2016 3rd Asia-Pacific World Congress on Computer Science and Engineering

Vehicle Ownership and Economic Development

Zhen Li*, Ken Ishibashi†, Yuta Kaneko†, Kei Miyazaki†, Hiromi Shioji‡ and Katsutoshi Yada†

*Faculty of Business Administration, Toyo University, Tokyo 112-8606, Japan.
Email: li@toyo.jp, Tel: +81-3-3945-7608
†Data Science Laboratory, RISS, Kansai University, Osaka 564-8680, Japan.
Tel: +81-6-6368-1228, Fax: +81-6-6330-3304
‡Graduate School of Economics, Kyoto University, Kyoto 606-8501, Japan.
Tel: +81-75-753-3400, Fax: +81-75-753-3492

***Abstract*—The purpose of this study is to develop a model to predict the number of vehicles owned in consideration of recent circumstances of emerging countries. In the previous studies, prediction models have been developed from different viewpoints such as energy issue. However, recent growth of the number of vehicles owned in the emerging countries has been more rapid than the predictions. On the other hand, big city in those emerging countries introduced the traffic restriction to prevent aerial pollution from the latter half of 2000s. In this paper, an attempt is made to develop a prediction model based on GDP, income gap and historical transition. Using statistical data of 47 countries from 1952 to 2014, the applicability of the proposed model is verified.**

***Keywords*—vehicle ownership, economic development, prediction model, developed countries, emerging countries**

I. Introduction

Historical process of countries indicates that there is significant relationship between vehicle ownership expansion and economic development. In many countries, per capita vehicles tend to increase in association with economic growth. In particular, the number of per capita vehicles rapidly increases when economy remarkably develops. On the other hand, variation of vehicle ownership is saturated under mature economy. Focusing on these features, future prediction is performed by using statistical data such as GDP, population and number of vehicles owned, and that result is applied to policy planning related to transportation, fuel and environmental issues.

In the research area, prediction of vehicle ownership for some emerging countries, such as China, Brazil, and India, is a big issue in recent years because saturation levels of owned vehicles vary in different countries. Focusing on this issue, several researchers have addressed the development of prediction model [1, 2, 3]. Their models forecast the number of owned vehicles and saturation level of each country in consideration of income, fuel problem and transportation. However, their models have possibilities not explaining recent circumstances of those emerging countries. One possible reason is that the growth of the number of vehicles owned has been more rapid than predictions. On the other hand, big cities in those emerging countries, like China and India, introduced traffic restriction using license plate number. This policy considers issues related to transportation and environment. Thus, saturation of vehicle ownership in the emerging countries is expected to occur at lower level than previous predictions.

The purpose of this study is to predict the number of vehicles owned in consideration of recent circumstances which include the cases of the developed and the emerging countries. In this paper, an attempt is made to develop prediction model based on per capita GDP, income gap and patterns of countries economy growth. Through the analysis using statistical data of 47 countries observed from 1952 to 2014, the applicability of the proposed model is verified.

The remainder of the paper is organized as follows. In section II, we review the relevant literature which addressed the relationship between countries' vehicle ownership and their economic development historically. Section III introduces the study design and data, followed by descriptions of variable measurements. In section IV, we estimate the traditional linear regression as benchmarks and then elaborate on nonlinear estimation approach with a Gompertz model. And last, section V concludes the study with its contributions, and directions for future research.

II. Literature Review

While there are many studies related to the relationship between vehicle ownership and economic development [4, 5], a few researchers address forecast of future vehicles owned using panel data of countries. Furthermore, issues which developing countries face in term of economic growth increase across the years. For example, environmental problems such as emission of CO2 from vehicles emerged in China and India. Thus, it is necessary to periodically reconsider the applicability of model for the prediction of vehicle ownership.

In Medlock and Soligo's study, effects of economic growth on vehicle ownership was verified by using panel data of 28 countries [1]. Moreover, they discussed future issues of energy based on their forecasts. Their model was developed by using the concept of user cost related to capital and the notion that the demand for vehicles can be saturated. From the forecast with data from 1978 to 1995, they found that saturation levels of vehicles varied in countries, and that user costs were a significant factor in the evolution of vehicle stocks.

Next, Dargay et al. attempted to expand the prediction model developed in their previous study [2, 6]. By using urbanization and population density observed from 45 countries that include 75 percent of the world's population, they developed a model that considered differences in saturation level of countries. The result of prediction to 2030 based on data from

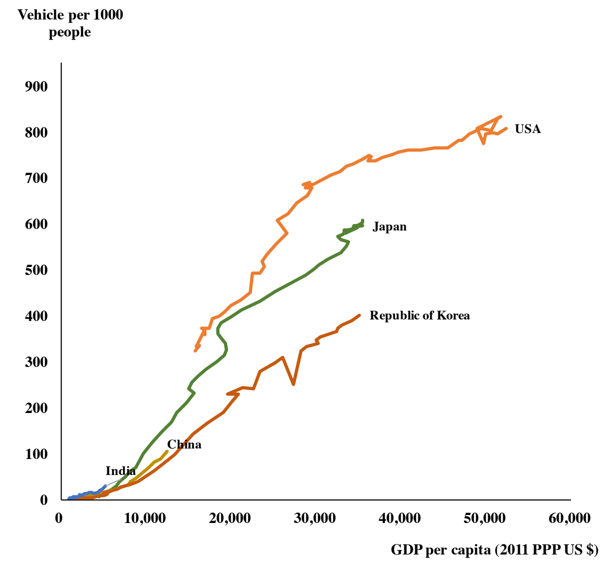

Fig. 1. Vehicle ownership and GDP per Capita from 1952 to 2014

1960 to 2002 indicated that Chinese vehicle stocks increase nearly twenty-fold, and that the speed of vehicle ownership expansion encourages rapid growth in oil demand.

