EASR

Engineering and Applied Science Research

https://www.tci-thaijo.org/index.php/easr/index

Published by the Faculty of Engineering, Khon Kaen University, Thailand

Determinants of individual vehicle type choice and energy consumption in a heavy traffic metropolis of Southeast Asia featuring the case of Metro Manila

Monorom Rith*[1, 2], Neil Stephen Lopez[1], Alexis M. Fillone[3] and Jose Bienvenido M. Biona [1, 4]

[1]Department of Mechanical Engineering, De La Salle University, Taft Ave, 1004, Metro Manila, Philippines
[2]Research and Innovation Center, Institute of Technology of Cambodia, Russian Conf. Blvd. Phnom Penh, Cambodia
[3]Department of Civil Engineering, De La Salle University, Taft Ave, 1004, Metro Manila, Philippines
[4]Center for Engineering and Sustainable Development, De La Salle University, Taft Ave, 1004, Metro Manila, Philippines

Received 15 June 2019
Revised 22 August 2019
Accepted 10 September 2019

Abstract

Sustained economic growth with insufficient public transport in metropolitan areas encourages private vehicle dependency, thereby increasing petroleum oil consumption and greenhouse gas (GHG) production. One way to mitigate these issues is to encourage private vehicle users to own smaller fuel-efficient vehicles. This paper intends to explore determinants (i.e., socio-economic characteristics, travel behavior, vehicle attributes and purchasing conditions, vehicle and gas prices, and built environment characteristics) of individual vehicle type owners and energy consumption in Metro Manila. The data sample of 846 observations and a copula-based joint discrete-continuous framework were employed. The findings highlighted that individuals using bank auto loans are more likely to choose SUVs than cars, thereby consuming more energy. Furthermore, people located in high population density areas and those with road-based public transport line dense areas prefer cars to SUVs. An increase in gas and vehicle cost contributes to energy saving and discourages SUV dependency. The developed models were also applied for a "what-if" scenario analysis to quantify the competing options as an innovative perspective for crafting proactive transportation policies. Understanding the determinants of vehicle type ownership and energy consumption is the precursor of designing consistent transportation policies to mitigate petroleum oil consumption and mobile emissions.

Keywords: Discrete-continuous choice model, Copula, Vehicle type ownership, Energy demand, Metro Manila, Southeast Asia

1. Introduction

Southeast Asia, with its roughly 640 million inhabitants, has been experiencing a fast-growing economy, $7.4 trillion in 2016 and an average growth of 5.2% per annum since 2000 [1]. Along with that, the total energy demand for the transport sector in the region doubled to about 120 million tonnes of oil equivalent (Mtoe) in 2016 compared with 2000, and imported petroleum oil was responsible for 94% of this increase [1]. Additionally, the number of new car sales exploded to about 3.33 million units in 2017 with an annual growth rate of 5% [2]. Vehicle stocks increased to 36 million units in 2016 [1]. The region is facing escalating motorization, energy demand, and CO_2 emissions [3].

Metro Manila, the national capital of the Philippines, has led all the provinces in its vehicle fleet with 38.61% of the total passenger vehicles (excluding motorcycles and buses) in the country [4]. At present, Metro Manila encounters the heaviest traffic congestion in southeastern Asia after Jakarta [5]. The average travel time of one person trip in Metro Manila is 1.17 h, that is projected to increase to 1.33 h in 2030 in the case of no strategic implementation to counter this trend [6]. The monetary value of transportation (i.e., operating and time cost) recently has been estimated as Php 3.5 billion a day, and this cost will increase to Php 5.4 billion a day by 2035 [7]. In 2012, the percentage share of private vehicle trips was 71.3% in terms of vehicles with an annual growth rate of 3.3% from 1996 to 2012 [6]. About 50% of the roads in the metropolis are operating already at volume/capacity (V/C) ratios above 0.80 [6]. The projected up-trend in vehicle ownership is expected to saturate the roads further. The total number of registered passenger vehicles (excluding buses and motorcycles) increased from 1.35 million units in 2010 to about 1.70 million units in 2016. This translates to an average annual growth rate of 1.58% [4]. Furthermore, the proportion of SUV ownership has increased from 29.18% in 2010 to 32.27% in 2016 [4]. The rapid growth in SUV ownership is mainly caused by sustained income growth, and it is expected to increase further. This is a sign of less efficient energy consumption for passenger mobility since the fuel consumption of an SUV is about 50% higher than for a car [8]. An increase in energy demand is highly correlated with increased greenhouse gas (GHG) production and urban air quality degradation. The CO_2

*Corresponding author. Tel.: +6396 6480 9818
Email address: rith_monorom@dlsu.edu.ph
doi: 10.14456/easr.2020.5

emissions from the road transport sector in 2015 was 13.78 million tonnes and this will more than double to 27.90 million tons in 2040 (roughly a 2% increase per year) in the baseline scenario [9]. These issues cannot be addressed unless a new paradigm for energy consumption and transportation planning is implemented. A better understanding of the determinants of private vehicle type ownership and energy consumption can provide practical insights in crafting consistent interventions to mitigate energy usage and greenhouse gas (GHG) production from private vehicles.

This paper intends to explore the determinants of vehicle type ownership and energy demand in a heavy traffic metropolis in Southeast Asia, featuring the case of Metro Manila. A comprehensive set of determinants including socioeconomic characteristics, travel behavior, vehicle attributes and purchasing conditions, vehicle and gas prices, and built environment characteristics are hypothesized to influence vehicle type choice and energy consumption. A data sample of 846 observations gathered from various traffic analysis zones (TAZs) throughout the metropolis in 2017 were employed to develop integrated individual vehicle type ownership and energy demand models using copula-based joint discrete-continuous choice modeling.

The remainder of the paper is structured as follows. Section 2 presents an overview of the determinants of vehicle type ownership and usage in other countries. Section 3 provides a brief description of data sources and methodology. Section 4 interprets the model estimation and simulation results for policy implications, and Section 5 concludes the findings and provides the direction for future research.

2. Literature review

There has been substantial literature from other countries similar to our case study. Those studies have covered influential determinants of household vehicle holdings and usage, such as socioeconomic characteristics, travel behavior, vehicle attributes, vehicle and operating costs, and built environment characteristics. Some studies did not include vehicle usage as a continuous output variable, mostly in developing countries. Evidently from the existing studies, household income is the most significant effect of household vehicle holdings and usage among the household characteristics [10-14]. Older households are more likely than younger households to own old vehicles [15]. The presence of children inclines households to own and use vehicles with larger seating and luggage space [16]. Households with seniors have a higher propensity to hold vehicles [17]. The number of family members, working adults, and drivers have a positive effect of owning larger and more vehicles, as well as travelling more miles [11, 13, 18]. Ethnicity also has an impact on vehicle ownership, type choice, and usage [19-20, 16]. The presence of family members with regular salaries is also associated with private vehicle ownership decisions [17].

