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EFFECT OF ECONOMIC FACTORS ON THE AUTOMOTIVE INDUSTRY IN MALAYSIA

MOE SHWE SIN*, SASHIVAARMAN ANBARASEN, TAI SHZEE YEW[2] AND WONG ZUN YUAN

Faculty of Business, Economics and Social Development, Universiti Malaysia Terengganu, 21030 Kuala Nerus, Terengganu, Malaysia. [2]Faculty of Accountancy and Management, Universiti Tunku Abdul Rahman, 43200 Kajang, Selangor, Malaysia.

**Corresponding author: moe.sin@umt.edu.my*
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Abstract: Transportation plays a significant role and is crucial for developing the country's economy. The automotive industry has hugely contributed to Malaysia's economy as a major factor in the economy's growth. The study analyses the effect of economic factors, Gross Domestic Product (GDP), inflation, and unemployment on long-term and short-term Automotive Sales (AS) using secondary time series data from 1990 to 2020 collected from Macro Trends and the Malaysian Automotive Association (MAA). The Autoregressive Distribute Lag model (ARDL) forecasts and disentangles long- and short-run relationships. ARDL model acquired the Error Correction Model (ECM) to estimate the short run. The results indicated that a long-run association does not exist between AS and economic variables. However, there is a short-run relationship between GDP with a positive effect and Inflation Rate (IR) and Unemployment Rate (UR) with a negative effect. Based on the findings, attention should be paid to reducing the negative impact of IR and UR, not to weaken the production and demand of the automotive industry. In future research, a more thorough analysis could be carried out in each vehicle category, such as passenger vehicles, industry-used vehicles, etc.

Keywords: Economic growth, automotive industry, Auto-Regressive Distributed Lag Model (ARDL), Inflation Rate (IR), Unemployment Rate (UR), Gross Domestic Product (GDP).

Introduction

In recent years, the Malaysian automotive industry has already reached a certain saturation level. Although the Malaysian automotive market has been declining in recent years, Malaysia is still in third place in the automotive industry ranking of ASEAN countries. Passenger cars are the most popular vehicles in Malaysia, and in 2019, the largest market share of about 382,000 vehicles were sold. Malaysia is the only country in Southeast Asia with two car brands, while Japanese car manufacturers dominate other Asian markets. National manufacturers Proton and Perodua share the Malaysian market. Until 2018, both manufacturers have been struggling with decreasing sales figures due to a lack of functionality in their cars. However, in 2019, Malaysian automotive manufacturers increased their sales and production. At the end of the year, they were first and second among the bestselling car brands in the country. Malaysia Automotive Robotics and Institute (MARI) figured that in 2019, the Total Production Volume (TPV) to Total Industry Volume (TIV) ratio increased to 95 percent, which has been the recorded figure since 2014. The Ministry of International Trade and Industry reported that in 2019, the automotive sector accounted for around 4.3 percent of Malaysia's Gross Domestic Product (GDP). The increased volume of domestic sales in 2019 represented a growth of 1 percent despite a challenging 2018. Other than that, the penetration of Energy-Efficient Vehicles (EEVs) in Malaysia is also one of the reasons that has contributed to GDP. The year 2019 recorded 87.6 percent in EEV penetration, signifying the public's increasing interest and demands for futuristic power trains, fuel savings, and carbon emission reduction.

Research Background

Malaysia's automotive industry is expanding motor vehicle sales and production to contribute to Malaysia's economic growth. Based on Khalifah (2013), the overall automotive industry in terms of technical efficiency is positively associated with the degree of vertical integration, establishments in the respective sub-area, a good quality workforce, and an increase in share of foreign ownership. According to Wad *et al*. (2011), even though the Malaysian automotive industry has the ability to expand sales and production, it has failed to upgrade its industry and compete in the global market because of the global value has limited participation, lack of political promotion for high support environment and low capabilities in term of technologies and marketing. Tariffs have been an effective measure widely used to promote industrial activities in Malaysia since the 1960s. In 1963, severe competition confronting new industries, lack of experience in the industrial sector, high production cost, and limited domestic market added to the need for Malaysia to impose such a protective measure. Malaysia attempted to expand Automotive Sales (AS) by promoting the local car producer, Proton, and to incise some "policy space" to continue a degree of protection during the liberalization of trade authorities. Besides, the safeguarding did not succeed in producing Proton and was internationally competitive with many vendors (Natsuda *et al*., 2013). Moreover, Afroz *et al*. (2019) identified the crucial barriers of 145 companies to Malaysia's automotive industry that can implement green supply management. The researchers figured that implicated cost, unawareness of buyers, corporate social responsibility shortages, globalization shortages, and insufficient technical assistance from authorities had been recognized as the utmost barriers.