Focusing on within-country income distribution factors, Chamon et al. explained the relationship between per capita GDP and vehicle ownership by using 122 countries' panel data and performing the household level survey for largest emerging markets [3]. They performed the analysis with data from 1963 to 2003. The number of vehicles owned tends to increase rapidly due to the economic growth. They found that the tendency begun when per capita GDP exceeded about 5,000 US dollar. When their research was performed, this increase tendency was not observed in China and India.

This study attempts to develop a model that considers circumstances of developing countries after the previous studies performed. In this paper, we use countries panel data from 1952 to 2014. The relationship between the economic development and the number of vehicles owned for several countries is shown in Figure 1.

Figure 1 represents the historical transition of per capita GDP and vehicles owned per 1,000 persons from 1952 to 2014. In this figure, relationship about 5 countries (USA, Japan, Republic of Korea, China and India) is plotted. The two indexes of all countries basically increase across the years. Except for India, the increased amount of vehicles per 1,000 persons proportional to the increase of per capita GDP is similar across countries. In addition, it is found that the vehicle ownership is saturated in USA and Japan.

Compared to the forecasts of existing studies described above, vehicles owned per 1,000 persons in China and India have greatly increased at 2014. On the other hand, big cities of developing countries, such as Beijing and New Delhi, recently introduced the traffic restriction to prevent aerial pollution. Under this restriction, available vehicles at one day are decided by their license plate number. For example, the availability of vehicle is decided by whether its license plate number is odd or even. By spreading this policy in developing countries, it is expected that their saturation levels of vehicle ownership become lower than advanced countries. It is necessary to develop a new prediction model in consideration of this circumstances.

III. Data and Variables

In this section, we need to combine data on economic development and auto industry, the two of which are collected from independent sources. Economic development data are primarily collected from the Penn World Table 9.0 and International Monetary Fund (IMF), which mainly involve the statistics of population and real GDP for each country in each year. Similarly, auto industry data are available from International Organization of Motor Vehicle Manufacturers (OICA) and Japan Automobile Manufacturers Association (JAMA), where we chiefly to obtain the number of vehicle ownership for each country in each year. We focus this study on GDP and vehicle popularity rate relationship at an overall level. The details of the study design and data collection processes are described subsequently.

A. Economic Development Data

Based on the statistical data of economic development level which were aggregate by IMF, we conducted a simply fundamental analysis to obtain the change law of GDP per capita in each country. We selected GDP per capita instead of the total GDP due to the reason of population. Some countries have a high total GDP but a relatively low GDP per capita, such as China and India.[1] The economic and social development level is measured not only by the general target but also by the per capita target, which is more important [6, 7]. In addition, relevant literature also usually uses GDP per capita as a measure to predict vehicle density [3].

Figure 2 depicts the movements of GDP per capita for the major economies from 1952 to 2014. From this figure, we notice that GDP per capita generally keeps rise all along in those countries, and its index for the developed countries is obviously higher than that for emerging countries.

B. Auto Industry Data

We follow previous studies and conducted a content analysis of auto industrial scale structure include in the economic development data to obtain the density of vehicle for each country or region. Vehicle density is measured by the number of vehicle ownership per 1000 people [3, 6].

Figure 3 shows the annual fluctuations of vehicle density for world's leading economies from 1950s to 2010s. Compared with the steady growth in the west, although there is a rapid rising in auto penetration in about 1990s, the numbers of automobiles owned by emerging countries are still relatively low.

Although there are some differences in economic foundation and potentials among each country, we expect to educe the correlation between vehicle popularity rate and economic development, and to find out some generalities.

[1] China ranks 2nd in total GDP but 75th in GDP per capita in 2015. Similarly, India ranks 7th in total but 141th in per capita that year.

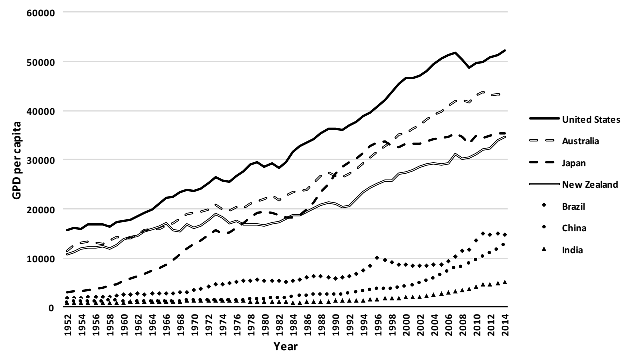

Fig. 2. Changes in GDP per Capita of Major Countries

C. Data Matching

We match the economic development data and auto industry data collected from these independent sources. We select years in the auto industry data that matched the economic development data by year and country. Note that all countries in our sample were featured with a long time span because of a relatively long lifecycle of automobile. We obtained unbalanced panel data for 47 countries with 63 years (from 1952 to 2014) after the matching.[2]

Figure 4 provides a plot of the relationship between GDP per capita and vehicles per 1000 people in major countries. The plot shows that the relationships in those countries are extremely similar on the whole with non-linear correlation, so care must be taken in modeling, which may affect fitting and estimation.

D. Variables

To simplified model to explore the common trend of auto penetration, we focus this study on two indicators, namely vehicle density and economic level. It is currently difficult to obtain accurate assessment of expenditure levels and the gap between rich and poor for each country with a long time span, thus we provide GDP per capita as a surrogate for the economic level. We follow previous studies and measured the vehicle density through two variables: vehicles per 1000 people [3], and vehicle population ratio [2, 6]. These two variables are similarly calculated by number of vehicle ownership divided by national population. Table I presents the panel summary statistics for the entire data of this study.