Additionally, travel behavior and weather conditions also affect vehicle usage in terms of fuel consumption [21]. The findings highlighted that those arriving home late and departing home earlier are likely to consume more fuel as a result of a long drive. Driving on hot days, cold days, and rainy days increases fuel consumption.

Household vehicle type choice and usage are significantly influenced by vehicle cost [15, 22-23] to a higher degree relative to gas taxes [23]. Penalty taxes on older SUVs leads to reduced emissions by inducing people to buy new SUVs or cars [22]. An increase in operating costs contributes to reduction of vehicle usage [12-13, 22, 24].

Distance from home to the workplace also affects vehicle ownership decisions [25, 18]. Households located in suburban areas are more likely than households in urban areas to own new and large vehicles [15]. For the built environment, households in high-density areas are likely to own fewer and smaller vehicles and drive fewer miles [12-13, 15, 26-27] due to the limited parking available in urban high-density areas [15, 28]. Households located in residential areas with more railway stations and bus stops have a lower propensity to own vehicles [28-30] and use vehicles [26]. Similar findings also confirm that the development of an urban transit system and improvement of public road transport lines discourage private vehicle dependency [31-32]. Neighborhoods with high bike lane density discourage private vehicle dependency, while high street block density communities induce households to hold smaller vehicles [15] and discourage private vehicle usage [26]. The presence of physical activity centers in communities did not affect vehicle type choice, but discouraged vehicle usage [16]. Inversely, residential areas with the presence of commercial and industrial centers induce households to own small vehicles, but had no impact on vehicle usage [15-16]. The availability of roadside parking space also encourages vehicle ownership [11, 32]. Those residing in a central business district (CBD) are willing to own small and luxury vehicles [11] and are less private vehicle dependent [26]. Similarly, mixed land use discourages household vehicle dependency [11, 18, 25, 32]. A summary of the determinants of household vehicle ownership, type, and usage decisions is tabulated in Table 1.

Most previous studies focused on very few determinants and used the household dimension of vehicle holdings and usage. For the household dimension, only the household head characteristics have been considered, while the characteristics of family members owing vehicles have never been included. A number of integral amenities such as schools, hospitals, markets, and recreational centers in the vicinity of residential areas have yet to be considered as the determinants of vehicle type ownership and usage. Furthermore, the impact of vehicle purchasing conditions on vehicle type choice and usage has remained unexplored, e.g., payment approach (full payment or installment), a status of a vehicle when purchased (new or second hand). Additionally, the impact of travel behavior for regular destinations on vehicle type ownership and usage has not been quantified yet, e.g., departure time from home to work or work to home, vehicle load (persons), and a number of days of travel for regular trips. Beyond that, investigation of these variables affecting private vehicle type acquisition and usage has been less conducted for developing countries in the southeastern sub-region of Asia. To the best of our knowledge, none of the previous studies have considered socioeconomic characteristics, travel behavior, vehicle attributes and purchasing conditions, vehicle and gas prices, and built environment characteristics as a comprehensive set of determinants for an exhaustive study.

Correspondingly, the presence of hospitals, schools, markets, and recreation centers in the vicinity of neighborhoods was taken into account to explore the peculiarities hypothesized to influence vehicle type ownership and energy consumption in our study. Also, vehicle purchasing conditions and travel behavior were considered.

Table 1 A summary of determinants of household vehicle ownership, type, and usage

Potential factors	References
Socio-economic characteristics	
• Household income, household size, and a number of working adults have a positive effect on household vehicle dependency.	[10], [11], [12], [13], [14], [25],
• Presence of children and seniors inclines households to hold more vehicles, and vehicles with larger seating and luggage capacity.	[16], [17]
• Presence of family member with regular salary encourages household vehicle ownership.	[17]
• Home-owning households are likely to hold more vehicles.	[11]
• Ethnicity has a significant impact on vehicle ownership, type choice, and usage.	[16], [19], [20]
Travel behavior	
• People arrive home late and depart home earlier are likely to consume more fuel. Driving on hot days, cold days, and rainy days increases fuel consumption.	[21]
Built-environment characteristics	
• Distance from home to the workplace has a positive correlation with household vehicle ownership.	[18, 25]
• Households in a rural area are more likely than those residing in an urban area to own vehicles.	[17]
• More roadside parking space encourages household vehicle ownership.	[11]
• Mixed land use has a negative effect on vehicle dependency.	[11], [18], [25]
• Population density, percentage share of roads with bike lanes, and bus stop density have a statistically negative impact on household vehicle ownership and usage for developed countries.	[11], [12], [13], [15], [19], [24], [25], [27], [28]
Taxes on Gas and Vehicle	
• A number of vehicles and vehicle type are significantly influenced by vehicle cost and at a higher degree compared with gas price.	[15], [22], [23]
• An increase in tax on the age of SUV induces people to buy cars or new SUVs in lieu of old SUVs to reduce emissions.	[22]
• An increase in gas price discourages vehicle usage.	[12], [13], [24]

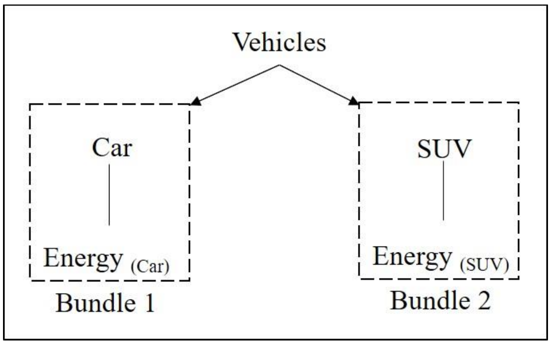

Figure 1 Structure of vehicle type classification

Table 2 Distribution of individual vehicle type ownership

Vehicle type	Frequency	Percentage share
Car	573	67.73 (%)
SUV	273	32.27 (%)

The previous discrete-continuous choice models made two different assumptions, 1) discrete and continuous choices are independent, and 2) discrete and continuous choices are inter-dependent based on the copula approach [13, 16, 20, 24, 33]. No study made the assumption that only the discrete choice affects the continuous choice, but the continuous choice does not affect the discrete choice. These three different assumptions were made in our study to develop and compare three joint models of individual vehicle type ownership and energy consumption for Metro Manila. As apparent from an overview of the earlier works, this study makes a considerable contribution to the literature.