Passenger Vehicles and Commercial Vehicles Production in Malaysia

The passenger vehicles produced from 2010 to 2019 are shown in Figure 1. In the years 2010 and 2011, the production did not increase significantly, and it fell off the GDP by 5 percent. Moreover, multiplier effects from the 10th Malaysia plan's projects as well as the ongoing economic transformation program's project. Passenger vehicles started to rise from 2012 to 2015, attributed to a stable economy and employment. Car companies make aggressive sales, especially towards the last few months of

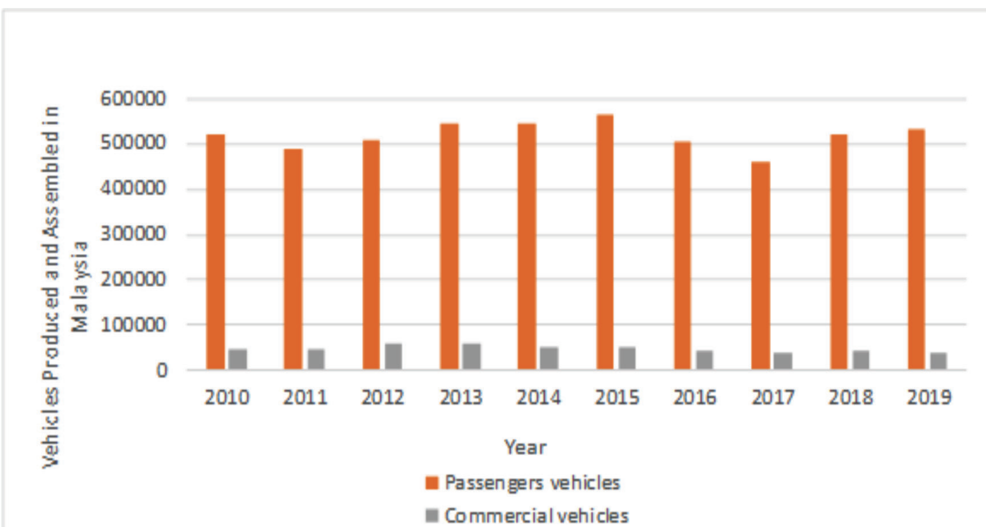

Figure 1: Passenger and Commercial vehicles produced and assembled in Malaysia. Source: Malaysian Automotive Association (2019)

the year. Several new models were introduced with the latest additional specifications and design styles at competitive prices. However, passenger vehicle sales declined from 2016 to 2017. They rose again from 2018 to 2019 due to the continuation of aggressive year-end promotional campaigns, especially by several players whose financial year ended in 2019.

The commercial vehicles produced from 2010 to 2012 increased with strong sales growth. Positive consumer sentiments are expected to continue owing to greater stability in the employment market. Furthermore, more job opportunities arise from investments that would be made in the 10th Malaysian Plan and the various Economic Transformation Program (ETP) entry projects. Besides, production from 2013 to 2017 showed a massive decline happened. This poor performance happened especially in 2016, with 9219 unit differences due to lower consumer spending and cautious business sentiment, and the sales performance of the automotive industry was weaker than in 2015. In 2017, it decreased due to the short working hours in view of the Hari Raya festive holidays. Lastly, commercial vehicles increased their sales production from 2018 to 2019, affected by strong demand for vehicles arising from attractive pre-Hari Raya promotions and offers by Malaysian Automotive Association (MAA) members.

The COVID-19 pandemic caused restrictions to be imposed on most social and business activities. The sales of new motor vehicles had been badly affected during the period. Automotive companies were facing headwinds in early 2020 with the sudden change in the customs department's Open Market Value (OMV) valuation methodology. This resulted in delays in new car launches and disruptions in selling their vehicles. Demand for new motor vehicles decreased due to economic uncertainties and consumer confidence erosion. Anyways, an improvement in Month-o-Month (M-o-M) sales from May to June 2020 after the announcement of a short-term economic recovery plan such as the short-term National Economic Recovery Plan (PENJANA) incentive where car buyers will enjoy tax exemption until the end of the year.

