2004, Chan and Ning 2005, Beydoun and Guldmann 2006, Ko and Cho 2006), hierarchical tree-based regression (e.g. Wolf *et al.* 1998), simultaneous equations (e.g. Washburn *et al.* 2001), logistic regression (e.g. Bin 2003, Beydoun and Guldmann 2006), multinomial Logit model (e.g. Beydoun and Guldmann 2006, Choo *et al.* 2007), Cox regression (e.g. Chang and Yeh 2006) and so on. Most of these studies, however, only considered the vehicle-related variables (i.e. direct factors), including vehicle age, engine capacity, fuel type, transmission type, brand, number of cylinders, catalytic converter and gas mileage. These data are, in general, recorded in the I/M database.

It is our interest to investigate key factors affecting vehicular emissions based on the I/M database in Taiwan. However, we also presume that other non-vehicle-related variables (i.e. indirect factors), such as driver/rider demographics, cumulative and annual mileages travelled and regional types, may also influence the use of such high-polluting vehicles. To propose effective management strategies, an insightful understanding of who, where and how these high-emitting vehicles are still in use is also imperative. Based on these, the objectives of the present article are twofold: (1) to identify the key direct factors significantly affecting the emissions of hydrocarbon (HC) and carbon monoxide (CO) of cars and motorcycles; (2) to further identify the indirect factors affecting the usage of high-emitting cars and motorcycles. Accordingly, two kinds of models are developed: the Direct Correlation (DC) models for cars and motorcycles by regressing HC and CO on direct factors and the Integrated Correlation (IC) models for cars and motorcycles by further developing structural equation models (SEM) to test some cause–effect hypotheses between the constructs of direct and indirect factors.

The remaining parts are organised as follows. Section 2 briefly introduces the datasets used for models building. The models specification and estimation results of the DC models are narrated in Section 3. Section 4 presents the conceptual framework of the IC models, the cause–effect hypotheses of which are tested by SEM based on the matched dataset. Section 5 discusses and proposes some possible management strategies based on the results of the DC and IC models. Finally, concluding remarks and suggestions for future research follow.

2. Data

To scrutinise both direct and indirect factors affecting the high emissions of cars and motorcycles in Taiwan, two datasets – the I/M dataset for cars and motorcycles and the vehicle registration dataset are utilised. The I/M dataset provides periodical inspection details for cars and motorcycles, while the vehicle registration dataset provides the information of vehicle owners for nationwide questionnaire survey. A brief introduction and some descriptive statistics of two such datasets are given below.

2.1. *I/M dataset*

In Taiwan, the I/M datasets of cars are maintained at seven Motor Vehicle Offices of the Directorate General of Highways (DGH) in different jurisdictions. The detailed information of two endogenous variables – HC and CO and six exogenous variables – vehicle age, brand, engine size, number of cylinders, weight and cumulative mileages travelled are extracted. Note that, by regulation, all new cars are exempted from inspection for the first 5 years; those cars aged over 5 years are subject to inspection once per year and those aged over 10 years will require inspection once per 6 months. Most of the variables are continuous, except for brand which is divided into seven categories – FORD, TOYOTA, NISSAN, HONDA, MITSUBUSHI, MAZDA and OTHERS (e.g. BMW, MERCEDES BENZ, LEXUS, BUICK, AUDI, VOLVO and so on) according to their market shares in Taiwan.

Due to the capacity of statistical software, a total of 71,388 samples (5% sampling rate from the entire dataset) with complete information are randomly extracted. The descriptive statistics are summarised in Table 1. Note that the means and standard deviations of HC and CO are 66.09 ppm, 0.32% and 64.66 ppm, 0.55%, indicating the large variations in car emissions. The average characteristics of the sampled cars are: vehicle age 9.81 years, engine capacity 1620 cc, number of cylinders 4.1, weight 1.15 tons and cumulative mileages travelled 105,405 km. In addition, the brand shares of these cars are: MITSUBUSHI (26.24%), FORD (24.25%), TOYOTA (20.06%), NISSAN (18.40%), HONDA (1.60%), MAZDA (1.03%) and OTHERS (8.41%).

Table 1. Descriptive statistics of the sampled cars from I/M dataset in Taiwan.

Variables	Mean	Standard deviation	Kurtosis	Skewness
HC (ppm)	66.09	64.66	6.89	2.11
CO (%)	0.32	0.55	12.78	3.35
Vehicle age (year)	9.81	2.72	−0.49	0.46
Engine capacity (cc)	1620.33	368.78	1.10	0.50
Number of cylinders	4.10	0.46	12.65	3.55
Weight (ton)	1.15	0.21	0.36	0.61
Cumulative mileages (km)	105,405.30	62,803.92	4.09	1.46

Table 2. Descriptive statistics of the sampled motorcycles from I/M dataset in Taiwan.

Variables	Mean	Standard deviation	Kurtosis	Skewness
HC (ppm)	2509.53	3000.84	0.54	1.12
CO (%)	2.13	1.97	0.73	1.00
Vehicle age (year)	9.53	3.57	−0.22	0.37
Engine capacity (cc)	94.83	34.05	−1.54	−0.39
Cumulative mileages (km)	30,088.59	18,853.22	0.68	0.93

The motorcycle I/M database in Taiwan is solely maintained by the Environmental Protection Administration (EPA). The detailed information of two endogenous variables – HC and CO and five exogenous variables – vehicle age, engine capacity, cumulative mileages travelled, brand and stroke type are extracted. Note that all new motorcycles are exempted from inspection for the first 3 years in Taiwan; those aged over 3 years will require inspection once annually. Again, a total of 43,095 samples (0.5% sampling rate from the entire dataset) with complete information are randomly extracted.