3. Methodology

3.1 Model formulation and data source

In our study, vehicles were classified into two main categories, cars and SUVs. Motorcycles and light-duty commercial vehicles (i.e., pickups, vans, minivans, and Asian utility vehicles) were excluded since the motorcycle is not the main driver of traffic congestion and excess energy consumption for passenger mobility. Light-duty commercial vehicles are typically used for commercial purposes. Ergo, the developed joint model can be applied to induce the private passenger vehicle owners to acquire small, fuel efficient vehicles (i.e., sedans and hatchbacks). Figure 1 illustrates the classification of vehicle types and energy demands. For the discrete choice component, vehicles are classified into cars and SUVs. For the continuous choice component, $Energy_{(Car)}$ is an amount of energy consumed by a car, while $Energy_{(SUV)}$ refers to an amount of energy consumed by an SUV. The models were developed using the revealed preference data gathered from various areas in Metro Manila in 2017. The paper-based survey technique along with a simple random sampling technique was applied. After cleaning the data sample, there were 846 observations, and the percentage shares of the data sample are comparable to the actual percentage shares in the Land Transportation Office (LTO) in 2016 [4]. Based on the Cochran formula, the data sample offers a confidence level of 95% and a margin of error of 3.37% if we assume the standard deviation to be 50% (a typical value). The vehicle distribution is shown in Table 2. Descriptive statistics of the energy demand and the explanatory variables are presented in Table 3.

Table 3 Descriptive statistics of energy demand and explanatory variables

Variables	Description	Min	Mean	Max	SD
Energy demand	Monthly energy consumption (MJ/month-vehicle)	374.23	3571.49	14847.93	1856.53
Socio-economic characteristics					
Marital status	1 = married, 0 = otherwise	0.000	0.794	1.000	0.404
Sex	1 = male, 0 = otherwise	0.000	0.778	1.000	0.416
Age	1 = car owner aged 40 years or above, 0 = otherwise	0.000	0.641	1.000	0.480
Occupation type					
Employee	1 = employee, 0 = otherwise	0.000	0.741	1.000	0.438
Self-employed	1 = self-employed, 0 = otherwise	0.000	0.202	1.000	0.402
Non-working adult (Ref.)	1 = no job, 0 = otherwise	0.000	0.057	1.000	0.231
Educational level	1 = bachelor degree or higher, 0 = otherwise	0.000	0.904	1.000	0.294
Home ownership	1 = own a home, 0 = otherwise	0.000	0.806	1.000	0.396
Family size	Number of family members	1.000	3.272	8.000	1.078
No. of working adults	Number of household income earners	0.000	1.981	6.000	0.837
No. of preschoolers	Number of small children not going to school	0.000	0.147	3.000	0.432
No. of school children	Number of children studying at K-12 schools	0.000	0.434	4.000	0.761
No. of OFWs	Number of family members working overseas	0.000	0.149	3.000	0.450
Travel behavior					
No. of travel days	Number of travel days for a regular trip per week (days)	1.000	5.005	7.000	0.995
Distance	Distance from home to a regular destination (km)	0.240	9.020	174.000	10.445
HTW departure time	Departure time from home to a regular destination	0.042	0.306	0.917	0.096
WTH departure time	Departure time from a regular destination to home	0.000	0.699	0.917	0.115
Vehicle load	Number of persons in a vehicle for a regular trip (persons)	1.000	1.241	5.000	0.558
Vehicle attributes and purchasing conditions					
Ownership duration	1 = 3 years or less than, 0 = more than 3 years	0.000	0.418	1.000	0.494
Vehicle status	1 = new vehicle when purchased, 0 = second-hand	0.000	0.708	1.000	0.455
Vehicle age	Age of a vehicle (years)	0.000	6.304	27.000	4.779
Mode of purchase	1 = full payment, 0 = down payment or bank auto loan	0.000	0.507	1.000	0.500
Vehicle and fuel costs					
Vehicle cost/income [a]	Vehicle cost divided by annual household income	0.252	0.932	6.036	0.565
Fuel cost/income [a]	10 × Weekly expenditure on gas divided by monthly household income	0.031	0.113	0.736	0.069
Built environment characteristics					
No. of hospitals	No. of hospitals located less than 1 km from a residential area	0.000	2.331	8.000	1.944
No. of Elementary schools	No. of elementary schools located less than 1 km from a residential area	0.000	4.812	13.000	3.039
No. of high schools	No. of high schools located less than1 km from a residential area	0.000	2.888	11.000	1.932
No. of colleges	No. of colleges located less than 1 km from a residential area	0.000	1.924	14.000	2.356
No. of markets	No. of markets located less than 1 km from a residential area	0.000	2.956	13.000	2.785
No. of recreation centers	No. of recreation centers located less than 1 km from a residential area	0.000	1.565	11.000	1.721
Population density [b]	Population density at TAZ level (10^3 persons/km^2)	2.485	64.753	329.732	39.250
Road density [b]	Road density at TAZ level (km/km^2)	0.419	10.368	28.201	5.090
CBD	Distance from home to the shortest central business district (km)	0.183	4.647	31.202	4.463
Railway station	Distance from home to the shortest railway station (km)	0.025	2.107	14.886	2.439
Line density [b]	Road public transport line density at TAZ level (km/km^2)	0.000	38.965	154.221	43.599

[a] Based on [15]
[b] Based on [34]
TAZ: Traffic analysis zone

The energy consumption is derived from the survey data. Each household was asked about their expenditures on vehicle gas in a monetary value per week for each vehicle, and the gas expenditure is converted into the amount of energy per month. The retail pump prices were 47 Php/liter (for gasoline RON97) and 30 Php/liter (for diesel fuel) in April 2017 [35]. These unit prices were used in our study because the household survey was carried out in April through May 2017. It is not surprising to see that the majority of vehicle owners are married and male because most household heads are male among one-vehicle households, and they are the ones holding vehicles. The presence of family members working overseas (OFW) was included in our study because a household with OFW member has higher income, which is likely to translate to higher purchasing power.