The economic impact on Malaysia's automotive industry, mainly during the COVID-19 pandemic, is a major concern of the study. Movement Control Order (MCO) was implemented from mid-March to mid-May. Malaysia's GDP increased to 0.7 percent for the first quarter of 2020 from 3.6 percent in the fourth quarter of 2019. This was the lowest growth rate recorded since 2009 -1.1 percent. The Unemployment Rate (UR) had escalated to 5.3 percent in May 2020 and was recorded as the highest rate in 30 years. Moreover, Malaysia's average Inflation Rate (IR) amounted to about -1.13 percent compared to the previous year. This research will find how the Malaysian automotive industry can recover the GDP through sales and production for the next decade to overcome the barriers, especially the virus outbreak of COVID-19. Previous research has primarily focused on the national and imported vehicles in Malaysia's automotive industry, with limited studies examining the effects of economic growth on AS, particularly concerning commercial and passenger vehicles. Therefore, this study analyses the economic factors such as GDP, Inflation Rate (IR), and Unemployment Rate (UR), which affect AS and production, and identifies the significant long-run and short-run relationship to the economic growth of Malaysia.

Literature Review

The Economic Impact of Automotive Industry

Automotive industries have played an important role in the growing economy in each country, and a way to strengthen the industry is to improve consumer insight into vehicle buying behavior. Car reliability, safety, and price significantly influence consumer buying behavior towards national cars in Malaysia (Lee & Govindan, 2014). Besides that, Saberi (2018) highlights that the automotive industry plays an immensely important role in driving both GDP growth and employment generation. Additionally, the industry's capacity to generate taxable revenue and contribute to state budgets is also emphasized in the study. According to Wu *et al*. (2014), the Gompertz function predicts China's vehicle ownership up to the year 2050. This function considers the per capita GDP and the stock of vehicles. It addresses the potential increase in energy consumption and Carbon dioxide (CO_2) emissions resulting from the demands of on-road vehicles. Clements and Kockelman (2017) analyzed how Connected and fully Automated Vehicles (CAVs) will affect the economy of 13 industries in the United States. They found that CAVs will soon become a central aspect of the automotive industry as software constitutes a greater proportion of the overall vehicle value. Zhang *et al*. (2016) employed a static regional Computable General Equilibrium (CGE) model to measure the economic effects of the automotive industry on Alabama's economy. The automotive industry's contributions to the economy can be interpreted broadly, including downstream activities related to the use of motor vehicles and socioeconomic employment (Túry, 2020). Barnes *et al.* (2004) conducted a study to analyze governance practices and value claims within the context of the automotive industry in South Africa. The study's findings shed light on the political economy dynamics rooted in German industry control.

Veloso (2006) presented a case study of the automotive sector to demonstrate how policies condition the decisions made by economic agents and can impact economic welfare. The results suggest that certain conditions of local content regulations can be beneficial. Williams (2006) discovered that efforts to address the economic and environmental effects of the automotive industry have mainly concentrated on technological advancements in products and services. The researcher combines analysis with environmental research to comprehensively understand shape change in the automotive industry. The researcher proposed the concept of Micro-Factory Retailing (MFR) as an approach to vehicle design that supports the economic feasibility of manufacturing facilities operating on a limited scale.

Ge and Jackson (2014) found that big data application strategy is used in cost reduction to measure the automotive industry risks. The automotive industry has extensively employed lean manufacturing and other conventional techniques to minimize wastage and improve efficiency. Big Data technologies rely on the newly implemented strategies for adaptive calibration and circular-economic development. Furthermore, Gromova (2019) found that the automotive industry in Russia has been emphasized with digital economy development results that can reduce product development time and non-value-adding activities at the development stage. Putri and Ginanjar (2018) showed how Industry 4.0 digitalizes and how the industry can remove Indonesia from several economic challenges and potentially contribute to diplomacy achievement. They found that Industry 4.0 strategies in the electronic and automotive industries can greatly increase exports, launch new markets, and attract more investment in Indonesia. Global Value Chain (GVC) analysis is used to explore the trends in the automotive industry (Sturgeon *et al*., 2008). The study concluded that the significant buying power of firms largely influences the economic geography of the industry.