HC and CO emissions are collected and recorded by vehicle exhaust analysers. By regulation, the accuracy of the analysers has to be examined every half-year. The accuracy in performing HC and CO emission tests can be assured.

The descriptive statistics are summarised in Table 2. Note that means and standard deviations of HC and CO are 2509 ppm, 2.13% and 3000 ppm, 1.97%, indicating the large variations in motorcycle emissions. The average characteristics of the sampled motorcycles are: vehicle age 9.53 years, engine capacity 94.83 cc and cumulative mileages travelled 30,088 km. The percentages for the top three brands have nearly equal market shares – YAMAHA (32.08%), KYMCO (31.02%), SYM (30.71%) and OTHERS (6.19%). The percentages of motorcycles with 2-stroke and 4-stroke engines are 42.83% and 57.17%, respectively. From Tables 1 and 2, the old cars and motorcycles aged over 10 years are rather prevailing in Taiwan, indicating the problems of serious air pollution and energy consumption because of the low gas efficiency and high emissions for old vehicles, in particular, motorcycles tend to be more polluting than cars in terms of HC and CO.

2.2. *Vehicle registration dataset*

To further scrutinise such indirect factors as driver/rider demographics, vehicle mileages, and regional types affecting the use of high-emitting vehicles, this article conducts a nationwide post-mailed questionnaire survey on the owners of cars and motorcycles in the period of 1–30 September 2007; each vehicle type contains 45,000 samples randomly drawn from Taiwan's Vehicle Registration (VR) Database, which is also maintained by the DGH. The VR Database contains the information of vehicle license plate numbers, names, addresses and telephone numbers of the owners, as well as some vehicle characteristics (e.g. brand, engine capacity, year of purchase, etc.). The VR dataset is confidential, but it may be used for some designated purposes under the permission of the DGH. Since this study was sponsored by the Institute of Transportation, Ministry of

Transportation and Communications, we had the privilege to access the VR Database for post-mailing the questionnaires purpose.

A total of 6310 valid questionnaires were returned, including 3454 car owners and 2856 motorcycle owners. The license plate number is further used for matching the I/M dataset with the returned valid questionnaires. After the matching, 748 car samples and 1322 motorcycle samples are found with complete information. Furthermore, 23 cities/counties in Taiwan are classified into three regional types – large city, medium city and small city – by K-means clustering method, based on the population density, car ownership rate, motorcycle ownership rate, average household income, road network density and public transportation service density. Tables 3 and 4 summarise the descriptive statistics for the continuous and categorical variables in the matched data, respectively.

3. DC model

It is presumed that vehicle-related factors (i.e. direct factors) are the most decisive factors affecting vehicular emissions. Thus, this article employs simultaneous regression method to develop the DC models for in-use cars and motorcycles, respectively, based on the I/M dataset.

In the belief of high correlational relationship between HC and CO, many studies employed simultaneous regression equations specification to develop the DC models. An example of similar specification can be found in the study of Washburn *et al.* (2001) as follows:

$$\begin{aligned} \mathrm{HC} &= \alpha + \beta\mathrm{CO} + \gamma X_n + \varepsilon_1 \\ \mathrm{CO} &= \lambda + \mu\mathrm{HC} + v U_n + \varepsilon_2 \end{aligned} \tag{1}$$

where, X_n is a vector of variables affecting HC, while U_n is the vector of variables affecting CO. α, β, λ, μ and ν are parameters to be estimated and ε_1, ε_2 are residuals. This article attempts the similar modelling specification for the DC models and estimates with 3-stage least squares (3SLS) method.

The variables affecting HC and CO (i.e. X_n and U_n) are selected according to related studies and the correlation analysis of the I/M dataset. The explanatory variables of HC consist of vehicle age, engine capacity, number of cylinders (for car), stoke type (for motorcycle, where stoke type = 1 represents 4-stroke engine) and weight (for car); while those of CO are engine capacity, number of cylinders (for car), weight (for car) and cumulative mileages. In addition, several dummy variables are used to represent the brands of cars and motorcycles. In the car DC model, a total of six dummy variables are used to, respectively, present the car brands of HONDA, MAZDA, NISSAN, TOYOTA, MITSUBISHI and OTHERS by setting FORD as the reference base. Similarly, three dummy variables are used to indicate the motorcycle brands of KYMCO, YAMAHA, and OTHERS by setting SYM as the reference base. Besides, to investigate the interaction between vehicle age and vehicle brand, corresponding interaction terms are also introduced.

In our first attempt at estimating the car DC model, one unanticipated result was found: weight had a negative effect on CO, failing to coincide with relevant studies and our prior knowledge. Thus, additional variable of weight-square (the squared weight) is introduced to capture the nonlinear effect of weight on HC and CO emissions.

Table 3. Descriptive statistics of continuous variables in the matched data.

