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PASSENGER CAR SALES FORECASTING: ASSESSING A FRAMEWORK USING COUNTRIES' SPECIFIC FACTORS

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ABSTRACT

The automotive industry growth in emerging and developed markets has important implications for economics planning and policies. Especially, projecting passenger car sale is essential for the effective operation and sustainable development of firms in automotive industry and the industry-related firms. This paper contributes to this aim by presenting, assessing and updating a framework which explicitly model the passenger car sale as a function of specific countries' factors: urbanization, population density, scrappage rate, the income level in term of GDP and the level of current vehicle stock. The framework is assessed on the basic of panel data including the time series data (2005-2017) and cross-section data for 38 countries which cover 80% of passenger car in use worldwide. The results suggest that the original framework can be a useful tool for forecasting the expected passenger car sales trend worldwide in the long term. However, the performance of the original framework in the short term at country level are materially different as the income elasticity of passenger car sales are widely varied. Therefore, this paper also adjusts the parameters in the original framework to mitigate the effects of different in income level on the performance of car sales forecasting at country level.

Key words: Automotive industry growth; passenger car sale; specific countries' factors

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1. INTRODUCTION

In order to boost the society development and living standard, improvement of transportation services and infrastructures is one of the prerequisites. Among transportation services, the automotive industry is referred as cornerstone for economic development in most of emerging

and developed economies. According to American automotive policy council (2018), the automotive industry contributed nearly 3 percent of GDP output in America in 2017 and created jobs more than any other manufacturing sectors. In India, the automotive industry might contribute to 12 percent of GDP in the next decade from 7.1 percent at present. It also produced more than 14 percent of Germany GDP in 2015. Globally, the automotive industry produced more than 95 million motor vehicles in 2017. In 2017, nearly 80 million cars sold worldwide increasing more than 40 percent of the average cars sold in the period 2005-2015. Especially, passenger cars represent the world's number two export product, only behind crude oil. Among the major three vehicle producers, manufacturing the half of all passenger cars and commercial vehicles in the world, belongs currently China (26.99% share of global total), U.S. (13.3%) and Japan (10.22%). Among the rest of major world motor vehicle producers belongs Germany, South Korea, India, Mexico, Spain, Brazil, Canada, France, Thailand and United Kingdom. In addition, the prosperity in automotive industry is also crucial for the sustainable development of other related upstream industries such as chemicals, steels, textiles, etc. as well as automotive aftermarket such as car repairment services, car insurances and car parts and equipment installation.

According to Kuhnert et al. (2017), there are five meta trends are forming and shaping the future of the automotive industry. The movements will focus on innovating user experiences with mobile vehicles by making it "much easier, more flexible and more individual for users" (Kuhnert et al., 2017). In general, the automotive industry has been transforming to become electrified, autonomous, shared, connected and yearly updated. By "electrified", the vehicle including passenger cars will be produced toward to the aim of emission-free. This trend has been supported by stricter regulations about environmental safety of vehicles using mainly fossil fuel in some developed markets. However, it is expected this trend will become global movement in the future. By "autonomous", vehicles especially recent cars have been well equipped with new technologies in machine learning and artificial intelligent. This autonomous trend will reduce the human intervention even in complexity traffic situations. By "shared", transportation using vehicles can be much more economically by sharing with each other via the "on demand" service. It is likely possible in the near future by the advancement in the autonomous vehicles' developments. By connected, cars in the future has been fully connected with the outside world including networking with other cars and connecting with the outside facilities via the Internets of Things technologies. By "yearly updated", the rate of innovation within automotive industry will increase much rapidly and surpassed the industry norm of model cycles of five to eight years.

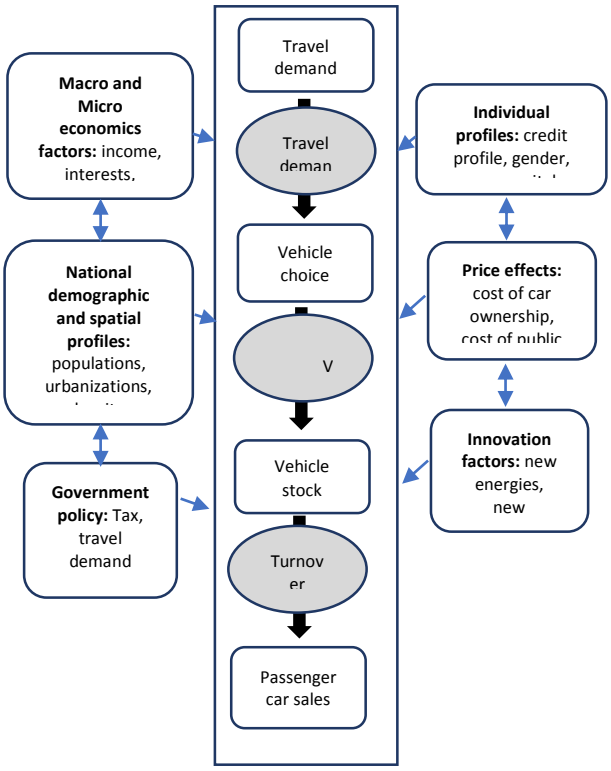
This paper acknowledges the dynamic and disruptive development in automotive industry in the future and attempt to contribute to this development by presenting and improving a framework for forecasting passenger car sales trend in long term across countries. Specifically, this paper aims to assess the predictive power of the forecasting framework for passenger cars from Haugh et al. (2010). This framework is chosen because it includes some essential country-specific factors in the framework such as demographic factors, automotive-related factors and income in term of real GDP which are the main characters defines passenger car sales trends in the long-term. Another main objective of this paper is to improve the Haugh et al. (2010)'s framework to better forecast the short-term car sales for specific group of countries.

For achieving these objectives, this paper is divided into following parts. First, the theoretical part is provided to give the background for passenger car analysis framework and factors affecting car sales trend. Second, methodology, data and tested hypotheses are presented. Third, the analysis and results are elaborated to see whether the framework can produce the meaningful forecasted car sales trend as well as the improvement suggested for the framework. Finally, the conclusion of the paper is discussed.