Automotive Sales (AS) in Malaysia

Any country's economy is greatly impacted by the automotive industry's role. Researching the possible factors that could impact sales volume is crucial, given the automotive industry's contribution to the economy. Previous studies have been conducted by researchers to investigate the nexus between economic variables and car sales. Shahabuddin (2009) found a strong correlation between economic variables and the sales of foreign cars but a weak correlation between these variables and the sales of domestic cars. The researcher suggested further exploration of the relationship between domestic car sales and other economic variables to identify possible reasons for the weak correlation. The study's findings could aid automotive companies in better understanding their business and inform strategic decision-making. Based on findings from Blanchard (1983), the behavior of inventories in the automotive industry studied characteristics of the demand process and stated that the production variant is larger than the sales variant, which is called destabilizing. Islam *et al*. (2016) conducted a study to investigate the nexus between macroeconomic variables and the sales of cars in Malaysia and to identify the factors that influence car sales. The findings of their research indicated a positive relationship between car sales and the GDP in Malaysia. The sale of national cars has become a concern for the government in recent years. This is because the national car market has declined in these few years due to aggressive competition from imported cars. Wochner *et al*. (2016) identified ramp-up challenges in sales and operation by developing a mixed-integer linear programming model. Extreme priority is given to fairness among the market results sales negatively affected in low efficient operations. Sangasoongsong *et al.* (2012) used a Vector Error Correction Model (VECM) to examine automobile sales at segment levels and to quantify the long-term effect of economic indicators on sales, showing that they have a long-run equilibrium.

The VECM model would improve the accuracy prediction of automobile sales for 12 months compared to time series techniques. Lim *et al*. (2014) coordinate sale requirements and industrial constraints in an uncertain environment using a simulation model based on industrial data. It proved useful for decision-makers in the supply chain and sales departments, enabling them to adjust stock margins and flexibility on specific vehicle features more efficiently. Gao *et al*. (2017) forecast automobile sales in China based on a hybrid optimization approach with four key indicators: highway mileage, GDP, automobile ownership, and the Consumer Price Index (CPI) to improve the quality result. During 2005-2011, Sivak (2013) conducted a study analyzing the correlation between car sales and GDP in 48 developing and developed countries. The results showed that the logarithm of GDP can be a powerful linear predictor for the logarithm of automobile sales. Pauwels *et al*. (2004) investigate marketing actions affected by short-term and long-term. They concluded that new product introduction and sales promotion play an important role in marketing strategy. Moreover, to increase sales volume, improvements were made in the Overall Equipment Effectiveness (OEE) of machines and in the production cost through Total Productive Maintenance (TPM). The results demonstrated that the increase in volume of sales led to a significant improvement in the company's market share. According to Johan (2019), the study was conducted to determine automobile sales in Indonesia. Using 30 years sample of automobile sales, the empirical findings showed that both car and motorcycle sales were influenced significantly by GDP growth. Besides that, Najeemudeen and Panchanatham (2014) figured out how the Automotive Mission Plan can accelerate and maintain the growth of the automobile sector in India and achieve the global stage. They found that the main market of automobile sales in the country was more easily accessible to finance, and the urban sector supposed the disposable income was increased.

Gross Domestic Product (GDP) and Economic Growth of Malaysia

GDP is used as the standard measure of value added in a country's production of goods and services during a specific period. GDP is the primary indicator used to gauge economic activity and reasonably measures people's material well-being. However, alternative indicators may be more suitable in some cases. According to Saberi (2018), the work reflects the extremely high role of the automotive industry in GDP growth and employment generation, the ability of the automotive industry to form a taxable base, and revenues of the state budget. In the modern age, the development of the economy of any country cannot be imagined without the automotive industry's development. In multiple exchanges of the automotive industry, the GDP structure is increasing, and the growth dynamics will create new jobs and increase the average wage. Other than that, the automotive industry contributes to developing auxiliary branches, influences scientific and technical progress, and testifies to the level of solvent demand and the standard of living of the population of the country. According to Muhammad *et al*. (2012), the GDP variable has led to a positive relationship with car sales. They also proved that the national income level has become an important determinant for the automotive industry.

On distinction, the spikes in inflation and URs were found to negatively impact AS. Philip *et al*. (2020) analyze the yearly contribution of the automotive sector to the Indian national GDP, and the sector has contributed around 8 percent to the total GDP rate. The Automotive Mission Plan 2016-2026, implemented by the Indian government, set a goal to increase the automotive sector's contribution towards India's GDP to 12 percent. In the future, they prove there will be a huge scope in the Indian automotive sector. According to Liu *et al*. (2015), China had a massive development in automobiles, with 8.7 percent of China's GDP in 2009, even though this country faces some environmental challenges. Dweiri *et al*. (2016) utilized the Analytic Hierarchy Process (AHP) to develop a supplier selection model for the automotive industry, providing decision-makers with greater confidence in the consistency and robustness of the process. Meanwhile, Kikkas (2018) presented a territorial-sectoral model based on an institutional functional approach for the development of the automotive industry. The Autoregressive Distributed Lag (ARDL) model results indicate an immediate increase in the proportion of imported lorries to total Russian imports and the proportion of the automotive industry in Russia's total GDP. Sharipov (2020) found that high-tech production impacts the total industrial production, which influences the GDP growth in Uzbekistan. In addition, Ambe and Badenhorst-Weiss (2011) determine the trends in the South African automotive industry's supply chain and the challenges they face using the theoretical approach. In 2010, South Africa's automotive industry contributed 6.2 percent to the GDP due to embracing technology and management practices that indicated moving away from the recession.