		Car				Motorcycle			
Category	Items	Mean	Standard deviation	Kurtosis	Skewness	Mean	Standard deviation	Kurtosis	Skewness
Driver/rider demographics	Age (year)	48.59	11.41	−0.39	0.17	41.48	12.91	−0.22	0.47
	Income (10,000NT)	5.21	11.82	522.74	21.39	3.41	2.72	105.52	6.99
	Driving experience (year)	21.42	9.5	−0.17	0.30	18.11	10.41	−0.13	0.57
Vehicle characteristics	Age (year)	9.31	5.22	−0.31	0.72	9.13	3.32	−0.80	0.22
	Engine capacity (cc)	1792.67	483.47	4.69	1.71	99.91	32.54	−1.16	−0.71
Vehicle mileages	Cumulative mileages (km)	13,3021.7	90,183.28	19.97	3.24	32,674.01	20,150.13	0.31	0.91
	Annual mileages (km)	11,656.91	6893.53	22.54	2.78	4466.46	3028.69	5.24	1.81
	Weekly commuting days (day)	2.59	2.6	−1.64	0.25	3.89	2.53	−1.19	−0.59
Emissions	HC (ppm)	115.93	177.23	39.91	4.87	2120.06	2890.72	1.41	1.44
	CO (%)	0.78	1.43	18.91	3.51	1.96	2.00	1.54	1.26

Table 4. Descriptive statistics of categorical variables in the matched data.

Category	Item	Attributes	Car		Motorcycle	
			Number	Percentage	Number	Percentage
Driver/rider demographics	Gender	Male	620	82.89	874	66.11
		Female	128	17.11	448	33.89
	Education	Elementary school and below	49	6.55	90	6.81
		Junior high school	67	8.96	101	7.64
		Senior high school	231	30.88	367	27.76
		University/College	340	45.45	612	46.29
		Graduate school	61	8.16	152	11.50
Vehicle characteristics	Transmission type	Manual	210	28.07	98	7.41
		Automatic	538	71.93	1224	92.59
	Stroke type (for motorcycles)	2-stroke engine	–	–	465	35.17
		4-stroke engine	–	–	857	64.83
	Fuel type	Unleaded gasoline #92	179	23.93	493	37.29
		Unleaded gasoline #95 and #98	569	76.07	829	62.71
Area in use	Regional type	Large city	296	39.57	570	43.12
		Medium city	114	15.24	424	32.07
		Small city	338	45.19	328	24.81

Table 5. Estimated car DC model by simultaneous regression equations.

	HC (ppm)		CO (%)	
Variable	Coefficient	*t*-value	Coefficient	*t*-value
Intercept	−9.52	−1.51	0.29	5.41***
CO	83.55	227.88***	–	–
HC	–	–	0.01	232.80***
Vehicle age (year)	2.56	17.35***	–	–
Engine capacity (1000 cc)	−2.21	−1.91*	−0.10	−9.78***
Number of cylinders	3.37	5.43***	0.01	2.32**
Weight (ton)	34.37	3.58***	−0.50	−5.90***
Weight-square (ton)	−20.55	−1.52	0.30	9.06***
Cumulative mileages (10,000 km)	–	–	0.28	1.82*
Brands (FORD as the reference base)				
HONDA	−11.61	−1.42	0.25	3.43***
MAZDA	8.34	1.17	−0.10	−1.54
NISSAN	−23.31	−6.61***	0.17	5.55***
TOYOTA	−3.99	−1.16	0.13	4.27***
MITSUBISHI	0.22	0.07	0.10	3.59***
OTHERS	11.46	3.51***	−0.23	−8.87***
Interaction terms				
Vehicle age*HONDA	1.91	2.12**	−0.03	−3.80***
Vehicle age*MAZDA	−0.76	−1.14	0.01	2.30**
Vehicle age*NISSAN	2.30	6.98***	−0.02	−6.41***
Vehicle age*TOYOTA	3.10	9.45***	−0.03	−10.54***
Vehicle age*MITSUBISHI	1.07	3.46***	−0.01	−5.34***
Vehicle age*OTHERS	−0.12	−6.99***	0.03	11.80***
Number of observations	–	–		71,388
System weighted R^2	–	–		0.42

Note: *indicates the significance at $\alpha = 0.1$; **indicates the significance at $\alpha = 0.05$ and ***indicates the significance at $\alpha = 0.01$.

However, such a problem does not exist in the motorcycle DC model, thus the weight-square variable has not been added.

The estimated DC models for cars and motorcycles are presented in Tables 5 and 6, respectively. Note from Table 5, the estimated 3SLS results for the car DC model show that, except for some dummy variables of brand, most of the variables show significant effects on HC and CO emissions. The overall fit of the simultaneous equations is good with a system weighted R^2 of 0.42.

Table 5 shows that cars are more likely to have a higher HC as CO increases, and vice versa. This result coincides with the internal combustion engine theory that when CO is formed in an incomplete combustion process, non-combusted fuel vapours or HC gases are also produced (Washburn *et al.* 2001). Vehicle age is the next most significant variable (with second highest *t*-value) with positive sign. It concurs with previous studies by Anilovich and Hakkert (1996), Washburn *et al.* (2001), Bin (2003) and Beydoun and Guldmann (2006). Our results show that additional year of car usage will, on average, lead to additional HC emissions by 2.56 ppm. Engine capacity significantly affects HC and

CO emissions with negative signs. That is, the cars with larger engines will emit less HC and CO. The reason is that the cars with larger engines are usually more expensive and of higher quality with furnishing higher standard anti-pollution equipments. Our results have also concurred with the findings by Bin (2003) and Beydoun and Guldmann (2006). On average, an increase of the engines by 1000 cc will lead to a decrease of the emissions by 2.21 ppm for HC and 0.10% for CO.