2. LITERATURE REVIEW

2.1. Framework for passenger car sales analysis

New meta trends are developing and shaping the futures of automotive industry since the introductions of new technologies, however, passenger car demand in present and future has been operating around four main indicators: travel demands (measured by passenger-kilometers), vehicle choice for travelling (measured by vehicle-kilometers), vehicle stocks (number of vehicle and passenger cars in used) and new registrations of passenger cars (Gärling, 2005; Eriksson et al., 2010; Ritter & Vance, 2013; Redman et al., 2013). The interrelationship between these four indicators are straightforward as presented in Figure 1. Fulfilling the personal desires, social and business tasks requires that people move from doors to doors or places to places to perform their behaviors such as working, shopping or leisure activities (Gärling, 2005). In addition, the spatial organizations of society and places are also key determinants of how people choose the degree and type of travel (Gärling, 2005; Bamberg et al., 2011). This activity-base view to travel demand assumes that the economic reasons play essential roles in affecting the demand for travelling. Travel demand are then combined with other factors such as socioeconomics, demographic factors and transports systems available to lead people to a particular preference for a travel choice over the others (Timmermans et al., 2003; Souche, 2010). For example, people who are time sensitive and pressure might prefer to use private cars more than public transports for their work-related travels. On the other hand, the developed public transport system can also draw people away from using private cars in some occasions. Or with environmentally friendly people, walking or cycling will be their priorities for non-work or even work events. In the next step, regarding to the passenger cars segment, people's choosing of sizes, types and the designs of car attributes with specific annual millage will decide the desired numbers of passenger cars used at a specific economy and timeframe (Haugh et al., 2010; Kuhnert et al., 2017). Finally, comparing this desired number with the current number of passenger cars used, the number of new registrations is estimated. However, this increased in number of required passenger car used is now usually referred as very limited in developed economies in Europe and North America because of the new changes in demographic profiles, life styles and policy to reduction of car used as well (Bamberg et al., 2011; Buehler, 2011; Vij et al., 2013; Van Wee, 2015; Klein & Smart, 2017). Thus, because of this "peak car" trend, the increase in new passenger car registration is assumed to come mainly from the rollover of the current cars used in Europe and North America in the future (Haugh et al., 2010; Kuhnert et al., 2017). The decision to replace old car with new one is usually referred as the big investment and required both short and long-term planning in the decision processes. At this stage, the economic reasons, socioeconomic factors, demographic profile, life styles, government policy, etc. will once again exert their complex interactions on the decision (Vij et al., 2013; Fouquet, 2012). For instance, the economic factors such as scrappage incentive or consumer confidences about future income will push or delay the decision of changing a new car (Leheyda & Verboven, 2016). Figure 1 summaries the mechanisms and the interactions between factors which together to decide the level of passenger car demands and new car registration. The specific impacts of considerable factors for forecasting car sales in the near future are addressed as following



Source: own research

Figure 1 Proposed framework for analysis of passenger car sales.

2.2. Factors affecting passenger car sales

Travel demand management (TDM)

Addressing the intolerably high side effects of high-level car-use which are congestion, air and noise pollution in urban areas, a broad array of policies is implemented by many governments especially in developed economies (Gärling, 2005). In general, the proposed measures are designed for reducing or changing demand for car use and are usually referred as Travel demand management (TDM) At specific level, TDM can be distinguished into five classes: transports systems/options improvements; incentives to choose alternative modes, land-use design, planning reform and support programs (Litman, 2003). Another system of classification suggested the TDM measures as associated with "targeting latent vs. manifest travel demand, time scale, spatial scale, coerciveness, top-down vs. bottom-up process, and market-based vs. regulatory mechanism" (Loukopoulos et al., 2004). For example, the TDM should focus on both measures to reduce congestion and ones to increase the public transport capacity. The building environments regrading as "density, diversity and design" are also one of the TDM-related influential factors to the travel demand. Researches on this topic found that increasing the density of the urban area, diversifying the usages of land, and designing pedestrian-oriented can reduce the car-use and increasing the non-auto travels using public transports system and other means (Cervero & Kockelman, 1997; Ewing & Cervero, 2001). The effects of TDM on car-use are varied across researches. Loukopoulos et al. (2004) revealed that the TDM have dictated the choice of adaption alternatives means of travels. However, the effects were small and further research needs to put more efforts on the principles how people actually set the car-use reduction goals. Gärling & Schuitema (2007) found that the increasing cost for car use or prohibiting car use may be necessary regarding to the insignificant effects of noncoercive TDM measures. However, these coercive TDM measures should be combined tightly with measures

providing attractive travel alternatives such as reducing fares and increasing quality of public transports (Gärling & Schuitema, 2007). These measures combined can create strong enough substitution effects of non-car travel alternatives to address the high level of car use at the moment.

Demographic factors

Population and income are the two dominant factors accounting for the strong growths of car sales from nearly a century ago till now (Metz, 2012; Ritter & Vance, 2013). However, the exploding trend in population growths has ended in most of the developed economies in Europe and North American leading to major shifts in demographics. These changes have significant effects on the preference to car ownerships in those regions. One of the dominant trends is about the effects of urbanization that large share of young people and new households choose to reside at the urban area instead of the rural or suburban making the demand for private care travel reduced (Ritter & Vance, 2013; Hjorthol, 2016). In addition to the urbanization, the travel demand managements with new policies such as mixed land uses, complex and multifunctional neighborhood or more accessible and quality public transports have also hindered the car uses in the urban area (Cervero & Kockelman, 1997; Ewing & Cervero, 2001). The second significant move in sociodemographic trends is about the less car-oriented among young people in developed economies (Ritter & Vance, 2013; Hjorthol, 2016). Klein & Smart (2017) found that young adult in America today own fewer cars than previous generation. However, the main reasons in America for this observation is about the financial insufficient of most of the young adult leading to the delayed of car purchasing. In Germany, UK and Norway, the same pattern was found that young people tend to live in highly dense urban area and are less car-oriented. In these Europe countries, the main reason is about the emerged new life styles of young people such as spending longer on education, delaying establishing a family or voluntary childless (Hjorthol, 2016; Metz, 2012; Buehler, 2011).