The automotive section of India has begun to move forward by improving environmental and social performance through Sustainable Supply Chain Management (SSCM) practices, making the country one of the biggest contributors to the nation's GDP and economy. An empirical study on Total Quality Management (TQM) has determined that the Iranian automotive industry contributes to the country's GDP as the main factor (Arumugam *et al*., 2011). The Double Diamond Model was applied in the Chinese and Indian automotive industries to compare with Korea to find the competitiveness among these three countries. As a result, in customer sophistication, Korea is considered more sophisticated as they have a strong educational index along with GDP per capita compared to China and India (Sardy & Fetscherion, 2009). In conclusion, the GDP has been significantly affected by car sales and the UR in each country. The government should pay more attention to GDP to increase car sales and focus on the inflation and URs.

Impact of Inflation and Unemployment on Automotive Industry

Inflation is a significant concern affecting businesses, governments, and consumers, as it occurs when the prices of goods and services consistently rise within an economy. The automotive industry is no exception due to the negative impact of inflation on various industries. Higher raw material costs result in increased expenses for manufacturers and producers, forcing them to raise the prices of goods to compensate. A study by Nawi *et al*. (2013) found a negative correlation between inflation and car sales, as an increase in the IR results in a decrease in car sales. Additionally, Ahmed (2020) demonstrated that an increase in

IRs in Pakistan had a negative and significant effect on the automotive industry's contribution to Pakistan's economy. However, Chifurira *et al*. (2014) found that inflation has a unidirectional causal effect on new AS using cointegration and causality tests during a sample period from 1963 to 2013. Rusli and Ali (2014) investigated the correlation between IRs, fuel prices, GDP per capita, and Proton's sales revenue. They found that fuel prices with an increased IR in Malaysia negatively affect Proton sales revenue in the long term. However, Namazi and Rezaei (2012) discovered that a significant positive nexus exists between inflation and earnings persistence in the automotive and machinery industry. Cummins and Tennyson (1992) provide an overview of the automobile insurance system. They figured that automobile insurance inflation in the 1980s caused an increase in cost factors, particularly inflation in the severity of personal injured claims.

Unemployment is a pressing issue in numerous countries, as well as Malaysia. The rise in the UR has substantial consequences for individuals, society, and the country as a whole. Historically, a 3.5 percent increase in GDP has been associated with a 1 percent point decrease in the UR. This relationship is usually referred to as Okun Law. Deviations from Okun's Law were balanced between any two periods, and the earlier historical data should be usable to perform forecasts going forward. The Great Recession has caused a change in the relationship between GDP growth and the UR (Sanchez & Liborio, 2012). According to Pavlínek (2015), the automotive industry regionally increased unemployment in the Czech Republic during the economic crisis from 2008 to 2009. Additionally, Muhammad *et al*. (2012) found that there is a significant correlation between GDP per capita, UR, and the volume of car sales. Badkar (2012) studied unemployment as one of the indicators of car sales. The research showed a strong negative correlation between unemployment and car sales. Sturgeon *et al*. (2008) apply GVC analysis using global automotive industry trends to examine the economic crisis. They found that job quality can be degraded with massive deindustrialization unemployment that remains high for the long term, so-called aggregate unemployment stabilizers.

Methodology

Source of Data and Analysis Method

Secondary data on variables such as GDP, inflation, UR, and AS were collected from the MAA and Macro Trends from 1990 to 2020. The dependent variable is represented by the AS along with the independent variables consisting of (i) GDP, (ii) IR, and (ii) UR. The impact of economic variables that affect AS is analyzed, and the relationship between inflation and unemployment in the automotive industry is identified to evaluate the importance of the automotive sector to economic growth in Malaysia. The analysis of data in this study is conducted using the Ordinary Least Square (OLS) regression model.