Number of cylinders has significantly positive effects on HC and CO emissions, suggesting that the cars with more cylinders will emit more HC and CO. It also concurs with the studies by Bin (2003) and Beydoun and Guldmann (2006). The increase in the number of cylinders by 1 will on average lead to an increase of the car emissions of HC and CO by 3.37 ppm and 0.01%, respectively. Weight has a significantly positive influence on HC, but has a negative effect on CO. However, to simultaneously consider both linear and squared terms of weight, heavier cars will still emit more CO. However, the squared term of weight insignificantly affect HC emissions. Finally, cumulative mileages travelled have a significantly positive effect on CO emissions. Every 10,000 km increase in cumulative mileages travelled will emit an additional 0.28% of CO.

Different car brands emitted significantly differently. In terms of HC, cars manufactured by NISSAN produced lower HC than other manufactures' engines. Cars of OTHERS will significantly produce higher HC. The brands are ranked from low emission to high emission as: NISSAN $\succ$ TOYOTA $\approx$ HONDA $\approx$ MAZDA $\approx$ NISSAN $\approx$ FORD $\approx$ MITSUBISHI $\succ$ OTHERS, where $\succ$ and $\approx$ stand for 'better than' and 'approximately equal to', respectively. In terms of CO, cars manufactured by HONDA, NISSAN, TOYOTA and MITSUBISHI will emit higher CO than those manufactured by FORD. Cars of OTHERS will significantly emit less CO than those of FORD. Therefore, in terms of CO, the ranking is: OTHERS $\succ$ MAZDA $\approx$ FORD $\succ$ MITSUBISHI $\succ$ TOYOTA $\succ$ NISSAN $\succ$ HONDA. In addition, as cars manufactured by HONDA, NISSAN, TOYOTA and MITSUBISHI become aged, they tend to emit more HC but less CO. Taking HONDA for example, additional year of car usage will lead to additional HC emissions by 4.47 (2.56 + 1.91) ppm but decrease CO emissions by 0.03%. However, MAZDA and OTHERS cars exhibit opposite phenomena.

Table 6 gives the estimated 3SLS results for the motorcycle DC model. The results show that all variables have shown significant effects on HC and CO emissions. The overall fit of the simultaneous equations is good with a system weighted R^2 of 0.74. Similar to the car DC model, it also indicates a very significantly positive relationship between HC and CO emissions. The dummy variable of stroke type is the second most significant variable with negative sign, indicating that motorcycles with 4-stroke engine can curtail the emissions of HC by 2026 ppm in comparison with 2-stroke ones, implying the imperative policy in restraining the usage of 2-stroke motorcycles. Vehicle age has a significantly positive effect on HC. One-year increase of motorcycle age will result in additional emissions of HC by 16.52 ppm. Engine capacity is also significant with negative sign, implying larger engine motorcycles will emit less HC and CO. On average, motorcycles engine capacity increased by 1 cc will lead to less emissions of HC by 24.54 ppm and CO by 0.02%. The cumulative mileages travelled has a significantly positive effect on CO emissions. An increase of 10,000 km in motorcycles' cumulative mileages will, on average, lead to an increase of emissions of CO by 0.02%.

The emissions of various brands of motorcycles also differ significantly. In terms of HC, the brands are ranked from low emission to high emission as: OTHERS $\succ$

Table 6. Estimated motorcycle DC model by simultaneous regression equations.

	HC (ppm)		CO (%)	
Variable	Coefficient	*t*-value	Coefficient	*t*-value
Intercept	4150.67	82.07***	−1.56	−28.11***
CO	715.06	178.40***	–	–
HC	–	–	0.0006	173.46***
Vehicle age (year)	16.52	4.16***	–	–
Engine capacity (cc)	−24.54	−61.86***	−0.02	−63.42***
Stoke type	−2026.00	−74.58***	–	–
Cumulative mileages (10,000 km)	–	–	0.02	5.61***
Brands (SYM as the reference base)				
KYMCO	306.05	5.46***	−0.41	−7.32***
YAMAHA	−185.72	−3.18**	−0.13	−2.16**
OTHERS	−737.56	−8.31***	0.74	8.30***
Interaction terms				
Vehicle age*KYMCO	−7.23	−4.89***	0.04	6.67***
Vehicle age*YAMAHA	54.43	9.56***	−0.02	−3.41***
Vehicle age*OTHERS	133.96	15.52***	−0.13	−14.52***
Number of observations				43,095
System weighted R^2				0.74

Note: *indicates the significance at $\alpha = 0.1$; **indicates the significance at $\alpha = 0.05$ and ***indicates the significance at $\alpha = 0.01$.

YAMAHA ≻ SYM ≻KYMCO. In terms of CO, the ranking reversely appears as: KYMCO ≻ YAMAHA ≻ SYM ≻ OTHERS. As YAMAHA and OTHERS motorcycles become aged, they produce higher HC but less CO. However, KYMCO motorcycles show an opposite trend.

4. IC models

To identify the factors affecting the usage of high-emitting vehicles, based on 748 cars and 1322 motorcycles matched data, this article further develops the IC models for cars and motorcycles, respectively, with SEM technique.

4.1. *Framework*

The correlation framework of the IC models is depicted in Figure 1. Seven cause–effect relationships are hypothesised below.

H1: Different driver/rider demographics would have different vehicle mileages travelled.
H2: Different driver/rider demographics would choose different types of vehicle (i.e. different vehicle characteristics).
H3: The vehicles used in different areas would have different vehicle characteristics.
H4: The vehicles used in different areas would have different vehicle mileages travelled.