Scrappage incentive

The way how scrapping program works is transparent: passenger car owners receive government money to change their old vehicles for new, usually more fuel-efficient ones (Leheyda & Verboven, 2016; Haugh et al., 2010). The schemes' underlying motive is also simple: a sudden slump in demand for vehicles in high volume car production countries might lead to bankruptcies and unemployment, thereby triggering severe consequences for workers in the car industry and other related industry. Hence, the scrapping programs intent to stimulus car purchases to adjust strong pro-cyclical demand behavior and expect to keep the accepted level of production and jobs (Palma & Kilani, 2008). Scrapping schemes had a strong stabilizing impact on total car sales in some Europe countries: if there had been no schemes in 2009, total sales would have been 30.5% lower in the countries with targeted schemes and 29.0% lower in countries with non-targeted schemes (Leheyda & Verboven, 2016). Moreover, the targeted scrapping schemes had significant environmental benefits in the form of improved fuel consumption of new purchased cars: absent the schemes, average fuel consumption would have been 3.6% higher in countries with targeted schemes (Leheyda & Verboven, 2016). In long term, car scrappage schemes also increase car use by lowering the transport cost (Brand et al., 2013).

Income

Economic development has historically been strongly associated with an increase in the demand for transportation and particularly in the number of road vehicles. This relationship is also evident in the developed and developing economies today. Surprisingly, very little research has been done on the determinants of vehicle ownership across the countries with different levels of income. The relationship between car ownership and income growth as well as the income elasticity of vehicle ownership is highly dependent on the income level of the country. This

relationship can be described by the Gompertz function (Dargay et al., 2007; Dargay & Gately, 1999). In Austria, high income levels country, as an example, the car ownership is already reach the saturation level and therefore the income elasticity is decreasing. This means that lower income elasticity has to be used (Kloess & Müller, 2011). Dargay et al. (2007) are one of the few investigating about the effects of income levels across countries as the main independent variables for determining the vehicle ownership of a country (Dargay et al., 2007). Their model is estimated on the basis of panel data consist of time-series (1960-2002) and data for 45 countries that include 75 percent of the world's population. The result suggests the non-linear relationship between vehicle ownership and level of income in most of the countries except for Luxembourg, Iceland, Ecuador, and Syria. More specifically, vehicle ownership rises in a slow pace at the lowest levels of per-capita income, then about twice as much as income growth at middle-income levels (from $3,000 to $10,000 per capita), and finally, about as fast as income growth at higher income levels, before reaching saturation at the highest levels of income (Dargay et al., 2007; Dargay & Gately, 1999). Fouquet (2012) also suggested that in 2010, the long run income and price elasticity of transport demand were much lower than the ones in mid-nineteenth century and may decline gradually in the future in developed economies. However, the energy and technological advancement might delay this declining trend in income and price elasticity of transport demand in developed economies (Fouquet, 2012; Kuhnert et al., 2017).

In this paper, country-specific factors including urbanization, population density, population, income in term of real GDP and vehicle stock are used in the framework of Haugh et al. (2010) to forecast the passenger car sales trend. This paper is interested in whether the combination of these country-specific factors in the Haugh et al. (2010) framework can produce the meaningful estimates for passenger car sale trend in the long term across countries. Using out-of-sample data, the framework is evaluated in the following parts of the paper.

3. METHODOLOGY

Framework for forecasting passenger car sale trend

This paper employs the original framework for forecasting passenger car sale from Haugh et al. (2010). In general, passenger car sales ($sales_{it}$) of country i in perioda t is given by:

$sales_{it} = \Delta stock_{it} + scrappage_{it}$

where $\Delta stock_{it}$ is the differences in passenger car stock in period t from previous period t-1 while $scrappage_{it}$ is the number of car scrapped and replaced in period t. The scrapped cars are calculated by multiple the historical average scrap rate (asr_i) and the car stock in previous year ($stock_{it-1}$): $scrappage_{it} = asr_i * stock_{it-1}$ where the historical average scrap rate (asr_i) is given by:

$$asr_i = \sum_{t=1}^{T} \frac{sale_{it} - \Delta stock_{it}}{stock_{it}}$$

The estimated passenger car stock in period t ($stock_{it}$) is the function of the passenger car stock per capita (pc_{it}) (per 1000 inhabitants) and the total population (pop_{it}): $stock_{it} = pc_{it} * pop_{it}$

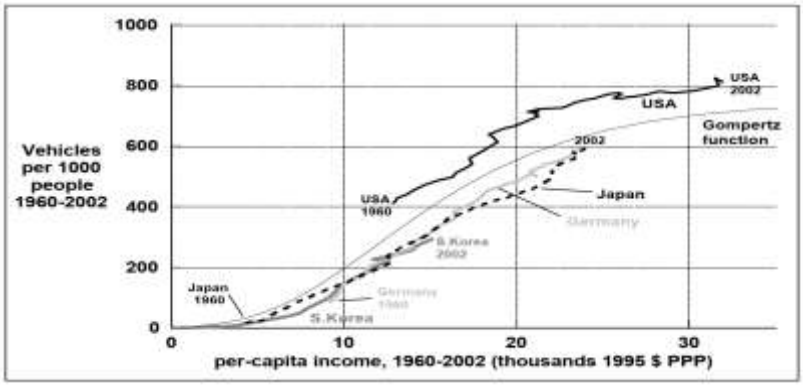
To calculate the the passenger car stock per capita (pc_{it}), the vehicle stock per capita (v_{it}) is obtained first. At this stage, this paper employed the model from Dargay et al. (2007) to determine the vehicle stock per capita (v_{it}). According to Dargay et al. (2007), the vehicle stock per capita (v_{it}) in period t is asummed to gradually adjusted toward the its long term equilibrium level (vlr_{it}) over time and is given by:

$$v_{it} = v_{it-1} + \theta(vlr_{it} - v_{it-1})$$

where, θ is the speed of adjustment ($0 < \theta < 1$) and the long-term equilibrium per capita vehicle stock (vlr_{it}) is obtained by the Gompertz function:

$$vlr_{it} = \gamma_i e^{\alpha e^{\beta_i GDP_t}}$$

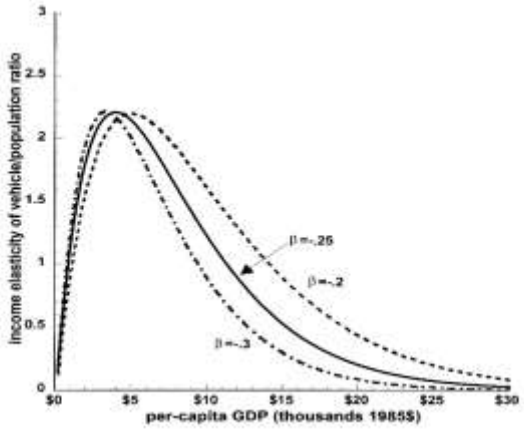
where, γ_i is the saturation level of per capita vehicle stock, α and β_i define the curvature of the function and GDP is real GDP per capita measured at purchasing power parity. Dargay et al. (2007) empirically estimated these parameters using pooled data sample from 45 countries in the period from 1960 to 2002. In this paper, the values of θ, γ_i, α and β_i estimated from Dargay et al. (2007) are used in the original framework of Haugh et al. (2010) for forecasting passenger car sales. Figure 2 illustrates the relationship between vehicle stock per capita and income for some countries together with the Gompertz function.



Source: Dargay et al. (2007)

Figure 2 Vehicle per capita and income per capita in USA, Korea, Japan and Germany from 1960 to 2002.

In the forecasting framework of Haugh et al. (2010), the speed of adjustment (θ) and the Gompertz parameters (α) which decided the max income elasticity of vehicle stock per captita are the same for all the countries. The saturation level for country i in time t (γ_i) determined in Dargay et al. (2007) from population density and urbanization is used in this paper. The β_i parameter determined the income elasticity of vehicle stock per capita. The bigger β_i, the sooner the country can reach the maximum income elasticity and the saturation level of vehicle stock per capita (Figure 3).



Source: Dargay & Gately (1999)

Figure 3 The income elasticity with three different Gompertz functions.

In the forecasting framework in this paper, β_i is updated for each country so that the sum of passenger car sales between 1996 and 2009 (the train period) is within +/- 2.5% of the sum of

actual sale over this period. Then the parameters is used in the framework of Haugh et al. (2010) to forecast car sales in the test period from 2010 to 2017.

Because vehicles are composed by passenger cars and other vehicles, passenger car stock per capita (pc_{it}) determined by: $pc_{it} = pcr_i * v_{it}$ where pcr_i is the historical average ratio of the passenger car stock to total vehicle stock.

Data

Data used in the framework of Haugh et al. (2010) are collected from 38 countries including all the biggest markets of automotive industry in different regions around the world. The data is presented in panel data including time series data of passenger car sales, population, countries' specific factors (density and urbanization), income data in term of real GDP and level of historical vehicle stock from 2005 to 2017 and cross sectional data for 38 countries such as Germany, United Kingdom, Italia, France, Japan, China, India, USA, Korea, Brazil, Czech Republic, Austria, Belgium, Australia, etc. Together, 38 countries in the sample together account for more than 80% of passenger car in use in 2017 (OICA). Table 1 provide some details about the types of data and sources.

Table 1 Variables required and their sources.

No	Variables	Definition	Data sources from
1	pop(t)	Total population at time t	United Nation database. The data is collected from 2005-2017.
2	population density (λ),	Calculated by diving total population by land area (square kilometer)	World bank's World Development indicators database from 2003-2017
3	urbanization (φ)	Percentage point of urban citizens on total population.	World bank's World Development indicators database from 2003-2017
4	θ	speed of adjustment short-term toward long term, $0< \theta < 1$	Dargay et al. (2007)
5	γ	Saturation level of vehicles per capita.	Dargay et al. (2007)
6	GDP	real GDP per capita measured at purchasing power parity(PPP), (GDP per capita expressed in 2010 $ (thousands), PPPs)	OECD, World bank report. The data is collected from 2003 – 2017 for evaluation and projection.
7	α	Common parameter defines the shape of the vlr function.	Dargay et al. (2007)
8	β	specific parameter for each country defines the shape of the vlr function.	Dargay et al. (2007)
9	v_{it}	Historical data of stock of vehicle from 2003-2017.	The International Organization of Motor Vehicle Manufacturers (OICA); report from the European Automotive Manufacturers Association (ACEA).

Source: own research

*T*ested Hypotheses

According to the framework of Haugh et al. (2010), income (GDP per capita) is the main indicator determining passenger car sale together with countries' factors such as population, population density and urbanization rate. In order to assess the predictive power of Haugh et al. (2010)'s framework, this paper calculated the forecasting errors of the framework when dealing with the out-of-sample data (period from 2010 to 2017). This paper also extends the number of the countries in the evaluation from 17 in original framework to 38 countries in total. First, this paper evaluates the ability of Haugh et al. (2010)'s framework to produce the unbiased estimate for the passenger car sales in the long-term across the countries. For achieving this predictive power, the framework should replicate the real averaged long-term growth rate of passenger car sales in the out-of-sample period from 2010 to 2017 across the countries. In addition, the framework's mean forecasting errors for total passenger car sale in the out-of-sample period

from 2010 to 2017 across the countries should be insignificant different from zero. Thus, following hypothesis should be tested:

H1A: Haugh et al. (2010)'s framework's growth rate forecasting of passenger car sale is insignificantly different to the real growth rate in period 2010-2017.