Ordinary Least Square (OLS)

The study employed the OLS regression model to test the relationship between the dependent variable and independent variables. The OLS model is specified as below:

$$y_t = \alpha_0 + \beta_1 x_t + u_t. \tag{1}$$

To determine the variables in this study, the estimable form of the equation is modeled as follows:

$$AS_t = \alpha_0 + \beta_1 GDP_t + \beta_2 IR_t + \beta_3 UR_t + u_t, \tag{2}$$

where is the AS, is the GDP, is the IR, and is the UR in the year t, respectively. Besides that, „ , and are the parameters to be estimated, and is the error term. The OLS method can be used to examine the interconnection of all variables. In fact, the unit root test indicates that all variables are stationary after analysis. This method can be estimated as:

$$Y_i = \beta_1 + \beta_2 X_i + e_i, \tag{3}$$

which can be written as: $e_i = Y_i - \hat{Y}$

$$= Y_i - \beta_1 - \beta_2 X_i.$$

The equation above indicates that the residuals (e_i) represent the difference between the actual value (Y_i) and the estimated value (). OLS method reduces the residual sum of squares in terms of choosing β_1 and β_2. As stated above, the pure outcome of stationary series using non-stationary will be successful by differencing, and the relationship can be easily analyzed. Nevertheless, it represented the difference only the changes of short-run and long-run information will be totally missed out. It is not advised to use this method for non-stationary variable analysis.

Unit Root Test

Unit root tests are tests for stationarity in a time series analysis. If the stationarity of the time series changes in time, it does not cause a change in the shape of the distribution, while unit roots are the ones caused by non-stationary. The null hypothesis of a unit root test typically involves the presence of a unit root, while the alternative hypothesis varies based on the type of test used and may be either static, trend stationary, or explosive root. This test aims to decide whether the trended data needs to be transformed through either differencing or regression with deterministic time functions to make it stationary. This test is also an important econometric task that determines the most appropriate form of the trend in the data. There are two types of methods to test unit root: Augmented-Dicker-Fuller (ADF) and Philip-Perron (PP) tests.

Augmented Dicker-Fuller (ADF) Unit-Root Test

The ADF unit root test is used to determine whether the variables, which are AS, GDP, IR, and UR, are stationary. The ADF model is a widely used method for testing the presence of a unit root in a series (yt). To test for unit root using the ADF model, the following steps are taken:

$$\Delta y_t = \beta_1 + \delta y_{t-1} + \alpha_i\, \Sigma^p{}_i - {}_1 \Delta y_{t-1} t + e_{t,}$$

where $\delta = \alpha - 1$, α = coefficient of y_{t-1}, Δyt = The first differencing operator for variable interest (AS, GDP, IR, UR). The ADF test's null hypothesis is $\delta = 0$, with an alternative hypothesis of $\delta < 0$. Failing to reject the null hypothesis indicates that the series is non-stationary, while rejecting the null hypothesis implies that the series is stationary.

Philips-Perron (PP)Unit Root Test

PP tests are another model used to test the presence of unit roots in a time series. The PP test method is as follows:

$$\Delta y_t = \pi\, y_{t-1} + \beta_i D_{t-i} + e_{t,}$$

where e_t is a I(0) with zero mean and D_{t-i} is a deterministic trend component. When the hypothesis $\pi = 0$, the main difference from the ADF test is that the PP test is non-parametric. This means that under the null hypothesis, it does not need to specify the form of the serial correlation of Δyt. The calculation procedure of the t-ratio to obtain the value of π is also different. Furthermore, the PP test corrects the statistics for autocorrelation and heteroskedasticity issues. For larger volumes of financial data, the PP test is recommended.

Autoregressive Distributed Lag (ARDL) Model

Autoregressive Distribute Lag (ARDL) is a regression model based on OLS that can be applied to non-stationary time series and time series with mixed-order integration. The model includes enough lag to capture the general data generation process in a specific modeling framework. The following simple model is presented to illustrate the ARDL modeling approach:

$$y_t = a + \beta x_t + \delta z_t + e_t. \tag{4}$$

Cointegration Test

The Johansen cointegration test analyses the long-term correlation between dependent and independent variables. Since all variables have the same order of integration, it is possible to determine the cointegration using this test. The cointegration test equation was proposed by Johansen in 1988 and is as follows:

$$\Delta Y_t = \pi Y_{t-1} + \sum_{i=1}^{p-1} \pi_i \Delta Y_{t-i} + BX_t + \varepsilon_t, \quad (5)$$

$$\pi = \sum_{i=1}^{p} A_i - 1,\ \pi_i = -\sum_{j=i+1} A_j, \quad (6)$$

where Y_t = k-vector of non-stationary variables, X_t = d-vector of deterministic variables, and ε_t = vector of white noises, respectively. The hypothesis of the cointegration test is as follows:

H_0: r = 0 (no cointegration exists between dependent and independent variables).