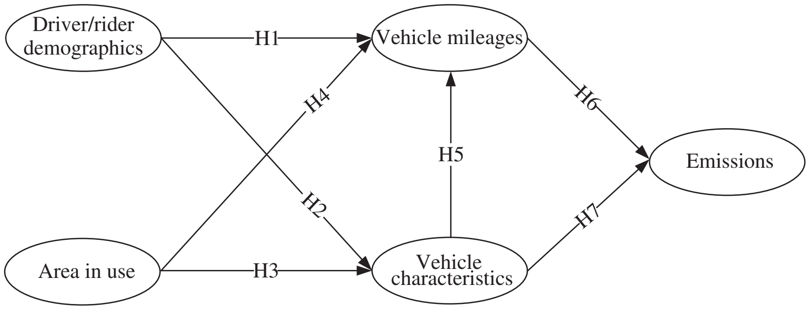

Figure 1. The conceptual framework of the IC models for cars and motorcycles.

Table 7. Overall CFA results for the car IC model.

Latent construct	Observed indicators	Regression coefficient	Factor loading	*t*-value	Composite reliability	Variance extracted
Driver demographics	Age	1	0.73	–	0.65	0.33
	Gender	0.75	0.33	8.45***		
	Education	−0.44	−0.36	−9.45***		
	Income	0.15	0.11	2.86***		
	Driving experience	1.22	0.94	14.12***		
Vehicle characteristics	Engine capacity	1	0.12	–	0.48	0.24
	Age	−8.49	−0.80	−2.76***		
	Transmission type	9.05	0.46	2.73***		
	Fuel type	5.52	0.29	2.61***		
Emissions	HC	1	0.56	–	0.56	0.39
	CO	1.25	0.68	9.49***		

Note: *indicates the significance at $\alpha = 0.1$; **indicates the significance at $\alpha = 0.05$ and ***indicates the significance at $\alpha = 0.01$.

H5: The vehicle usage would significantly differ depending upon vehicle characteristics.
H6: Different vehicle mileages travelled will lead to different levels of emissions.
H7: Different vehicle characteristics will have significantly different levels of emissions.

4.2. *Car model*

Confirmatory Factor Analysis (CFA) for the car measurement model that relates the observed indicators to the latent constructs is first conducted. Since all data in this study are real numbers, not measured in Likert scale, it makes the factor loadings of some variables rather low (less than 0.3). Nonetheless, all observed variables are significant. Besides, since the construct of vehicle mileages fails to be convergent, thus the variable – annual mileages travelled – will be used to represent this construct. The final results of car measurement model are presented in Table 7. Note that all observed variables are significantly tested and all constructs have high composite reliability and variance extracted.

Table 8. Goodness-of-fit indices for the car IC model.

Absolute fit measures					Incremental fit measures			Parsimonious fit measures		
χ^2	χ^2/df	GFI	RMSEA	RMR	AGFI	NFI	CFI	PNFI	PGFI	CN
290.02	4.83	0.94	0.07	0.01	0.91	0.80	0.84	0.62	0.62	228
–	<5.00	>0.90	<0.08	<0.05	>0.90	>0.90	>0.90	>0.50	>0.50	>200

Note: χ^2 = Chi-square; df = degrees of freedom; GFI = goodness-of-fit index; RMSEA = root mean square error of approximation; RMR = root mean residual; AGFI = adjusted goodness-of-fit; NFI = normed fit index; PNFI = parsimonious normed fit index; PGFI = parsimonious goodness-of-fit index; CFI = comparative fit index.

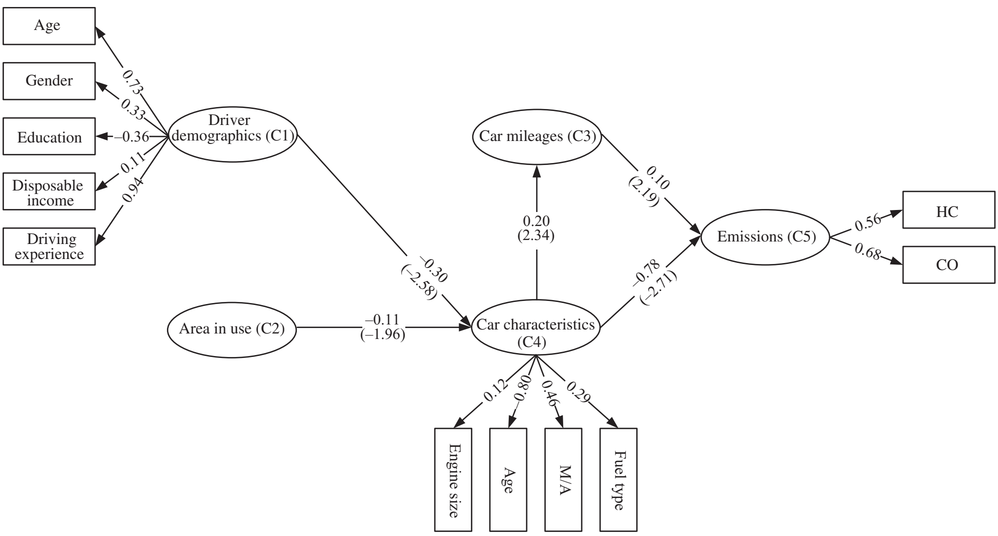

Figure 2. Car IC model with standardised coefficients (*t*-values) and factor loadings.