For the departure time factor, it was converted into a numerical value that can be coded for model estimation. For instance, if departure time from home to work is at 7:15, it is written as (7+15/60)/24= 0.30208. The values of 60 and 24 are 60 minutes per hour and 24 hours per day, respectively. The average departure times from home to the regular destination and from the regular destination to home are 0.306 (or 7:20) and 0.699 (16:46). The distance from home to a regular destination is the distance derived from Google Maps using the fastest road by car mode. 70.8% of the vehicle owners buy new vehicles, and about half of the vehicle owners use a down payment or bank auto loan services.

Of the samples, 401 vehicles were purchased after 2013 as extracted from the data sample. The average purchase cost of one vehicle is Php 905,418 (SD[1] = 384,611), and the average weekly expenditure on gas for one vehicle is Php 920 (SD = 469). The ratios of these average values relative to household income were used in our study to capture the impacts of vehicle cost and gas price on vehicle type choice and energy consumption[2]. In our model development, we assumed that vehicle cost has no impact on vehicle usage but affects vehicle type choice, while the gas price has no effect on vehicle type choice but affects vehicle usage.

The empirical findings also confirmed that driving costs or operating costs have no effect on vehicle ownership and type choice, but affects vehicle usage [12-13, 24]. A 96% gas price increase could change a vehicle type ownership by about 1% only, which is very marginal [16].

For the built environment patterns, a number of critical facilities less than 1 km from home were computed based on an approximate distance using the CDXDistance2WP function of the CDXZipStream tool, as this approach is more

[1] SD is standard deviation.
[2] This approach make more sense as compared to using the actual purchase cost relative to the household income of the survey year. Some vehicles last more than ten years, and the consumer price index (CPI) in the last ten years is much lower than the CPI of the survey year.

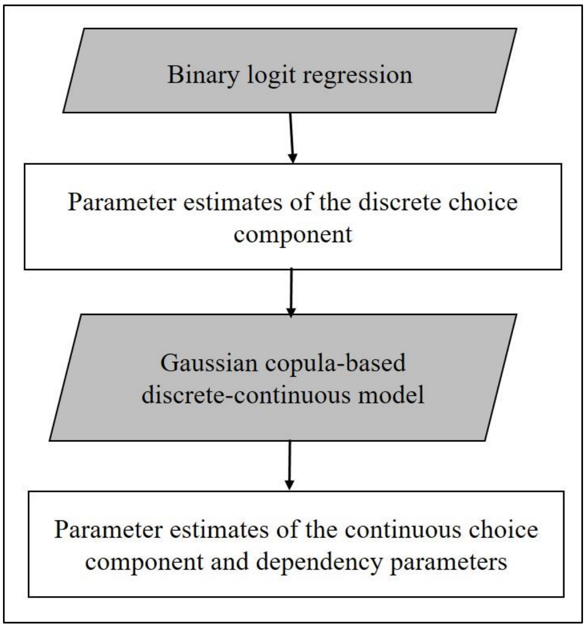

Figure 2 Procedure of model estimation for the joint model 3

accurate and reliable than the Euclidean and Manhattan methods. There are 655 licensed hospitals [36], 508 primary schools, 310 secondary schools [37], and 203 colleges [38] with official addresses in Metro Manila. A list of 333 markets (87 public markets and 246 supermarkets) and 161 recreation centers (shopping malls) was obtained from the pop-up menu of Google Maps, since there is no official list with addresses from any government departments or agencies. Distances from homes to the shortest CBDs and railway stations were also computed using the CDXZipStream tool. There are 8 CBDs in Metro Manila and 67 railway stations on 4 lines (LRT-1, LRT-2, MRT, and PNR).

3.2 Joint discrete-continuous choice model

As discussed above, there are two different output variables, individual vehicle type choice (discrete choice) and fuel consumption (continuous choice). The discrete choice was modeled using binary logit regression, as in equation 1 [39]:

$$F(\varepsilon_{nt}) = Pr(V_{nt} > V_{nT}) = Pr(t) = \frac{exp(\beta_t{}' x_{nt})}{exp(\beta_t{}' x_{nt}) + \sum_{T \neq t} exp(\beta_T{}' x_{nT})} \quad (1)$$

where the indices t and n are the alternative and individual, respectively. $V_{nt} = \beta_t{}' x_{nt}$ and $V_{nT} = \beta_T{}' x_{nT}$ are the observed terms. ε_{nt} is the random error term, $F(\varepsilon_{nt})$ is the implied cumulative distribution of the random error term of the chosen alternative *t*, made by an individual *n*. x_{nt} is a column vector of explanatory variables including a constant, and β_t is a column vector of the corresponding coefficients.

The continuous choice was assumed to be log-normally distributed because the continuous choice is positive, or the logarithm of energy consumption is normally distributed. Ergo, the probability density function and cumulative distribution function of the standard normal distribution are expressed in equations 2 and 3, respectively [40].

$$f(\eta_{nt}) = Pr\big(ln(L_{nt}) = ln(l_{nt})\big) = \frac{1}{\sigma_{nt}} \phi\left(\frac{ln(l_{nt}) - \alpha' y_{nt}}{\sigma_{nt}}\right) \quad (2)$$

$$F(\eta_{nt}) = Pr\big(ln(L_{nt}) \leq ln(l_{nt})\big) = \Phi\left(\frac{ln(l_{nt}) - \alpha' y_{nt}}{\sigma_{nt}}\right) \quad (3)$$

where *l* and *L* are the amounts of energy consumption, y_{nt} is a column vector of the explanatory variables including a constant, α is a column vector of the corresponding coefficients used as the generic parameters for all the vehicle types, and η_{nt} defines the unobserved term. The ϕ and Φ are the probability density and cumulative distribution functions of the standard normal distribution, respectively.

Vehicle type choice and energy consumption were linked together to become a single bundle of two dimensions. In our study, we made three different assumptions:

- Joint Model 1: Vehicle type choice and energy consumption were assumed to be independent, and the independence-based joint model is expressed as equation 4:

$$LL = \sum_{n=1}^{N} \sum_{T=1}^{M} R_{nT} [ln(F(\varepsilon_{nT})) + ln(f(\eta_{nT}))] \quad (4)$$

where R_{nT} $[R_{nT} = 1]$ defines a dummy variable of a chosen vehicle type *T*, made by an individual *n*, *N* = 846, and *M* = 2.