IV. Modeling and Analysis

In this section, we first provide a pooled regression with traditional linear model and logarithm linear model to briefly confirm the correlation between vehicle density and economic level, followed by estimations of a panel version of it. A Durbin–Wu–Hausman test was used to verify the endogeneity of fixed effect model (FE) and random effect model (RE). Next, we apply a Gompertz model to estimation because the plot of the relationship between GDP per capita and vehicles per 1000 people shown by Figure 4 display slow-fast-slow growth rhythm, the curves of which showed S-shaped basically. Fitting degree among each approach are also compared in this section.

To investigate the accuracy of the prediction, this study divides the entire data into two parts: the year before 2005 for estimating and the rest for prediction.

A. Classic Estimations

A naive approach to assessing the effect of economic development on vehicle ownership is to include these factors in a whole linear model which easily regard all samples as cross-section without considering the possibility of autocorrelation among error terms. We called this approach pooled regression.

Based on the relevant literature, the simplest version of the pooled regression, we called Model 1, is specified as follows:

$$y_k = \alpha_0 + \alpha_1 x_k + \epsilon_k$$

where y_k indicates the number of vehicles ownership per 1000 people in sample k, and x_k is the value of GDP per capita. Error term ϵ_k represents factors other than x_k that affect y_k and be assumed to be i.i.d. normally distributed, that is, $\epsilon_k \sim N\left(0, \sigma^2\right)$.

Table II shows the estimation results of Model 1. Consistent with the results in prior research, parameter estimates of Model 1 indicate that GDP per capita has a significant and positive effect on vehicles per 1000 people with the coefficient of 0.01 (at $p < 0.01$). However, we also notice that the fitting of Model 1 is very weak (Figure 5). This is because the slope estimates we obtained with the value of 0.01 means that each additional $1000 of GDP per capita is predicted to nearly increase the number of vehicles ownership by 10 for all situations due to linear nature. It may not be reasonable in fact.

Given the "Law of Diminishing Marginal Utility," the marginal effect of GDP per capita on vehicles ownership should be decreased. Therefore, as an alternative model, logarithmic regression seems to be more reasonable. We specify the Model 2 as follows:

$$y_k = \beta_0 + \beta_1 \ln x_k + \epsilon_k$$

where all variables are defined the same as previously.

As Table III shows, log-GDP per capita positively relates to the number of vehicles ownership as expected (at $p < 0.01$). In this model, we obtained the coefficient of 138.61, which means that each additional 1% of GDP per capita is predicted to increase vehicle ownership nearly by 1.4 units. Compared with Model 1, this result is relatively reasonable. Meanwhile, fitting degree in Model 2 is also better (the value of R-sq is 0.59).

B. Panel Estimations

As we introduced before, the approach of pooled regression regards all samples as cross-section under the condition that any of two error terms are independent of each other. That is to say, the covariance of ϵ_k and ϵ_j for each $k \neq j$ must equal to zero. In our study, however, given the characteristic of panel data, there is usually autocorrelation among error terms

[2]Economicdevelopment data in some countries have gaps due to the missing value of statistics.