H_1: r ≠ 0 (cointegration exists between dependent and independent variables). The trace test was preferred despite the different results generated by the trace test and the maximum eigenvalue test.

Error Correction Model (ECM)

The Error Correction Model (ECM) is obtained from the ARDL model using a linear transformation, and it combines the short-run dynamics and long-run equilibrium to avoid spurious relationships caused by non-stationary time series data. This allows the model to retain the long-run information while still considering short-run dynamics. The relationship above can be written in log form as below:

$$y_t = k + x_t. \quad (7)$$

The general dynamic relationship between *y* and *x is* as follows:

$$y_t = \beta_0 + \beta_1 x_t + \beta_2 x_{t-1} + \alpha_1 y_{t-1} + u_t. \quad (8)$$

Set $y_t = y^*$ and $x_t = x^*$ and set $u_t = u^*$. Thus, we get

$$y^* = \beta_0 + \beta_1 x_t + \beta_2 x^* + \alpha_1 y^*,$$

$$(1-\alpha_1)y^* = \beta_0 + (\beta_1 + \beta_2)x^*,$$

$$Y^* = \beta_0 / (1-\alpha_1) + \beta_1 + \beta_2 / (1-\alpha_1)\, x^*. \quad (9)$$

If the above corresponds with equation (6):

$$\beta_0 / (1-\alpha_1) = k,$$

$$\beta_1 + \beta_2 / (1-\alpha_1) = 1.$$

The second relationship above is $\beta_1 + \beta_2 = (1-\alpha_1)$. Let γ denote the common value of these two terms. Then, β_2 can be written as $\gamma - \beta_1$, and α_1 can be written as $1 - \gamma$. Therefore equation (9) becomes:

$$Y_t = \beta_0 + \beta_1 x_t + (\gamma - \beta_1)x_{t-1} + (1-\gamma)y_{t-1} + u_t$$

$$y_t = \beta_0 + \beta_1 x_t - \beta_1 x_{t-1} + \gamma x_{t-1} - \gamma y_{t-1} + y_{t-1} + u_t,$$

$$y_t - y_{t-1} = \beta_0 + \beta_1(x_t - x_{t-1}) + \gamma(x_{t-1} - y_{t-1}) + u_t,$$

$$\Delta y_t = \beta_0 + \beta_1 \Delta x_t + \gamma(x_{t-1} - y_{t-1}) + u_t,$$

where $\Delta x_t = x_t - x_{t-1}$, and this is the ECM specification, where changes in one variable are related to the change in another variable.

Results and Discussion

Unit-Root Test Results

Table 1 shows the unit root test results of the variables using both the ADF and PP Tests. The results showed that, in the ADF test, AS, GDP, and IR are stationary at level, but the UR rate is determined as non-stationary because the significance level is more than 5 percent. Therefore, the first difference of all variables results in being stationary. These indicate that the integration of the Malaysian automotive industry and economic variables are stationary at the First difference I(0) with Trend & Intercept with ADF test. The PP test results also showed that UR is non-stationary in level and only stationary at first difference I(0) and other variables as well. Therefore, the unit root test results for all variables showed that the data are stationary at first difference I(0) with trend and intercept with PP test.

The next step is to select the optimal number of lags for the ARDL model. Table 2 shows that the lag order selection estimated by the Vector Autoregression (VAR) model to determine the lowest values of the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) as the VAR model is fitted for various lag lengths. The optimum number of lags for the ARDL model is selected with the lowest value of AIC and SIC. The VAR model is run with different lags, and the values of AIC and SIC are noted. The results showed that the lag length at 2 with the smallest values is selected as the standard ARDL model with optimal lags.

Table 1: Result of Unit Root test

Variable	UNIT ROOT TEST (ADF)				UNIT ROOT TEST (PP)			
	Level		First Difference I(0)		Level		First Difference I(0)	
	Intercept	Trend & Intercept	Intercept	Trend & Intercept	Intercept	Trend & Intercept	Intercept	Trend & Intercept
AS	0.0000**	0.0002**	0.0000**	0.0000**	0.0000**	0.0002**	0.0001**	0.0000**
GDP	0.0045**	0.0417**	0.0004**	0.0025**	0.0009**	0.0015**	0.0001**	0.0000**
IR	0.0190**	0.0041**	0.0000**	0.0000**	0.0137**	0.0038**	0.0000**	0.0000**
UR	0.0561	0.3655	0.0019**	0.0053**	0.0576	0.5095	0.0037**	0.0102**

Notes: (**) means that the significance level is less than 5 percent and the rejection of the null hypothesis.