- Joint Model 2: Vehicle type choice and energy consumption were assumed to be interdependent using the Gaussian copula approach. The Gaussian copula-based joint model is expressed as equation 5 [20, 39]:

$$LL = \sum_{n=1}^{N} \sum_{T=1}^{M} R_{nT} \left[ln\left(\frac{\partial C_\theta(F(\varepsilon_{nT}), F(\eta_{nT}))}{\partial F(\eta_{nT})}\right) + ln(f(\eta_{nT}))\right] \quad (5)$$

where the partial derivative of the Gaussian copula function $\frac{\partial C_\theta(F(\varepsilon_{nt}), F(\eta_{nt}))}{\partial F(\eta_{nt})} = \Phi\left[\frac{\Phi^{-1}(F(\varepsilon_{nt})) - \theta \Phi^{-1}(F(\eta_{nt}))}{\sqrt{1-\theta^2}}\right]$, and θ is a dependency parameter representing the linkage between the two univariate distributions. The dependency parameter of the Gaussian function ranges from -1 to +1.

- Joint Model 3: It was assumed that the vehicle type choice affects the energy consumption, but the degree of energy consumption does not affect the vehicle type choice. In this context, we first estimated a subset of discrete choice parameters using the binary logit regression (see equation 1) and then fixed the parameter estimates of the discrete choice model by estimating the remaining parameters using the Gaussian copula-based discrete-continuous choice model (see equation 5), as illustrated in Figure 2.

The mathematical expressions of the independence-based discrete-continuous model and the Gaussian copula-based discrete-continuous model are detailed in [16, 20, 24, 33, 39, 41]. An R programming language script was written to estimate the parameters by maximizing the log-likelihood value, applying a Newton Raphson type optimization routine. A core i7 laptop with 4 GB of random access memory (RAM) was used to estimate the models.

Table 4 Model estimation results – coefficient (standard error)

Parameters	Model 1	Model 2	Model 3
Vehicle type choice			
Marital status	0.619 (0.209)**	0.580 (0.185)**	0.619 (0.210)**
Sex	0.623 (0.200)**	0.484 (0.174)**	0.623 (0.200)**
Emloyee	-0.694 (0.173)***	-0.720 (0.163)***	-0.694 (0.173)***
Vehicle load	0.450 (0.123)***	0.446 (0.117)***	0.450 (0.123)***
Mode of purchase	-0.423 (0.161)**	-0.353 (0.155)*	-0.423 (0.161)**
Vehicle cost/income	-0.855 (0.173)***	-0.847 (0.159)***	-0.855 (0.173)***
Population density	-0.010 (0.002)***	-0.008 (0.002)***	-0.010 (0.002)***
Line density	-0.005 (0.002)**	-0.004 (0.001)*	-0.005 (0.002)**
Energy consumption			
Intercept	7.967 (0.070)***	8.094 (0.071)***	8.077 (0.068)***
Age	0.088 (0.029)**	0.067 (0.029)*	0.069 (0.028)*
Self-employed	0.088 (0.037)*	0.126 (0.037)***	0.122 (0.034)***
Family size	0.035 (0.013)*	0.044 (0.013)***	0.044 (0.013)***
Vehicle load	0.060 (0.027)*	0.066 (0.026)*	0.066 (0.025)**
Mode of purchase	-0.138 (0.028)***	-0.164 (0.03)***	-0.168 (0.028)***
Fuel cost/income	-1.402 (0.220)***	-1.723 (0.234)***	-1.678 (0.215)***
CBD	0.008 (0.003)*	0.008 (0.003)**	0.008 (0.003)**
Standard deviation of the lognormal distribution			
Car	0.378 (0.011)***	0.438 (0.018)***	0.431 (0.017)***
SUV	0.501 (0.023)***	0.452 (0.019)***	0.455 (0.020)***
Dependency parameter			
Car	–	0.769 (0.050)***	0.746 (0.053)***
SUV	–	-0.184 (0.074)*	-0.200 (0.070)**
Log-likelihood value at convergence / AIC			
Binary logit regression	–	–	-468.56 / 953.13
Joint discrete-continuous model	-924.77 / 1885.55	-880.59 / 1801.18	-881.77 / 1787.55

Car was used as the reference category.
Coefficients of the continuous choice component are generic.
*significant at 5% level; ** significant at 1% level; *** significant at 0.1% level

4. Results and discussion

4.1 Model estimation results

The streamlined model estimation results are summarized in Table 4. The insignificant factors with p-values higher than 0.05 level were deliberately removed using the forward elimination approach. Only the significant factors below the 0.05 significance level remain in the table. As apparent from the last two rows of the table, Model 2 was superior in terms of its log-likelihood value, followed by Model 3 and Model 1. Model 3 was found superior in terms of Akaike Information Criteria (AIC). However, Models 2 and 3 are very comparable in terms of the log-likelihood values and the AICs. The estimation of Model 3 required much less computation time relative to the estimation of Model 2, according to our heuristic work (i.e., the computation time of model 3 was 27.69% of model 2's). It is not surprising to see that the parameter estimates of the discrete choice component of Models 1 and 3 exactly matched, even though the estimation procedures are different. As discussed earlier, the vehicle type choice is independent of the energy consumption for these two models. Also, the standard errors of the parameter estimates (values in parentheses) of these three models should not be overlooked. The standard errors of Model 2 were found to be the lowest for the vehicle type choice component, while the standard errors of Model 3 were found the lowest for the energy consumption component. Correspondingly, in terms of the standard errors, Model 2 outperforms for the discrete choice component, whereas Model 3 outperforms the continuous choice component.

It is noteworthy that a number of key facilities located in the vicinity of a residential area, such as hospitals, schools, markets, and recreation centers were statistically insignificant. However, this does not mean that those main facilities have no effect on vehicle type choice and energy consumption. Other approaches are required for future research. In other words, a number of critical facilities might affect vehicle ownership decisions (own or not own) rather than vehicle type choice (car or SUV). It is not surprising to see that the distance from home to the nearest railway station is insignificant because the train is not the dominant public transport mode in Metro Manila, or this factor might affect vehicle ownership decisions (own or not own) rather than vehicle type choice (i.e., car or SUV) and usage. The urban railway accounted for 5.91% of the passenger kilometers traveled (PKT), while the Jeepney and bus were responsible for 76.29% and 23.71% of PKT, respectively [6].