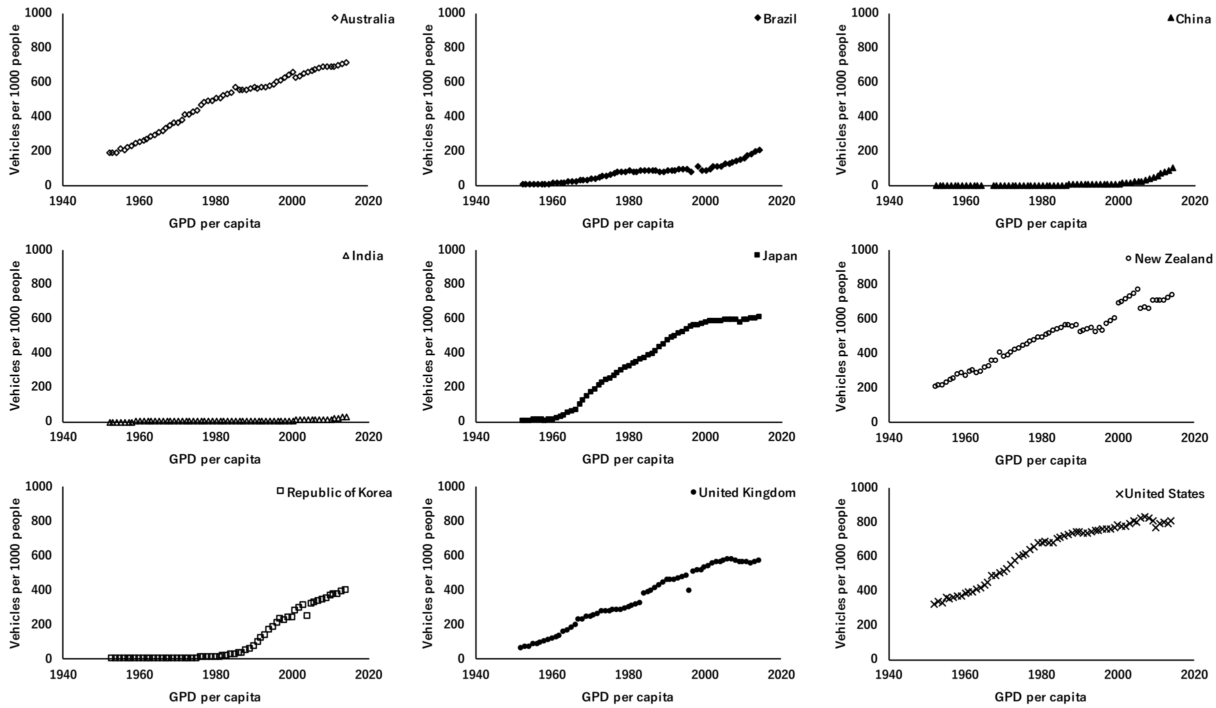

Fig. 3. Annual Fluctuations of Vehicle Density from 1950s to 2010s

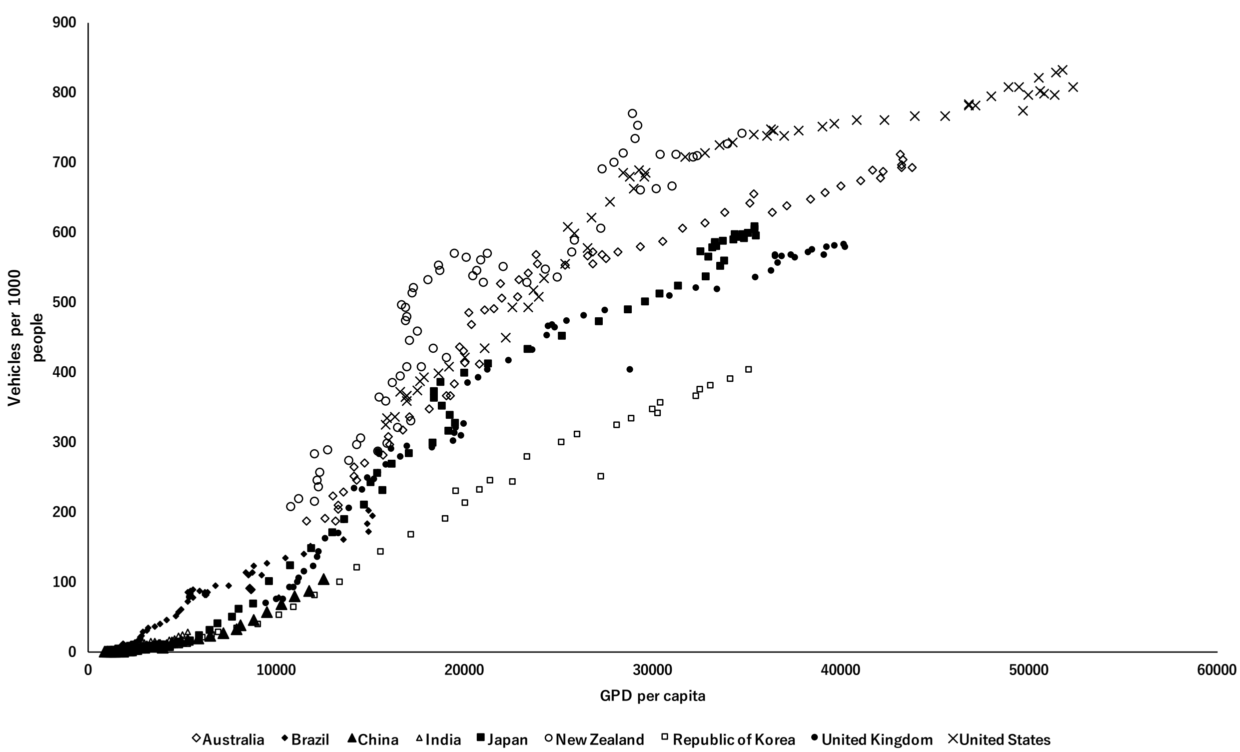

Fig. 4. Plot of GDP and Vehicles Relationship

TABLE I. SUMMARY STATISTICS FOR THE DATA

Variable		Mean	Std. Dev.	Min	Max	Obs.
GDP per capita	Overall	16775.44	18275.28	542.99	221818.50	N = 2773
	Between		16855.32	1738.40	109948.00	n = 47
	Within		10764.94	-36682.42	128646.00	T-bar = 59
Vehicles per 1000 people	Overall	207.79	207.55	0.09	832.77	N = 2773
	Between		159.61	4.03	632.86	n = 47
	Within		131.34	-157.27	592.81	T-bar = 59
Vehicle Ratio	Overall	0.21	0.21	0.00	0.83	N = 2773
	Between		0.16	0.00	0.63	n = 47
	Within		0.13	-0.16	0.59	T-bar = 59

TABLE II. PARAMETER ESTIMATES OF MODEL 1

Vehicles per 1000 people	Coef.	Std.Err	t
GDP per capita	0.01	0.00	30.99 ***
Intercept	94.89	4.30	22.09 ***
Obs.		2303	
F(1, 2301)		960.07	
Adj R-sq		0.29	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

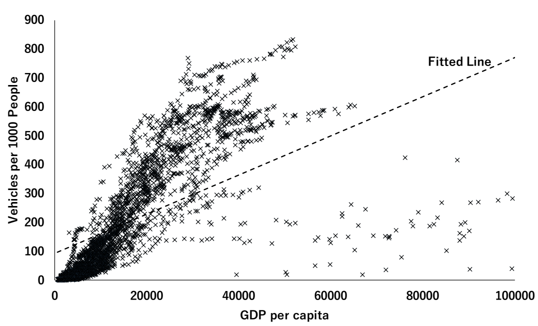

Fig. 5. Fitting of Model 1

TABLE III. PARAMETER ESTIMATES OF MODEL 2

Vehicles per 1000 people	Coef.	Std.Err	t
log-GDP per capita	138.61	2.40	57.76 ***
Intercept	-1080.49	21.96	-49.19 ***
Obs.		2303	
F(1, 2301)		3335.82	
Adj R-sq		0.59	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

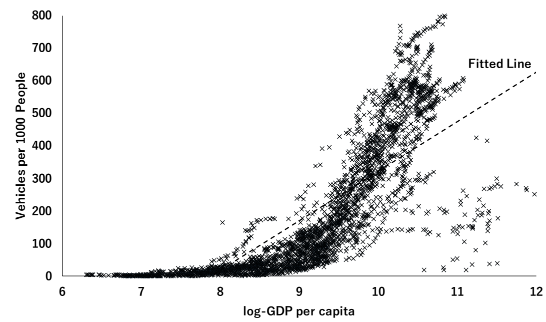

Fig. 6. Fitting of Model 2

in time series especially for the same individual. Thus, the pooled regression approach may not apply to our dataset.