Three types of goodness-of-fit indices are used here to evaluate the model performance: absolute fit measures, incremental fit measures and parsimonious fit measures. An absolute fit index is used to directly evaluate how well the *a priori* theoretical model fits the sample data. An incremental fit index assesses the proportionate fit by comparing a target model with a more restricted, nested baseline model. A parsimonious fit measure is used to diagnose whether model fit has been achieved by over fitting the data with too many coefficients (Hu and Bentler 1995). Table 8 gives the goodness-of-fit indices for the car measurement model. Note that all three types of goodness-of-fit indices in the car measurement model are acceptable, except for NFI and CFI values (0.80 and 0.84) slightly falling below 0.9.

Figure 2 shows the estimated structural model. Note that except for two hypotheses – H1 and H4, all hypotheses are successfully validated.

As noted from Figure 2, the construct of emissions (C5) is significantly and positively affected by the annual mileages (C3) but negatively affected by the construct of car

Table 9. Total effects among constructs and variables for the car IC model.

Construct/ variable	C3 Path	C3 Total effects	C4 Path	C4 Total effects	C5 Path	C5 Total effects
C1	C1 → C3 C1 → C4 → C3	0.01	C1 → C4	−0.30	C1 → C3 → C5 C1 → C4 → C5 C1 → C4 → C3 → C5	0.24
C2	C2 → C3 C2 → C4 → C3	−0.02	C2 → C4	−0.11	C2 → C3 → C5 C2 → C4 → C5 C2 → C4 → C3 → C5	0.09
C3	–	–	–	–	C3 → C5	0.10
C4	–	–	–	–	C4 → C5 C4 → C3 → C5	−0.76

characteristics (C4). By further looking into the regression coefficients in Table 9, these two paths suggest that an intensive use of cars (more annual mileages) will significantly lead to higher emissions. Cars with low age, large engine, automatic transmission and using unleaded gasoline #95 or #98 will emit less HC and CO. In contrast, those with high age, small engine, manual transmission and using unleaded gasoline #92 are identified as the high-emitting cars.

Note that the annual mileages of the aforementioned low-emitting cars are also large; it mutually neutralises the effects on paths C4 → C5 and C4 → C3 → C5. The construct of car characteristics (C4) is both negatively affected by the driver demographics (C1) and area in use (C2). The former causal relationship implies that the old, male, low-educated drivers with high income, long driving experience tend to use high-emitting cars. The latter suggests that car emissions are more serious in small cities than in large or medium cities. Perhaps a comparatively lower income in small cities has made the drivers possess high-emitting vehicles, which are usually cheaper than the low-emitting vehicles. Table 9 sums up the total (direct and indirect) effects of all constructs and variables on the emissions (C5). Note that the C4 construct (car characteristics) has the largest total effects (−0.76), followed by the C1 construct (driver demographics) with total effects of 0.24. The C2 construct (area in use) has the smallest total effects (0.09).

4.3. *Motorcycle model*

The motorcycle model follows most of the car model, except for the introduction of a dummy variable – stroke type – into the construct of motorcycle characteristics. The transmission-type variable is not significant and the vehicle age variable is highly correlated to both cumulative mileages and annual mileages. Thus, these two variables are not included in the motorcycle measurement model. The final results of motorcycle measurement model are presented in Table 10. Note that all the observed variables are significantly tested and all constructs have high composite reliability and variance extracted.

Table 10. Overall CFA results for the motorcycle IC model.

Latent construct	Observed indicators	Regression coefficient	Factor loading	*t*-value	Composite reliability	Variance extracted
Rider demographics	Age	1	0.96	–	0.65	0.35
	Gender	0.30	0.14	4.71***		
	Education	−0.38	−0.40	−12.63***		
	Income	0.20	0.21	7.00***		
	Riding experience	0.78	0.77	18.63***		
Motorcycle characteristics	Engine capacity	1	0.88	–	0.76	0.57
	Fuel type	0.33	0.20	7.01***		
	2-/4-stroke	1.57	0.95	43.84***		
Motorcycle mileages	Cumulative mileages	1	0.80	–	0.61	0.40
	Annual mileages	0.79	0.73	10.01***		
	Weekly commuting days	0.29	0.15	4.55***		
Emissions	HC	1	0.99	–	0.77	0.64
	CO	0.45	0.55	17.63***		

Note: *indicates the significance at $\alpha = 0.1$; **indicates the significance at $\alpha = 0.05$ and ***indicates the significance at $\alpha = 0.01$.

Table 11. Goodness-of-fit indices for the motorcycle IC model.

Absolute fit measures					Incremental fit measures			Parsimonious fit measures		
χ^2	χ^2/df	GFI	RMSEA	RMR	AGFI	NFI	CFI	PNFI	PGFI	CN
504.77	7.11	0.95	0.07	0.01	0.92	0.91	0.92	0.71	0.64	266
–	<5.00	>0.90	<0.08	<0.05	>0.90	>0.90	>0.90	>0.50	>0.50	>200

Note: χ^2 = Chi-square; df = degrees of freedom; GFI = goodness-of-fit index; RMSEA = root mean square error of approximation; RMR = root mean residual; AGFI = adjusted goodness-of-fit; NFI = normed fit index; PNFI = parsimonious normed fit index; PGFI = parsimonious goodness-of-fit index; CFI = comparative fit index.