H1B: Forecasting errors of Haugh et al. (2010)'s framework of total passenger car sale in period 2010-2017 across countries is insignificantly different from zero.

Second, this paper concern about the applicable range of the Haugh et al. (2010)'s framework. In other word, the framework should yield the consistent results overtime and in different contexts to overcome the over-fitting issue. If it is the case, the framework is reliable and the parameters used in the framework are not bias for any specific period of the market or any type of market. Therefore, forecasting results should be insignificant different when applying the model in different period and specific group of countries. For the attempt to test the applicable range of Haugh et al. (2010)'s framework, this paper extends the sample of countries to 38 countries rather than only 17 countries in the original sample of Haugh et al. (2010) which focused on OECD countries and other large economies. For the extended sample, we also attempt to include most of the important market for passenger sale cars in different geographic regions in Europe, North America, Latin America, Asia, Oceania and Africa. Concerning these issues, following hypothesis should be tested:

H2A: Haugh et al. (2010)'s framework's average forecasting errors are not significantly different for original countries and extended countries in the period 2010-2017.

H2B: Haugh et al. (2010)'s framework's average forecasting errors are not significantly different between in-sample period 2005-2009 and out-of-sample period 2010-2017.

Third, concerning the short-term prospect and by observing the forecasting errors across the income level, it appears that the forecasting errors seems to vary widely across different levels of country's income (read GDP) (Table 2). There are countries the prediction errors are very small indicating very good forecasting results such as Germany, France, Austria, Norway, Switzerland, Sweden, Netherland, Finland, Turkey, Canada, Japan, China, Korea, Israel, Morocco, and South Africa. Some other countries have the moderate forecasting results such as Czech, Spain, Belgium, UK, USA, Mexico, India, Greece, Brazil, Argentina, Ecuador, Egypt, and Pakistan. Finally, there are few countries which have very bad forecasting results with large errors such as Poland, Hungary, Ireland, and Indonesia. Moreover, the different levels of countries' income are consistent with the different level of long-term vehicle stock per capita level across these groups of countries. It is understandable that higher income countries are much likely to spend more on vehicle and lead to the higher vehicle ownership per 1000 inhabitants. Thus, this paper is interested in testing whether the performance of the Haugh et al. (2010)'s framework is difference between difference group of income level or vehicle stock per capita level.

Table 2: Descriptive value of MAPE for 3 groups of countries

	Groups of countries	Mean	95% Confidence Interval for Mean of MAPE		Average car sale 2010-2015	Average GDP per capita 2015 (thousand $)
			Lower Bound	Upper Bound		
MAPE (%)	Good: 18	6.87%	5.6368%	8.1410%	1,881,469	36,614.4
	Moderate: 15	19.74%	15.5775%	23.7558%	1,242,234	22,664.7
	Bad: 5	106.66%	59.3792%	153.8208%	551,492	29,036.4
	Total : 38	25.08%	13.4279%	36.6774%	1,454,143	30,110.8

Source: own research

In addition, it seems that the dramatic differences in vehicle stock per capita level across countries might be the direct reasons in the framework which lead to the significant differences in forecasting errors between group of countries. Thus, in order to achieve better forecasting results, the speed of adjustment (θ) for calculating the current level of vehicle stock from the long-term level of vehicle stock per capita should be different for each group of countries with different income level to mitigate this income effects. Concerning this issue, following hypothesis should be tested:

H3A: Forecasting errors are significant different between higher income countries and lower income countries.

H3B: Because different groups of countries with different level of incomes might lead to the considerable differences in level of vehicle stock per capita (v_t), using different speed of adjustment (θ) parameter in the Haugh et al. (2010)'s framework for each group of countries can improve the accuracy of short-term forecasting.

4. ANALYSIS AND RESULTS

4.1. Assessing Haugh et al. (2010)'s framework

For testing H1A which assumes that Haugh et al. (2010)'s framework's growth rate forecasting of passenger car sale is insignificantly different to the real growth rate in period 2010-2017, paired sample t-test procedures in SPSS 22 is employed to see if their means of growth rates are significant different or not. Table 3 shows the result of the test which suggests that the difference between forecasted and real growth rate is insignificant when there are not enough statistical evidences to reject the hypothesis that the two means are the same (p-value = .833 > 0.05). This finding supports the H1A.

Table 3: Independent Samples Test of growth rate.

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	Estimated	.0379	38	.27792	.04508
	Real	.0289	38	.05087	.00825

Paired Samples Test

	Paired Differences					t	df	Sig. (2-tailed)
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference Lower	Upper			
Estimated - Real	.00894	.26041	.04224	-.07665	.09454	.212	37	.833

Source: own research

For testing H1B which assumes that forecasting errors of Haugh et al. (2010)'s framework of total passenger car sale in period 2010-2017 across countries is insignificantly different from zero, one-sample t-test procedure in SPSS 22 is employed. Mean Absolute Percentage Error (MAPE) is used for evaluating the forecasting errors in this case because it can ignore the scale effects which affect other error measures like Mean Absolute Difference (MAD) or Root Mean Square Error (RMSE). The result is presented in Table 4 supports the hypothesis that the mean error is not significant different from zero in the period 2010-2017 (p-value = 390 > 0.05). The H1B is supported.

Table 4: One-Sample t-test for medium term projection error

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
MAPE (%)	38	-.06549	.463884	.075252

One-Sample Test

	Test Value = 0					
	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
MAPE (%)	-.870	37	.390	-.065494	-.21797	.08698

Source: own research

For testing H2A which assumes that Haugh et al. (2010)'s framework's average forecasting errors are not significantly different for original countries and extended countries in the period 2010-2017, the independent t-test procedures in SPSS 22 is employed. Table 5 shows that the Levene's Test for Equality of Variances is not significant indicating that the variance of two group is likely the same. Thus, the result of t-test is given by the p-value with equal variance assumed. In this case, the results still show that there is no significant difference for Mean Absolute Percentage Error (MAPE) between the original samples and extended samples (p-value = 615 > 0.05). Thus, the result of t-test is given by the p-value with equal variance not assumed. Therefore, the H2A is supported.