Given the multi-dimensional data frequently involving measurements over time, we proceed to Model 3, in which we introduce the time span and composite error term. Model 3 is denoted as follows:

$$y_{i,t} = \beta_0 + \beta_1 \ln x_{i,t} + \epsilon_{i,t}$$
$$\epsilon_{i,t} = u_i + e_{i,t}$$

where i is the individual dimension and t is the time dimension, which identify country and year respectively in this study. u_i is individual-specific and time-invariant effects, while $e_{i,t}$ represents the error which is dependent with both individual and time. As well, GDP per capita is fetched logarithm. Different assumptions can be made on the precise structure of this general model.

Due the model describes the case where no lag of explained variable is used as regressor, we simply compare the estimation result with fixed effects (FE) and random effects (RE). Table IV shows that the mean parameter estimates, standard errors, and some other statistical parameters of error terms. A Durbin–Wu–Hausman test is used to differentiate between fixed effects model and random effects model in our study.[3] The result from the Wu–Hausman statistic indicates

[3]Random effects (RE) is preferred under the null hypothesis due to higher efficiency, while under the alternative fixed effects (FE) is at least consistent and thus preferred.

TABLE IV. PARAMETER ESTIMATES OF MODEL 3

Vehicles per 1000 people	FE Model		RE Model	
	Coef.	Std.Err	Coef.	Std.Err
log-GDP per capita	156.77	3.37 ***	154.91	3.29 ***
Intercept	-1245.68	30.73 ***	-1233.68	32.80 ***
sigma_u	97.52		91.70	
sigma_e	82.89		82.89	
rho	0.58		0.55	
Obs.	2303		2303	
R-sq	Within = 0.49		Within = 0.49	
	Between = 0.62		Between = 0.62	
	Overall = 0.59		Overall = 0.59	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

that the fixed effects model is preferred ($\chi^2(1) = 5.89$, $p < 0.05$) to obtain accurate assessment of the effect of economic development on vehicle ownership. In addition, the outcomes of model fitting in panel estimation are also better than it in pooled regression approach.

C. Nonlinear Estimation

In the previous section, we noticed that the plot of economic development and vehicle ownership relation displays slow-fast-slow growth rhythm, the curves of which appears to be nonlinear. Building on this finding, we apply a typical sigmoid function, namely Gompertz model, which is a type of mathematical model for a time series, where growth is slowest at the start and end of a time period. We specify the following model, which is called Model 4.

$$z_{i,t} = \alpha \cdot \exp\{-\beta \cdot \exp\{-\gamma \cdot x_{i,t}\}\}$$

In Model 4, parameter α indicates an asymptote,[4] β sets the displacement along the x-axis, and γ sets the growth rate. Both β and γ in theory are positive numbers. For the sake of brevity, in this model, we use vehicle population ratio as $z_{i,t}$ instead of the specific numbers of vehicle ownership to simply keeping the parameter α with a constant value of 1.

The parameter estimates of the Gompertz model appear in Table V. Satisfying the theory prerequisite, estimation results for the parameters β and γ in the model are significant and positive. Through testing with related experimental data, we notice that the model has high fitting degree and applicability. Figure 7 provides the plot and its fitted curve of the distributions of economic development and vehicle ownership relation.

Table VI outlines the estimates for the major countries in the world. Meanwhile, their fitted curves are shown in Figure 8. The results indicate that both the values of parameter β and γ are much smaller for the traditional developed countries than that for the emerging countries, which means motorization is relatively less developed in emerging countries but progressing fast in future.

Finally, actual results and prediction curve of the relationship between vehicle ownership and economic development in

[4] $\lim_{x\to\infty} \alpha \cdot \exp\{-\beta \cdot \exp\{-\gamma \cdot x\}\} = \alpha \cdot \exp\{0\} = \alpha$

TABLE V. PARAMETER ESTIMATES OF MODEL 4

Vehicle Ratio	Coef.	Std.Err	t
Beta	3.38105	0.072	46.99 ***
Gamma	0.00005	0.000	47.33 ***
Obs.		2303	
Adj R-sq		0.75	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