The goodness-of-fit indices of the motorcycle model are depicted in Table 11. Note that all indices show good fit of the model, except for χ^2/df. According to Golob (2003), χ^2 is easily affected by the number of samples. Large sample size (1322 samples in our motorcycle model) usually leads to a large χ^2. Thus, CN is used to assess the model fit instead. As shown in Table 11, CN is equal to 266, larger than 200; hence, all indices of the motorcycle measurement model are acceptable.

To test the hypothesised structural model, a test of the overall model and individual tests of the relationships among latent constructs are performed. Figure 3 shows the estimated structural model. Note that except for three hypotheses, H1, H3 and H4, all hypotheses are successfully validated.

As shown in Figure 3, the construct of emissions (C5) is significantly and positively affected by the construct of motorcycle mileages (C3) but negatively affected by the construct of motorcycle characteristics (C4). By further looking into the regression coefficients in Table 10, these two paths imply that the intensive use of motorcycles

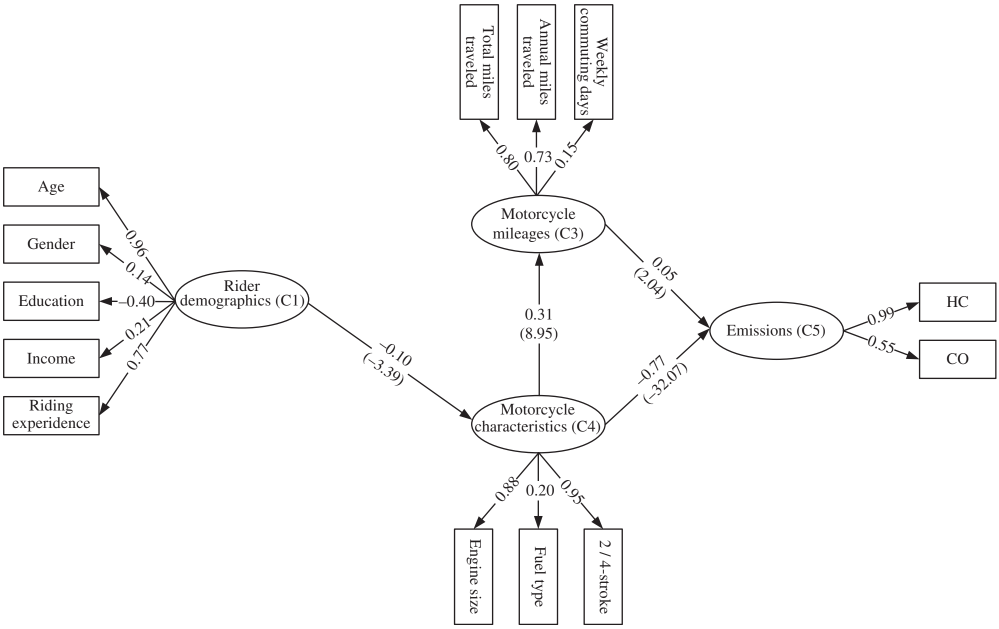

Figure 3. Motorcycle IC model with standardised coefficients (*t*-values) and factor loadings.

(high cumulative mileages travelled, annual mileages travelled and weekly commuting days) will significantly lead to high emissions. Motorcycles with 4-stroke and larger engine using unleaded gasoline #95 or #98 tend to emit less HC and CO, and vice versa. Furthermore, the construct of motorcycle mileages (C3) is not significantly affected by riders' demographics (C1) or area in use (C2), but it is significantly affected by the motorcycle characteristics (C4). This path implies that motorcycles with 4-stroke and larger engine using unleaded gasoline #95 or #98 are generally utilised more intensively with higher cumulative mileages travelled, annual mileages travelled and weekly commuting days. That is, the path $C4 \rightarrow C3 \rightarrow C5$ will somewhat neutralise the effect of the path $C4 \rightarrow C5$. The construct of motorcycle characteristics (C4) is only affected (negatively) by the rider demographics (C1), implying that the old, male, low-educated motorcyclists with high disposable income, long riding experience tend to use high-emitting motorcycles. Compared with the car model, the area in use (C2) does not matter for the motorcycle model.

In terms of total effects as shown in Table 12, motorcycle characteristics (C4) is still the most decisive latent construct affecting the motorcycle emissions (C5) with negative total effects (−0.76), followed by rider demographics (C1) with total effects of 0.08. Motorcycle usage (C3) has the smallest total effects (0.05) on the emissions (C5).

5. Discussions

The significant explanatory variables as well as influence paths (cause–effect relationships) for both car and motorcycle DC and IC models are very similar. For both vehicles,

Table 12. Total effects among constructs of the motorcycle IC model.

	C3		C4		C5	
Construct	Path	Total effects	Path	Total effects	Path	Total effects
C1	C1 → C3 C1 → C4 → C3	−0.05	C1 → C4	−0.10	C1 → C3 → C5 C1 → C4 → C5 C1 → C4 → C3 → C5	0.08
C3	–	–	–	–	C3 → C5	0.05
C4	–	–	–	–	C4 → C5 C4 → C3 → C5	−0.76

obviously, vehicle characteristics are the key factors affecting HC and CO emissions. Particularly, the vehicles which are old, small engine, manual transmission, high cumulative mileages travelled, using unleaded gasoline #92, and 2-stroke engine (for motorcycle) can be identified as 'high-emitting' vehicles. The usage of such vehicles should be strictly restrained or rectified. Some possible strategies can be considered: for instance, raising the pollution fine, increasing the enforcement frequency and coverage of pollution crackdown, shortening the exhaust inspection periods, encouraging the disposal of high-emitting vehicles, etc. Fortunately, these high-emitting vehicles tend to be less intensively used (supported by H5 hypothesis) in Taiwan.