Table 5: Independent samples t- test for original sample and extended sample

Group Statistics

Group		N	Mean	Std. Deviation	Std. Error Mean
MAPE (%)	Original	17	28.3529%	32.54025%	7.89217%
	Extended	21	34.6667%	42.04323%	9.17459%

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means				
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
MAPE (%)	Equal variances assumed	1.160	.289	-.508	36	.615	-6.31373%	12.43468%
	Equal variances not assumed			-.522	35.947	.605	-6.31373%	12.10204%

Source: own research

Source: own research

For testing the H2B which assumes that the Haugh et al. (2010)'s framework's average forecasting errors are not significantly different between in-sample period 2005-2009 and out-of-sample period 2010-2017, the independent sample t-test for different type of forecasting

errors between the two groups are employed. The results in Table 6 show that there are not significant differences between the error metrics for in-sample and out-sample for all three types of error metrics (MAD, RMSE, and MAPE). The p-value in all three t-test are larger than 0.05 level. These results indicate that Haugh et al. (2010)'s framework can produce consistent forecasted passenger car sale number overtime. The H2B is supported.

Table 6: Independent samples t- test for in-sample period and out-of-sample period

		Levene's Test for Equality of Variances		t-test for Equality of Means	
		F	**Sig.**	**t**	**Sig. (2-tailed)**
MAD (1000 units)	Equal variances assumed	6.561	.012	-1.642	.105
	Equal variances not assumed			-1.642	.106
RMSE (1000 units)	Equal variances assumed	5.915	.017	-1.547	.126
	Equal variances not assumed			-1.547	.128
MAPE (%)	Equal variances assumed	5.654	.020	-1.157	.251
	Equal variances not assumed			-1.157	.253

Source: own research

Improving Haugh et al. (2010)'s framework for short-term projection

Concerning the short-term projection for specific countries and testing H3A and H3B, first, cluster analysis is employed to test the statistical different between groups of countries with different levels of income level. Because number of groups is not known, two-step cluster analysis is used in SPSS 22. The variables are used for clustering groups are 2015 real GDP per capita and 2009 level of current stock of vehicle (v_t), the average differences between vlr_t and v_t (vlr_t- v_t) and the MAPE. The results are presented as in Figure 3.

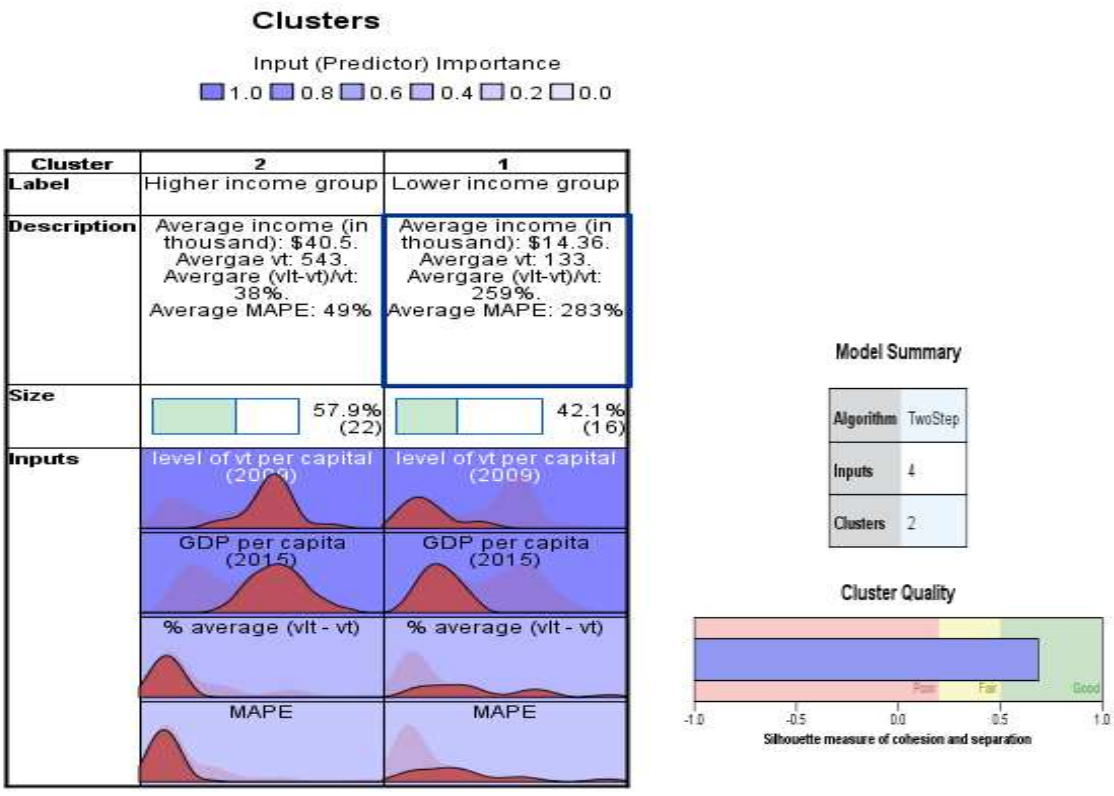


Figure 4. Clusters analysis' result

According to the cluster analysis, we have 2 separated groups with good level of separation (Average Silhouette = 0.7). The group with higher income level (22 countries) have average GDP per capita is around 40.5 (thousand $), much higher the lower income group (16 countries) with only 14.36 (thousand $). There are also big differences between levels of vt per capita and MAPE as presented in the Figure 4. In addition, the most important factors for explaining the separation of two groups is GDP per capita and level of v_t per capita.

With the two separated groups according to income level resulted from the Cluster analysis, the independent t-test procedure is employed in SPSS 22 to test the H3A which assumes that forecasting errors are significant different between higher income countries and lower income countries. Results are presented in Table 7.