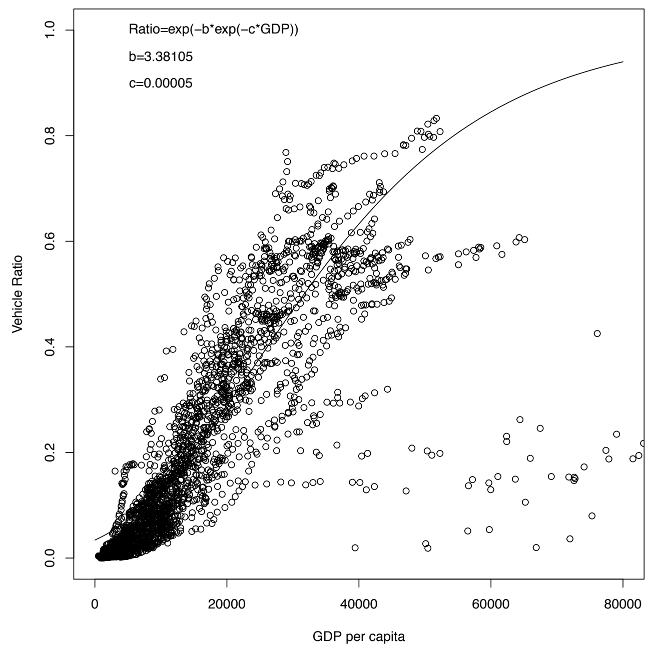

Fig. 7. Fitting of Model 4

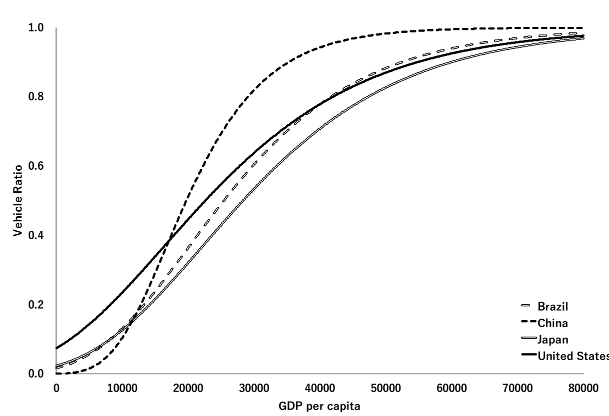

Fig. 8. Gompertz Curves for Major Countries

TABLE VI. GOMPERTZ ESTIMATION FOR MAJOR COUNTRIES

Developed Countries

	Australia		Japan		New Zealand		Republic of Korea		United Kingdom		United States	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Beta	2.88886	0.186	3.73915	0.181	3.54639	0.338	5.10660	0.218	3.25280	0.186	2.59467	0.151
Gamma	0.00006	0.000	0.00006	0.000	0.00008	0.000	0.00006	0.000	0.00005	0.000	0.00006	0.000
Obs.	45		53		53		52		53		53	
Adj R-sq	0.796		0.987		0.987		0.978		0.981		0.996	

Emerging Countries

	Brazil		China		India	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Beta	4.06349	0.172	7.58400	0.170	8.04886	0.230
Gamma	0.00007	0.000	0.00012	0.000	0.00025	0.000
Obs.	52		51		53	
Adj R-sq	0.935		0.956		0.925	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

those representative countries appear in Figure 9. The figure intuitively provides the evidence for the fitting of model. Additionally, the comparison with prediction shows that the development of motorization consists of three phases: (1) below the forecast level, followed by (2) exceeding, and then (3) below again, which consistent with the theoretical tendency proposed by prior research [5, 8].

V. CONCLUSIONS AND DISCUSSION

Although prior research has been used in statistical model to predict the relationship between vehicle ownership and economic development, most of them are confined to involving a small number of specific countries with short-term data. In addition, estimation method in the previous studies are limited in linear prediction. Relevant literature lacks a more accurate estimation approach, particularly in using panel data which involve multi-dimensions. In this study, we matched economic development data and auto industry data, predict the relationship between vehicle ownership and GDP per capita with different approach involving linear and non-linear estimations, and compare their accuracy of the prediction and the fitting precision of the models.

Our study attempts to grasp the motorization process. In order to do that, we investigate the relationship between the actual number of vehicle ownership and economic development, and develop the concept of its prediction curve. Furthermore, to locate the situation in the motorization process of each country, this paper also analyze the divergence of the two indexes – actual and predicted value. Through strict statistical estimations, in this study, we confirmed the positive correlation between vehicle ownership and economic development, and clarified their non-linear feature rather than linearity in the literature. Utilizing Gompertz model, this study obtains a better fitting result and effectively reveals the influences of per capita GDP, income gap and patterns of countries economy growth on the level of motorization.

An interesting finding generated by our analysis demonstrates that similar with the feature in traditional approach, divergence of the actual and predicted value of vehicle ownership in our proposed approach – nonlinear estimation – also will face three stages. In first and third stage, the number of actual vehicle ownership is no more than the prediction in most of the countries, while this relationship has been upside down in the second stage, in which we define as the period of motoring.

This study contributes to the existing literature in two ways. Compared to traditional linear estimation, the approach of nonlinear regression used in our study has more accurate assessment of prediction. Meanwhile, we contribute by providing the empirical evidence for improving the theory development with more relevance and effectiveness.

Inevitably, there are also some limitations to this study. First, we listed only a limited number of representative countries as the case study in our paper. Second, explanatory variable in the present study is only one – GDP per capita. The problem of omitted variables may result in non-unbiasedness and inconsistency of the estimators. In light of these, we suggest that it is necessary to further discuss the prediction model with more accurate indicators and richer cases to further validate the conclusions and to analyze the trend of motorization continually.

ACKNOWLEDGMENT

This work was supported by “Strategic Project to Support the Formation of Research Bases at Private Universities”: Matching Fund Subsidy from MEXT (Ministry of Education, Culture, Sport, Science and Technology), 2014-2018.

APPENDIX

In addition to the modeling on vehicle ownership and economic development relation, our study also proposes an