The drivers/riders who tend to use high-emitting vehicles have been identified as aged, male, low-educated, long-driving/riding-experience and high income. The propaganda materials for cutting back high-emitting vehicles usage should be specially designed for these 'targeted' persons. Since high-emitting cars are more frequently used in small cities, suggesting that the frequency of crackdown on high-emitting cars in small cities should be more intensively enforced.

It is noteworthy that stroke type is the most decisive factor affecting motorcycle emissions. The 2-stroke engine motorcycles will emit much more HC (2026 ppm) than 4-stroke motorcycles. To strictly regulate or even forbid the usage of 2-stroke motorcycles is obviously an imperative solution for reducing motorcycle emissions. To do so, the EPA of Taiwan has gradually imposed five inspection standards on new mass production motorcycles since 1 January 1988. In the fourth inspection standard, effective 1 January 2004, HC emitting standard of 2-stroke engine motorcycles is set as 2000 ppm at idle test which is even stricter than that of 4-stroke motorcycles so as to discourage the production of 2-stroke motorcycles. Now the fifth inspection standard has already been implemented, which is similar to the third inspection standard of European Union (EU3). However, these standards are only valid for the newly manufactured motorcycles. How to reduce the ownership and usage of existing 2-stroke motorcycles is also imperative. The EPA of Taiwan and many local environmental protection authorities provided NT$1500–2500 (about US$50–80) to compensate for recycling these high-emitting 2-stroke motorcycles. However, the fact of high percentages of such motorcycles still in use explains that this incentive may not be strong enough. Thus, to provide higher subsidy together with stricter and more frequent crackdown on motorcycle exhaust inspection at road sides are worth attempting.

Both vehicle age and engine capacity have significantly affected the emissions of cars or motorcycles, suggesting that different management strategies may be considered by vehicle ages and engine sizes. For instance, to impose varied license taxes and fuel fees by vehicle ages and engine sizes or to shorten the exhaust inspection period for old vehicles.

Attracting more private vehicle users to public transportation is the main fundamental to cut the car and motorcycle emissions. Providing subsidies and taxes exemption or reduction to the transit operators have long been recommended by the transportation experts to lower the transit operating costs and the pressure of fare increase. Also strongly recommended was raising the out-of-pocket expenses of private vehicle ownership and usage to reflect the external costs. Under such a 'carrot-and-stick' philosophy, the policy for developing the public transport in Taiwan was formulated. This rationale was clearly documented in the Transportation Policy White Book in 1995, the first transportation policy book in Taiwan, which definitely proclaimed to develop the public transport (Lan *et al.* 2006). Following this White Book, providing higher mobility and accessibility for public transportation is undoubtedly the top priority. For instance, Taipei city nowadays has the most convenient and dense bus and metro services in Taiwan and the percentage of daily trips using public transportation has reached as high as 50%; while in most of the other small cities, the figure is normally below 5%.

6. Conclusions

This article employs simultaneous regression equations and SEM techniques to develop DC models and IC models for cars and motorcycles, respectively. Based on the I/M dataset matching with the vehicle registration dataset, a nationwide questionnaire survey on vehicle owners has been conducted. To the authors' best knowledge, this is the first work employing SEM to test the vehicle emissions correlation relationships in literature. Most previous works have employed the statistical methods. Our results show that the significant factors affecting vehicle emissions and the structural framework of car and motorcycle models are very similar. Besides, the results of the IC models are consistent with those of the DC models for the direct factors.

The vehicle characteristics is the most decisive construct affecting the vehicle emissions. The high-emitting vehicles have been identified as old, small engine, manual transmission, high mileages and 2-stroke engine (for motorcycle) vehicles. The second most influencing construct is the driver/rider demographics. Aged, male, low-educated car drivers and motorcyclists with high income, long driving/riding experience tend to use high-emitting vehicles. Moreover, our results also show that emissions of cars are more serious in small cities than in large or medium cities; however, this relationship is not existent in the motorcycle model.

Some directions for future studies are suggested. Firstly, since the conceptual framework of SEM is originally attempted in the present study, more practical evidence and theoretical support to this SEM framework should be elaborated in the future study. Especially, due to the considerations of high correlational relationship between HC and CO and compactness of the model, two pollutants are represented by an emissions index in our proposed conceptual framework. However, one may directly relate two pollutants to other constructs for providing more detailed information. Secondly, during the data matching we found that the number of valid samples have been largely reduced due to a serious data missing problem in the I/M dataset. The updated maintenance of I/M database requires more effort and attentions. Thirdly, the related information of cleaning devices of testing vehicles, such as catalytic converter and direct injection engine, have not been recorded in Taiwan's I/M database yet, making it hard to identify their contribution to emissions reduction. Thus, we suggest adding the information into the database while performing inspection tests. Fourthly, vehicles maintenance records could be another potential construct affecting the vehicle emissions. It is worthy of validating such a relationship. Last but not least, the car/motorcycle emission models are developed independently. However, it is quite common that a household in Taiwan owns both car and motorcycle. The cross-relationship between car and motorcycle and the substitution of one vehicle for another within a family require further investigation by a more sophisticated conceptual framework.

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