Table 7: Independent samples t- test for 2 groups with different level of income

		Levene's Test for Equality of Variances		t-test for Equality of Means	
		F	**Sig.**	**t**	**Sig. (2-tailed)**
MAPE (%)	Equal variances assumed	18.392	.000	4.327	.000*
	Equal variances not assumed			3.698	.002*
GDP per capita (2015)	Equal variances assumed	1.144	.292	-10.453	.000*
	Equal variances not assumed			-10.981	.000*
level of v_t per capital (2009)	Equal variances assumed	.033	.856	-11.077	.000*
	Equal variances not assumed			-11.031	.000*

*The mean difference is significant at the 0.05 level. Source: own research

The results confirm that there are statistically significant differences in the GDP per capita and current vehicle stock (v_t) between two groups characterized by theirs level of real GDP per capita (the p-value < 0.005) confirming the Cluster analysis result. Especially, the mean of MAPE is statistically different between higher income countries group and lower income countries group (p-value =.000 < 0.05). Thus, H3A is supported.

Results from table 8 confirm the observation that vehicle stock per capital (v_t) is the direct variables which leads to the huge differences in forecasting errors between higher income countries and lower income countries in the framework of Haugh et al. (2010). In other word, vehicle stock per capita transmit the effect of differences in income level on the forecasting errors. Tables 9 show that there are significant different between the mean of forecasting error of vehicle in stock (MAPE_v_t) between higher income countries and lower income countries (p-value =.000 <0.05). Specifically, the mean of forecasting error of vehicle in stock (MAPE _v_t) of higher income countries is just 8.2% compare to 53% from lower income countries.

Table 8: Independent samples t- test of MAPE (vt) for 2 groups with different level of income

Group Statistics

		N	**Mean**	**Std. Deviation**	**Std. Error Mean**
MAPE_vt	Lower income countries	16	.5359	.47380	.11845
	Higher income countries	22	.0829	.06107	.01302

Independent sample test

		Levene's Test for Equality of Variances		t-test for Equality of Means	
		F	**Sig.**	**t**	**Sig. (2-tailed)**
MAPE_vt	Equal variances assumed	31.447	.000	4.456	.000
	Equal variances not assumed			3.801	.002

*The mean difference is significant at the 0.05 level. Source: own research

The original framework of Haugh et al. (2010) assumes that the speed of adjustment is the same across countries and level of income ($\theta = 0.1$). This paper contrasts this assumption in the original framework and the H3B assumes that using different speed of adjustment (θ) parameter in the Haugh et al. (2010)'s framework for each group of countries can improve the accuracy of short-term forecasting. In order to test this hypothesis, sensitive analysis regarding the change of speed of adjustment (θ) is used. Because most of the forecasted car sales overestimate the real passenger car sales across countries, the speed of adjustment is likely to be overestimated. Thus, the base line value of speed of adjustment in the framework are used as the reference as the high-level value for the sensitive analysis. In this analysis, high-level of speed of adjustment are given the value 0.08, 0.09 and 0.1; the medium-level of speed of adjustment are given the value 0.04, 0.05, 0.06 and 0.07 and low-levels of speed of adjustment (θ) is given the value 0.01, 0.02 and 0.03. These values of speed of adjustment (θ) are used to estimate the vehicle stock per capita (v_t) and forecasting errors of vehicle stock per capita ($MAPE_v_t$) in both groups of higher income countries and lower income countries. Then the Two-Way ANOVA procedures in SPPSS 22 are used to compares the differences in forecasting errors of vehicle stock per capita ($MAPE_v_t$) at different level of the speed of adjustment (θ) between the two groups of countries. The results are summarized in the Table 9.

Table 9. Summary of Two-Way Anova of the mean of $MAPE_v_t$ at different level of speed of adjustment (θ)

Descriptive Statistics

Dependent Variable: $MAPE_v_t$

Income	Speed_of_adjustment	Mean	Std. Deviation	N
H	H	7.605%	5.5128%	69
	L	2.564%	2.5997%	69
	M	4.457%	3.8510%	92
	Total	4.833%	4.5659%	230
L	H	47.661%	42.6187%	48
	L	10.786%	10.6354%	48
	M	27.721%	26.6407%	64
	Total	28.622%	32.5169%	160
Total	H	24.038%	33.8424%	117
	L	5.937%	8.1420%	117
	M	14.001%	20.7113%	156
	Total	14.593%	24.1190%	390

Tests of Between-Subjects Effects

Dependent Variable: $MAPEv_t$

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	87018.780[a]	5	17403.756	47.985	.000
Intercept	104576.611	1	104576.611	288.335	.000
Income	52686.672	1	52686.672	145.266	.000
Speed_of_adjustment	24969.972	2	12484.986	34.423	.000
Income * Speed_of_adjustment	14360.684	2	7180.342	19.797	.000
Error	139273.357	384	362.691		
Total	309344.468	390			
Corrected Total	226292.136	389			

Source: own research

According to the results from the Two-Way ANOVA analysis, in overall, the forecasting errors for vehicle stock per capita (MAPE_v_t) is significant different between different level of speed of adjustment (θ) and two income level. The p-value of the F-statistic in the ANOVA test of Speed of adjustment (θ) and Income is much lower than the significant level of 0.05 indicating that the null hypotheses of equal means of MAPE_v_t between the groups are rejected. Especially, from the descriptive statistics of means of MAPE_v_t, the low level of speed of adjustment (θ) have the best forecasting results in both higher income countries and lower income countries. This claim is confirmed by the evidences from Post Hoc Test of speed of adjustment (θ) in Table 10. The mean of MAPE_v_t is statically different between all three group of level of speed of adjustment (θ) with significant level of 0.05 and the lower the speed of adjustment, the better the results of forecasting errors.