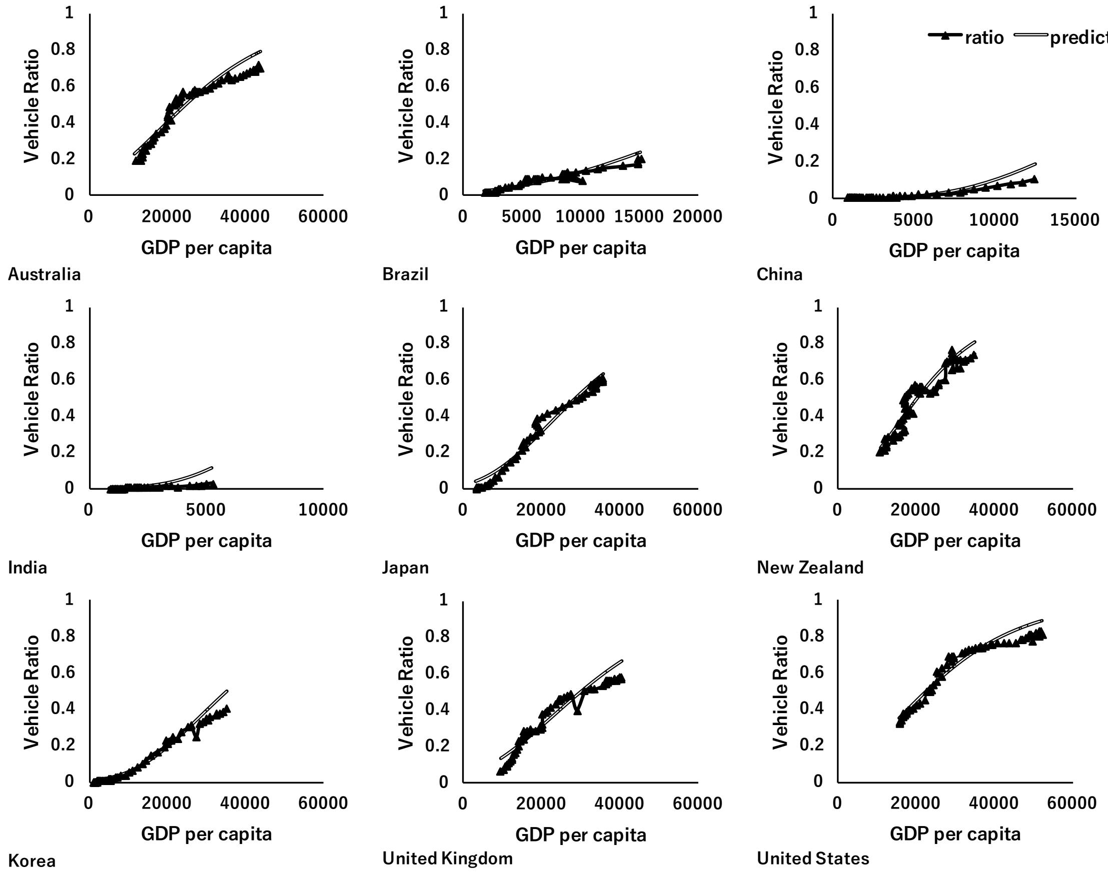

Fig. 9. Prediction of Vehicle Ownership and Economic Development

autoregressive model to explore the change over time in vehicle ownership. The ARIMA (autoregressive integrated moving average) model, used herein, is a model that is fitted to univariate time-series data. In this model, p is the order of the autoregressive model, d is the degree of differencing, and q is the order of the moving-average model, expressed as follows:

$$\triangle^d y_t = \sum_{i=1}^{p} \phi_i \triangle^d y_{t-i} + \triangle^d e_t + \sum_{j=1}^{q} \psi_j \triangle^d e_{t-j}$$

where $\triangle^d y_t$ and $\triangle^d e_t$ express the difference of time series and residuals, respectively, whereas φ and ψ are coefficients. In this paper, we shall use ARIMA(p, d, q) to represent use of the ARIMA model with variables p, d and q. We must note here that depending on the combination of these three parameters, there can be a great number of ARIMA models available. As AIC (Akaike information criterion) is commonly used as a standard for model selection, this analysis will also select models based on AIC. We choose three typical countries, the United States, China, and New Zealand, to estimate the parameters and to validate the model.

United States

Utilizing data from 1952 to 2004 for our model fitting, we forecast the variation in the time-series from 2005 to 2014. This analysis does not utilize indicators such as growth rates, instead directly applying the time-series model to the data. Our parameter estimation for the United States model led us to adopt ARIMA(3,0,1). This model, rounded to the nearest thousandth, is as follows:

$$y_t = 1.783y_{t-1} - 0.592y_{t-2} - 0.192y_{t-3} + e_t - 0.759e_{t-1}$$

We return to an ARMA (autoregressive moving average model), another type of autoregressive model, for the purpose of ensuring there is no difference in our model. Figure 10 shows the results of our forecast. The vertical axis represents vehicles owned per thousand persons, and the horizontal axis represents the number of calendar years after the t period. The black line represents the time series data fitting, whereas the red points and lines represent test data and those interpolations. The blue line represents the prediction of the model, with the darker shaded region the 70% confidence interval and the lighter shaded region the 95% confidence interval. Though all forecast data falls within the 95% confidence interval, half of these do not fall within the 70% confidence interval. Though a moderately-asymptotic state is forecasted, this can also be expressed as a Gompertz curve. The results are that in the forecast, all points are included within the 95% confidence interval, and that half of the points are included in the 70%

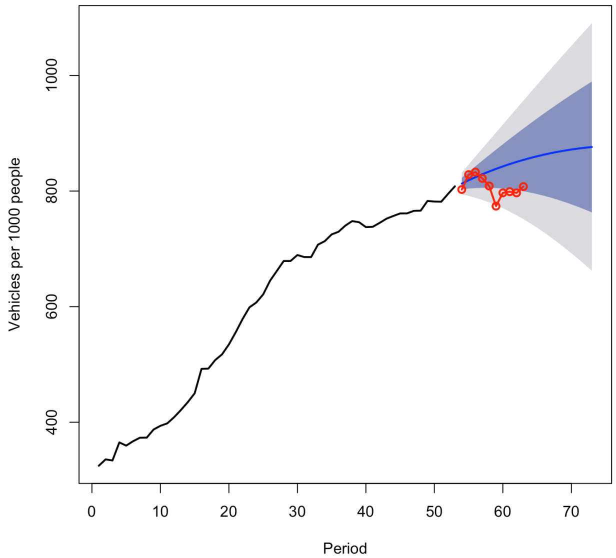

Fig. 10. Demand Prediction in the United States

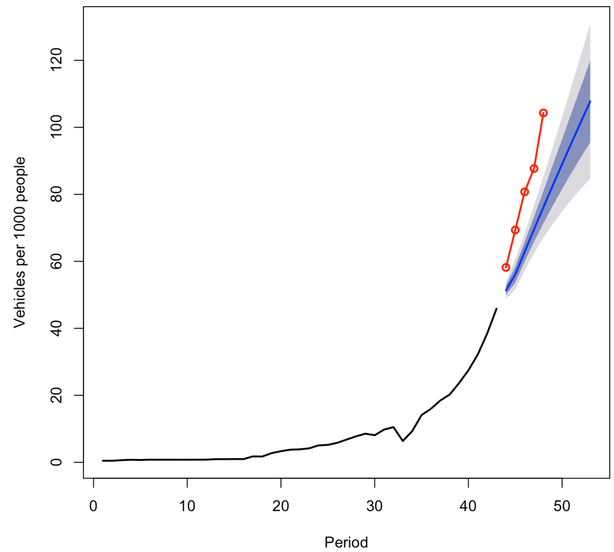

Fig. 11. Demand Prediction in China

confidence interval.