Rows 3 through 10 of Table 4 show the estimated parameters of the discrete choice component. The car was used as the reference category. It is understandable that males and married people are generally more likely than females and single people to own SUVs. Employees have a lower propensity to own SUVs relative to cars. Vehicle owners with passengers for regular destinations are willing to acquire SUVs, intuitively, on account of larger seating and luggage capacity. People using a down payment (partial payment or bank auto loan service) approach are more likely to choose SUVs because the SUV costs 1.68 times the car on average according to our data sample. Some people may not afford to pay for a large amount at one point in time for SUVs. Individuals with higher household incomes have a higher baseline propensity to hold SUVs than those with lower household incomes. However, an increase in vehicle purchasing cost has an extremely significant impact on discouraging SUV ownership. People located in high

Table 5 Comparative assessments among the three different assumptions

Model	Discrete choice component		Continuous choice component		
	Car (% share)	SUV (% share)	Total energy consumption (MJ/month)	RMSE	MRE
Actual	67.73%	32.27%	3,021,477	–	–
Model 1	67.56%	32.44%	2,661,357	1,752	0.3298
Model 2	66.75%	33.25%	2,988,093	1,678	0.3815
Model 3	67.56%	32.44%	2,956,069	1,680	0.3752

population density zones are more likely to own cars than SUVs. Therefore, building a compact city or encouraging urban densification contributes to increasing the percentage share of small-sized vehicle ownership. It was also confirmed by empirical findings in the USA [15] and Japan [28], presumably on account of space constraints for parking and maneuverability. A similar finding was found for people living in residential areas with high road-based public transport line density.

Rows 11 through 19 of Table 4 present the generic parameter estimates of the energy consumption model. Rows 20 through 22 of the table demonstrate the standard deviations of energy consumption, and rows 23 through 25 of the table show the dependency parameters between a vehicle type choice and the corresponding energy consumption. The dependency parameters suggest that SUV owners have a higher baseline preference than car owners to consume energy (see [16]). Older people (aged 40 years or above) are likely to consume more energy than younger people. Self-employed people prefer to consume more energy than employees and non-working adults, intuitively since self-employed people are likely to have more business trips. Vehicle owners with large families are associated with higher energy consumption, probably as a result of more vehicle trip activities. A similar result was observed for vehicle owners having regular travels with passengers. Vehicle owners using the full payment approach are less likely to consume energy because those people are more likely to hold cars rather than SUVs (as discussed above). Individuals with higher household income have a tendency to consume more energy than those with lower household incomes, and an increase in gas price can mitigate energy consumption. Similar findings are also shown in the USA by [12-13, 22]. Vehicle owners located close to CBDs tend to consume less energy because CBDs are in the proximity of mixed land use with better public transport accessibility and eco-friendly sidewalks resulting in a reduction of private vehicle-related trips. A similar finding in China was also reported [26].

As previously stated in terms of a log-likelihood value, AIC, and standard errors of the parameter estimates, the performance of Models 2 and 3 was very comparable, and these two models outperformed Model 1. For further clarification, these three models were used to estimate the output variables and then compared with the actual output variables. Table 5 presents the estimated percentage shares of vehicle types and estimated total energy consumption, root mean square errors (RMSEs), and mean relative errors (MREs) of the continuous choice component. For the discrete choice component in terms of the estimated percentage shares, Models 1 and 3 performed marginally better than Model 2. The estimated total energy consumption of Model 2 was close to the actual value, followed by Models 1 and 3. The lowest RMSE value was found for Model 2, while the lowest MRE value was found for Model 1. These comparative criteria are among the three different assumptions of discrete-continuous choice models. They are informative for choosing appropriate assumptions to fit the target of the study. It is noteworthy that all the comparative criteria of Models 2 and 3 are quite similar. However, the estimation of Model 3 required much less computation time than Model 2. In some cases, simultaneous estimation of the copula-based joint model did not converge because variances of some parameter estimates were negative, and correspondingly, the root mean squares of the negative variances make the standard errors were then NaN (Not a Number). For the next subsection, Models 2 and 3 were applied in “what-if” scenario analysis.

4.2 Model application

Four different scenarios were designed to simulate the percentage changes in energy consumption in "what-if" scenario analysis as the following:

- Scenario 1: a 25% increase in population density
- Scenario 2: a 25% increase in road public transport line density
- Scenario 3: a 25% increase in vehicle cost
- Scenario 4: a 25% increase in fuel cost
- Scenario 5: integration of scenarios 1 through 4

A 25% increase for each scenario is large enough to allow us to see the trend and magnitude of the impact of the variation of variables of interest on the output. Figure 3 illustrates the percentage changes in energy consumption in response to changes in the input variables. A negative sign indicates a decrease. For all the scenarios, the absolute percentage changes of Models 2 and 3 are comparable. The absolute percentage changes of scenarios 1 through 3 are found slightly lower for Model 2 than to Model 3 because the standard errors of the discrete choice component of Model 2 are relatively lower. The absolute percentage change of scenario 4 is slightly lower for Model 3, compared to Model 2. It is not surprising to see that all the absolute percentage changes are marginal because these values are among vehicle owners only (cars or SUVs), and not among all people (owning and not owning vehicles). An increase in gas price was found as the most effective option to mitigate energy consumption by vehicle owners, compared to increases in vehicle cost, population density, and road public transport line density. If scenarios 1 through 4 were integrated, it would have reduced energy consumption by about 5% among vehicle owners. However, this value would be much higher if we consider the alternative of owning or not owning in the choice set. For instance, people might not own any vehicle types or postpone vehicle ownership if the vehicle price increases.

An increase in vehicle cost is more effective than an increase in fuel price to reduce energy consumption if the choice of not owning a vehicle is included in the discrete choice set. This was empirically reported by Feng et al. [22].

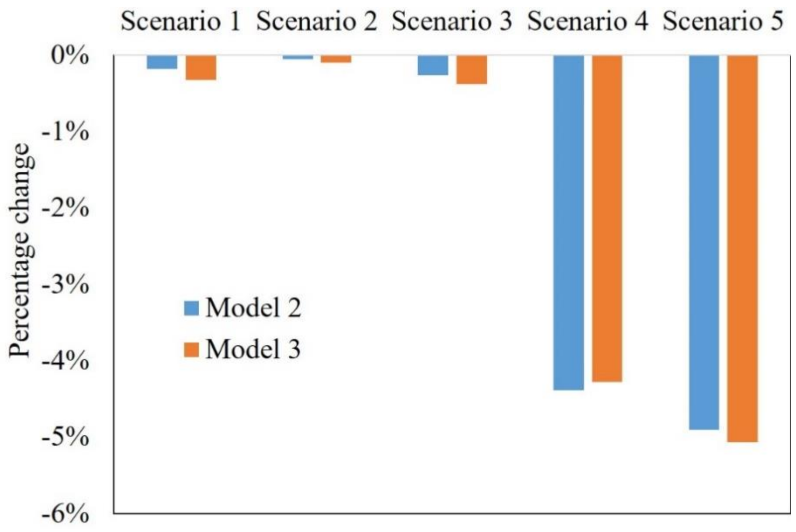

Figure 3 "What-if" scenario analysis of energy consumption

The output of our paper makes a considerable contribution to empirically navigating future work to use the computation procedure of Model 3 (as illustrated in Figure 2) to save computation time or reduce computation costs and minimize the up-popping problem during the model estimation. Regarding the estimation and simulation results, Models 2 and 3 are highly comparable in terms of log-likelihood values, AICs, standard errors, RSMEs, MREs, estimated percentage shares, and estimated total energy consumption.