Table 10: Post Hoc test of speed of adjustment (θ)

Dependent Variable: MAPEvt

Tukey HSD

(I) Speed_of_adjustment	(J) Speed_of_adjustment	Mean Difference (I-J)	Std. Error	Sig.
H	L	18.101%*	2.4899%	.000
	M	10.037%*	2.3291%	.000
L	H	-18.101%*	2.4899%	.000
	M	-8.064%*	2.3291%	.002
M	H	-10.037%*	2.3291%	.000
	L	8.064%*	2.3291%	.002

*The mean difference is significant at the .05 level.

Source: own research

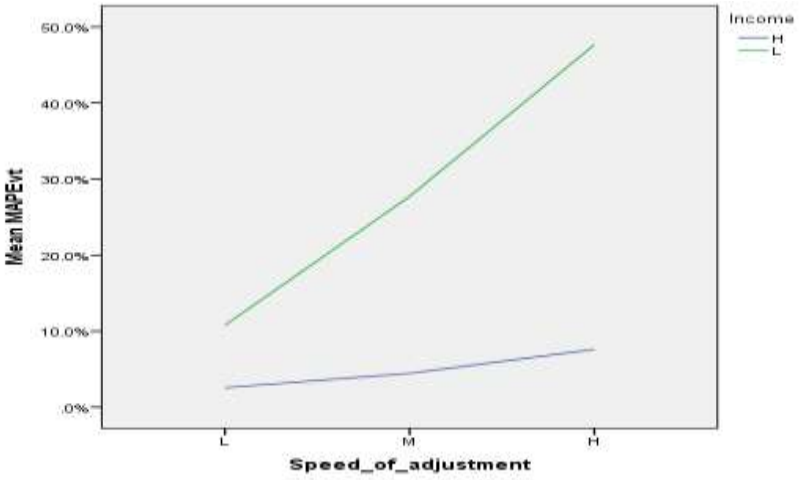


Figure 5: Mean of MAPE_v_t by the interaction between Speed of adjustment and Income. Source: own research

In addition, the interaction of Income and Speed of adjustment in the ANOVA test is also statistically significant indicating that the effects of different levels of speed of adjustment (θ) on MAPE_v_t depend on the Income level. As presented in Figure 5, the high level of speed of adjustment (θ) produces much worse forecasting errors in lower income countries than in higher income countries. Therefore, it is necessary to use different speed of adjustment (θ) parameters in the Haugh et al. (2010)'s framework for each group of countries to improve the accuracy of

short-term forecasting. As suggested in Figure 5 and ANOVA tests, lower level of speed of adjustment (θ) (0.01 to 0.03) in lower income countries can produce much better forecasting result for vehicle stock per capita and then passenger car sales. Hypothesis H3B is supported.

This paper also attempts to update the parameters for the framework using different speed of adjustment (θ) parameters for two group of higher income countries and lower income country. Using panel data from 1991 to 2017 in 38 countries (data is available only from 2004 to 2017 for most of non-OECD countries in the sample), parameters from Dargay et al. (2007) model is re-estimated using Stata 14 and regression analysis with dummy variables. Table 11 show the results of the estimation.

Table 11. Results of the re-estimation of parameters used in the forecasting framework

Source	SS	df	MS		
Model	9.0718e+12	8	1.1340e+12	Number of obs =	792
Residual	104914.371	784	133.819351	R-squared =	1.0000
				Adj R-squared =	1.0000
Total	9.0718e+12	792	1.1454e+10	Root MSE =	11.56803
				Res. dev. =	7156.897

vt	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
/gama	848.85	37.82987	22.44	0.000	774.5902	923.1098
/lamda	-.5340081	.1413907	-3.78	0.000	-.8115574	-.2564589
/phi	-5.447631	6.25353	-0.87	0.384	-17.72328	6.828013
/thetaR_H	.0386517	.0068604	5.63	0.000	.0251847	.0521186
/thetaF_H	.0263174	.0110409	2.38	0.017	.0046441	.0479907
/thetaR_L	.019542	.0037519	5.21	0.000	.012177	.026907
/thetaF_L	.0182051	.0061275	2.97	0.003	.0061768	.0302334
/alpha	-3.268939	.7143861	-4.58	0.000	-4.671275	-1.866603

Source: own research

The results of the estimation confirm that the speed of adjustment (θ) used in higher income countries (thetaR_H and thetaF_H) and lower income countries (thetaR_L and thetaF_L) are differences and much lower than the base value in the original framework (0.018 - 0.038 comparing to 0.1). This is consistent with the findings about the level of speed of adjustment (θ) should be used in the framework. All other parameters are statistically significant at 0.05 level except the parameters for urbanization.

5. CONCLUSIONS

This paper assesses the predictive power of Haugh et al. (2010)'s framework for forecasting passenger car sales. Using out-of-sample data, this paper measures the forecasting errors of the framework with 38 countries for evaluating the framework. As a conclusion, Haugh et al. (2010)'s framework can be used to produce reliable and unbiased forecasted passenger car sales trend in the long-term across countries by exploiting the relationship between countries' specific factors (population, urbanization, population density, income and level of vehicle stock per capita) and passenger car sale. From the evaluation of the framework, the paper also suggests ideas to improve the framework for short-term forecasting purpose. Although the MAPE_vt of higher income countries is not so sensitive with the level of speed of adjustment (θ), however, lower income countries are much more sensitive with the level of speed of adjustment (θ). Thus, using theta with low level at 0.01 to 0.03 yield much better forecasting results with these countries. Even with higher income level, the base value of speed of adjustment (0.1) used in the framework overestimate the current level of vehicle stock per capita. Therefore, it is suggested in this paper to econometrically estimated again the original

framework with new updated data and with different speed of adjustment for different income level. The parameters re-estimated in this paper can be used as a reference for practitioners and managers in forecasting the trend of car sales overtime. However, they should be used with cautions for short-term forecasting of passenger car sale because of the limited data available in the analysis. Future researches on this topic can used the Haugh et al. (2010)'s framework as the foundation to integrate more factors from the automotive sectors such as cars characteristics or factors from socio-economics factors such as household incomes to calibrate the framework for improving accuracy of short-term forecasting.

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