China

China presents a somewhat special case. The recent economic boom has led to what can be considered non-linear acceleration in motorization. Given the more drastic changes versus the United States, we use five years of data here for validation purposes. For fitting, we utilize forty-three years of data from 1967 to 2009, using five years of data from 2010 to 2014 for model comparison. Our ARIMA model adopted here is ARIMA$(1, 1, 3)$.

$$\begin{aligned}\triangle y_t &= 0.976\triangle y_{t-1} + \triangle e_t - 0.517\triangle e_{t-1} \\ &\quad - 0.671\triangle e_{t-2} + 0.731\triangle e_{t-3} + 2.673\end{aligned}$$

Figure 11 shows the results of forecasting using the same model used for the United States. Despite the use of a short five-year period, this vehicle ownership data grows beyond that of the model's forecast. This explosive growth is not only effected by autoregressive trends but also the economic climate and environmental policy in concert.

New Zealand

We conclude by analyzing New Zealand. This case is special from the rest in that ownership in this nation is observed as having linear growth. The data structure is the same as that of the US; we use sixty-three years of data from 1952 to 2004 for fitting, and use ten years of data from 2005 to 2014 for forecasting model comparison. Our model adopted here for New Zealand is ARIMA$(4, 0, 0)$.

$$\begin{aligned}y_t &= 1.001y_{t-1} + 0.300y_{t-2} + 0.031y_{t-3} \\ &\quad - 0.340y_{t-4} + e_t + 486.283\end{aligned}$$

This is a simple autoregressive forecasting model, with results shown in Figure 12. Four points fall within the 70%

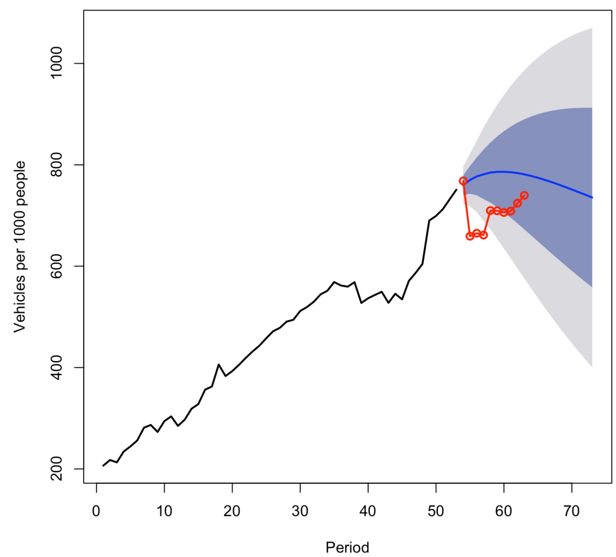

Fig. 12. Demand Prediction in New Zealand

confidence interval, with three points falling only within the 95% confidence interval. This forecast was unable to take into account for an unknown factor that caused a severe drop in ownership in 2006. The model predicted a moderate drop in ownership, but actual data reveals that a growth trend does continue (after the aforementioned severe drop) in the opposite direction of the forecasted data.

Model Validity

It is ideal for residual to be independent and normally-distributed in a time-series model. The results of a Ljung-Box test on that independence are displayed in Table VII. Residual

TABLE VII. Test Results of Ljung-Box and Jarque-Bera

	Ljung-Box		Jarque-Bera	
	X-squared	p-value	X-squared	p-value
USA	0.002	0.965	13.059	0.001
China	0.761	0.383	5.867	0.053
New Zealand	0.508	0.476	20.408	0.000

for each nation's model was independent. Further, the results from a Jarque-Bera test on normal distribution reveal that the only model that cannot reject the null hypothesis at the 5% level is the China model (see Table VII). This likely means that there is room for improvement in defining variables for the United States and New Zealand.

References

[1] K. B. Medlock and R. Soligo, "Car Ownership and Economic Development with Forecasts to the Year 2015," *Journal of Transport Economics and Policy (JTEP)*, vol. 36, no. 2, pp. 163–188, 2002.

[2] J. Dargay, D. Gately, and M. Sommer, "Vehicle Ownership and Income Growth, Worldwide: 1960-2030," *The Energy Journal*, pp. 143–170, 2007.

[3] M. Chamon, P. Mauro, and Y. Okawa, "Mass Car Ownership in the Emerging Market Giants," *Economic Policy*, vol. 23, no. 54, pp. 244–296, 2008.

[4] H. Shioji, "Main Tasks of a Dealer's Internet Activities in New Automobile Sales," *International Journal of Automotive Technology and Management*, vol. 4, no. 4, pp. 384–393, 2004.

[5] ——, "How Can We Grasp the Motorization Process in the Developing Countries?" *Journal of Asian Management Studies*, vol. 22, 2016.

[6] J. Dargay and D. Gately, "Income's Effect on Car and Vehicle Ownership, Worldwide: 1960–2015," *Transportation Research Part A: Policy and Practice*, vol. 33, no. 2, pp. 101–138, 1999.

[7] N. Hicks and P. Streeten, "Indicators of Development: The Search for a Basic Needs Yardstick," *World Development*, vol. 7, no. 6, pp. 567–580, 1979.

[8] H. Shioji, "Competitiveness of the Japanese, Korean, and Chinese Automobile Industries," *The Kyoto Economic Review*, vol. 81, no. 1, pp. 48–63, 2012.