4.3 Policy implications

The model estimation and simulation results can provide insights into crafting consistent interventions to reduce energy consumption among private vehicle users. People with higher household incomes have a greater baseline preference for SUVs over cars. It indicates that steady economic growth is aligned with a higher propensity to buy larger and more comfortable vehicles. However, SUVs have a lower fuel economy relative to cars, thereby consuming more energy and producing more CO_2 emissions. It is a sign of less efficient energy consumption for passenger mobility. Also, it is noteworthy that offerings of bank auto loan services encourage SUV choices. This problem can be addressed by banning bank auto loan services for the purchase of the fuel-inefficient passenger vehicles. Building a compact city and encouraging urban densification can discourage large fuel-inefficient vehicle ownership. This idea is widely accepted and applied in developed countries [15-16].

Improvement of public transport line density contributes to a reduction of energy demand for passenger mobility by inducing people to shift from SUVs to cars. All of the previous studies, especially in developed countries, used the bus stop density (or distance from home to the nearest bus stop) and railway station density (or distance from home to the nearest station) to capture the impact of these factors on household vehicle ownership, vehicle types, a number of vehicles, and vehicle usage. However, these factors might not have an impact on the output variables in Metro Manila because the Public Utility Jeepney (PUJ), whose features are similar to the mini-bus, is the dominant public transport mode. Therefore, improvement of road public transport line density could be a better solution in Metro Manila to combat CO_2 emissions and reduce petroleum demand.

Two other approaches to mitigate energy consumption from private vehicles are increases in gas prices and vehicle costs. In January 2018, the government launched the Tax Reform for Acceleration and Inclusion (TRAIN) law or RA No. 10963 to increase gas and vehicle prices [42]. It was reported that Philippine auto sales dropped by 14.4% for the first eleven months of 2018 compared to the same period of last year [43]. A decrease in new vehicle sales is consistent with a reduction in private vehicle dependency, which should translate to a reduction in road transport energy demand.

Reduction in distance from residential areas to key facilities or an increase in the number of key facilities in residential areas might be ineffective to mitigate vehicular energy consumption from private vehicle users, based on our empirical findings. However, improvement of mixed land use and development of eco-friendly walkways could be potential solutions to discourage private vehicle trips.

5. Conclusions

This paper explores a comprehensive set of the potential determinants of individual vehicle type ownership and energy consumption in the massive traffic metropolitan area of Southeast Asia, i.e., Metro Manila. Three different integrated models of vehicle type choice and energy consumption were developed based on three different assumptions, Model 1 (the two choices are independent), Model 2 (the two choices are interdependent), and Model 3 (the discrete choice affects the continuous choice). The findings highlighted that vehicular energy consumption is significantly affected by vehicle type choice. The impacts of determinants on vehicle type choice and energy consumption are concluded as follows. Males and married people generally prefer SUVs to cars, and older people are more likely than younger people to consume energy. Employees prefer cars to SUVs, and self-employed people are willing to consume more energy than employees and non-working adults. An increase in household income and availability of bank auto loan services are associated with a higher propensity to buy SUVs and consume more energy. Reduction of vehicular energy demand can be reached by increasing fuel and vehicle prices. An increase in road public transport line density and building compact cities also contributes to a reduction in private vehicular energy consumption.

The impact of key facilities (i.e., hospitals, schools, markets, and recreation centers) in the residential areas on private vehicle type choice and usage was statistically insignificant in our study. Further research is required to consider the impact of these key facilities in the workplace or other methods (e.g., mixed land use, accessibility index) to capture the simultaneous impact of the abovementioned factors on vehicle type ownership and energy consumption.

6. Acknowledgments

The outcomes of this research paper are mainly funded by (1) the Japan International Cooperation Agency (JICA) under the AUN/SEED-Net project for a Ph.D. Sandwich program at De La Salle University, Philippines and Osaka University, Japan, (2) the Commission on Higher Education Development for a Project of Development and Application of Transport Desirability Index for the Assessment and Planning of Transport Systems in the Philippines, and, (3) the Big Data Analytics and Applications (MTNN:BDAA) project of the Department of Science and Technology (DOST), Philippines.

7. References

[1] International Energy Agency. Southeast Asia energy outlook 2017. France: International Energy Agency; 2017.

[2] Yamakawa H. ASEAN New Car Sales Reach 3.33 Million in 2017-Two-thirds the scale of the Japanese market. Japan: Institute for International Studies and Training; 2018.

[3] Bakker S, Contreras KD, Kappiantari M, Tuan NA, Guillen MD, Gunthawong G, et al. Low-carbon transport policy in four ASEAN countries: development in Indonesia, the Philippines, Thailand and Vietnam. Sustainability. 2017;9:1-17.

[4] Philippine Statistics Authority. Philippine statistical yearbook. Philippine: Philippine Statistics Authority; 2017.

[5] Numbeo. Traffic Index 2018 Mid-Year [Internet]. 2018 [cited 2019]. Available from: https://www.numbeo.com/traffic/rankings.jsp.

[6] ALMEC. Roadmap for transport for infrastructure development for Metro Manila and its surrounding areas. Final project report - technical report No. 2. Philippines: Japan International Cooperation Agency (JICA) and the National Economic Development Authority (NEDA); 2014.

[7] Japan International Cooperation Agency. JICA to help Philippines ease traffic congestion in Metro Manila [Internet]. 2018 [cited 2019]. Available from: https://www.jica.go.jp/philippine/english/office/topics/news/180920.html.

[8] Clean Air Asia Center. Establishing Baselines for Fuel Economy of Light Duty Passenger Vehicles in the Philippines. Philippines: Clean Air Asia; 2015.

[9] Ahanchian M, Biona JB. Energy demand, emissions forecasts and mitigation strategies modeled over a medium-range horizon: the case of the land transportation sector in Metro Manila. Energ Pol. 2014;66:615-29.

[10] Cirillo C, Liu Y, Tremblay J. Simulation, numerical approximation and closed forms for joint discrete continuous models with an application to household vehicle ownership and use. Transport. 2017;44:1105-25.

[11] Jiang Y, Gu P, Chen Y, He D, Mao Q. Influence of land use and street characteristics on car ownership and use: Evidence from Jinan, China. Transport Res Transport Environ. 2017;52:518-34.

[12] Liu Y, Cirillo C. Small area estimation of vehicle ownership and use. Transport Res Transport Environ. 2016;47:136-48.

[13] Liu Y, Tremblay J, Cirillo C. An integrated model for discrete and continuous decisions with application to vehicle ownership, type and usage choices. Transport Res Pol Pract. 2014;69:315-28.

[14] Fang HA. A discrete-continuous model of households' vehicle choice and usage, with an application to the effects of residential density. Transport Res Methodological. 2008;42:736-58.

[15] Bhat C, Sen S, Eluru N. The impact of demographics, built environment attributes, vehicle characteristics, and gasoline prices on household vehicle holdings and use. Transport Res Methodological. 2009;43:1-18.

[16] Spissu E, Pinjari AR, Pendyala RM, Bhat CR. A copula-based joint multinomial discrete-continuous model of vehicle type choice and miles of travel. Transport. 2009;36:403-22.

[17] Choudhary R, Vasudevan V. Study of vehicle ownership for urban and rural households in India. J Transport Geogr. 2017;58:52-8.

[18] Potoglou D, Kanaroglou PS. Modelling car ownership in urban areas: a case study of Hamilton, Canada. J Transport Geogr. 2008;16:42-54.

[19] Oakil A, Manting D, Nijland H. Determinants of car ownership among young household in the Netherlands: The role of urbanization and demographic and economic characteristics. J Transport Geogr. 2016;51:229-35.

[20] Bhat CR, Eluru N. A copula-based approach to accommodate residential self-selection effect in travel behaviour modeling. Transport Res Methodological. 2009;43:749-65.

[21] Li D, Li C, Miwa T, Morikawa T. An exploration of factors affecting drivers' daily fuel consumption efficiencies considering multi-level random effects. Sustainability. 2019;11:1-13.

[22] Feng Y, Fullerton D, Gan L. Vehicle choices, miles driven, and pollution policies. J Regul Econ. 2013;44:4-29.

[23] West SE. Distributional effects of alternative vehicle pollution control policies. J Publ Econ. 2004;88:735-57.

[24] Nguyen NT, Miwa T, Morikawa T. Vehicle type choice, usage, and CO2 emissions in Ho Chi Minh city: analysis and simulation using a discrete-continuous model. Asian Transport Stud. 2017;4:499-517.

[25] Soltani A. Soicial and urban form determinants of vehicle ownership; evidence from a developing country. Transport Res Pol Pract. 2017;96:90-100.

[26] Wang X, Shao C, Yin C, Zhuge C. Exploring the influence of built environment on car ownership and use with a spatial multilevel model: A case study of Changchun, China. Int J Environ Res Public Health. 2018;15(9):1-14.

[27] Brownstone D, Fang HA. A vehicle ownership and utilization choice model with endogenous residential density. J Transp Land Use. 2014;7:135-51.

[28] Yang J, Kato H, Ando R. Comparative analysis of the household car ownership between Toyota city and

Nagoya city. J Eastern Asia Transport Stud. 2015;11:626-39.

[29] Caulfield B. An examination of the factors that impact upon multiple vehicle ownership: the case of Dublin, Ireland. Transport Pol. 2012;19:132-8.

[30] Rith M, Doi K, Gue IH, Fillone A, Soliman J, Mayol AP, et al. Understanding of determinants of household vehicle ownership level toward urban sustainable transportation in Southeast Asia - a case study in Metro Manila. 10th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM); 2018 Nov 29 - Dec 2; Baguio City, Philippines. USA: IEEE; 2018.

[31] Long S, Klungboonkrong P, Chindaprasirt P. Impacts of urban transit system development on modal shift and greenhouse gas (GHG) emission reduction: a Khon Kaen, Thailand case study. Eng Appl Sci Res. 2018;45(1):8-16.

[32] Rith M, Abad RP, Fillone A, Doi K, Biona JB. Understanding the impact of urban form attributes on household vehicle ownership and choice in metro manila: modeling, simulation, and application. Eng Appl Sci Res. 2019;46(3):238-47.

[33] Habib KN, Day N, Miller EJ. An investigation of commuting trip timing and mode choice in the Greater Toronto Area: application of a joint discrete-continuous model. Transport Res Pol Pract. 2009;43(7):639-53.

[34] MUCEP. The project for capacity development on transportation planning and database management in the republic of the Philippines. Philippines: MUCEP; 2015.

[35] DOE (Department of Energy). Retail pump prices - Metro Manila [Internet]. 2018 [cited 2019]. Available from: https://www.doe.gov.ph/oil-monitor.

[36] Department of Health. Health facilities [Internet]. 2018 [cited 2019]. Available from: http://ncroffice.doh.gov.ph/RLED/Details.

[37] Department of Education. Master list of public school [Internet]. 2017 [cited 2019]. Available from: https://www.gov.ph/data/dataset/masterlist-public-school.

[38] Commission on Higher Education. List of CHED recognized program [Internet]. 2018 [cited 2019]. Available from: http://www.ched.ph/central/page/ncr-national-capital-region.

[39] Lee LF. Generalized econometric models with selectivity. Econometrica. 1983;51:507-12.

[40] Johnson NL, Kotz S, Balakrisnan N. Continuous univariate distributions. NY: John Wiley & Sons Inc; 1994.

[41] Rith M, Biona JB, Fillone A. Impact of dependency parameters of each discrete-continuous choice on model estimation results using frank copula-based discrete-continuous model. 11th ATRANS Annual Conference on Transportation for a Better Life: Lesson Learnt from Global Experiences to Local Best Practices; 2018 Aug 24; Bangkok, Thailand.

[42] Department of Finance. Republic Act No. 10963 - Tax reform for acceleration and inclusion (TRAIN) [Internet]. 2018 [cited 2019]. Available from: http://www.ntrc.gov.ph/images/train/Tax-Changes-You-Need-to-Know-under-RA-10963.pdf.

[43] Co B. Philippine auto sales down 5.7% in November 2018 [Internet]. 2018 [cited 2019]. Available from: https:// www.autoindustriya.com/auto-industry-news/philippine-auto-sales-down-5-7-in-november-2018.html.