Table 2: Lag Order Selection criteria for the ARDL model

Lag Order Selection AIC and SIC		
Lag length	**Akaike information criterion (AIC)**	**Schwarz information criterion (SIC)**
2	18.49994*	20.5512*
4	18.81747	22.13281

Notes: * indicates lag order selected by the criterion

After testing the variables for unit root effects, an ARDL model is constructed with an appropriate lag difference. Suppose the ADF test shows that all variables have the same order of integration. In that case, the analysis proceeds to identify the level of cointegration using the Johansen-Juselius Cointegration test, which employs the VECM approach. It has an optimum lag of 2. The standard ARDL model with the optimum lag is expressed as follows:

D(AS)C + D[AS(-1)] + D[AS(-2)] + D[GDP(-1)] + D[GDP(-2)] +D[IR(-1)] + D[IR(-2)] + D[UR(-1)] + D[UR(-2)] + + + LNFA(-1) +AS(-1) – GDP(-1) + IR(-1) – UR(-1) +ε

Moreover, the Breusch Grofey Serial Correlation Lagrange multiplier (LM) test result (Table 4) showed that serial correlation does not exist since probability and Chi-Square is insignificant and exceeds the significance value of 5 percent. The result showed that the probability of Chi-Square is 0.8534 of lag (2). Therefore, the decision is to reject the null hypothesis and accept the alternative positive serial correlation hypothesis. Regarding classical linear regression of assumption, the serial correlation LM test has fulfilled the criteria of the model.

Model validation test is applied using Cumulative Sum (CUSUM) charts to enhance the potential to observe the chart's small shifts that incorporate previous and current data values. The red line represents the 5 percent level of significance. According to Figure 2, the data of all variables were between two red lines or defined as data between two lines of 5 percent level significance. In conclusion, no points exceed a control limit, and no run or trend rules are violated.

Long Run Association of Economic Factors on Automotive Sales (Cointegration Test)

Next, the Johansen Cointegration test is utilized to identify the long-run correlation between AS, GDP, IR, and UR. The cointegration test offers a suitable outline to determine some proportion of the parameters through the probability tests. This study's main objective is to investigate whether there is a cointegration relationship between the Malaysian automotive industry and economic variables. The EViews output releases trace statistics and Max-Eigen Statistics.

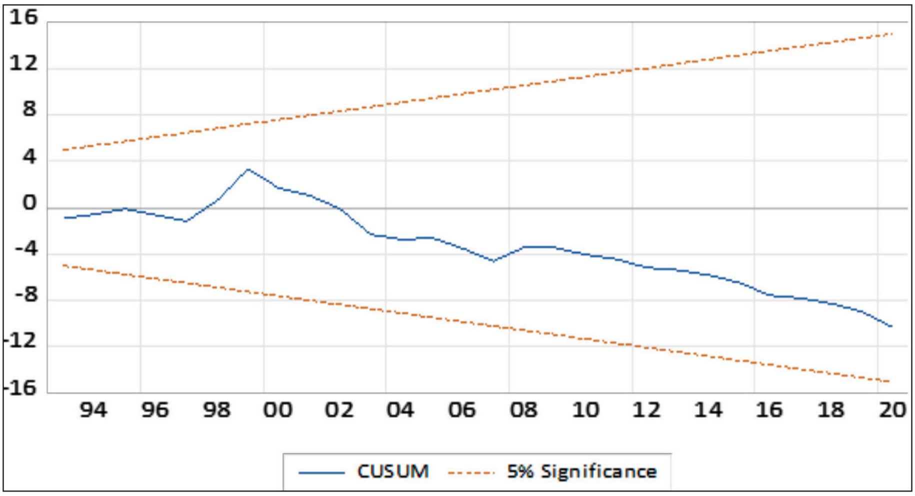

Figure 2: Charts of CUSUM test from serial correlation LM test

The Johansen tests, including the maximum eigenvalue and trace tests, are used to evaluate the long-term association between the variables. Both the maximum eigenvalue and trace test of the Johansen test examine the null hypothesis of no cointegration among the variables, with the alternative hypothesis being the presence of cointegration.

Maximum Eigenvalue test is conducted to determine whether the largest eigenvalue is zero or not. If the largest eigenvalue is zero and the rank is also "0", then there is no cointegration. On the other hand, if the largest eigenvalue is non-zero, the rank matrix is at least "1", and there might be more cointegration vectors. The test of the maximum (remaining) eigenvalue is a likelihood ratio test. The test statistic is, $LR\ (r_0; r_0 + 1) = -T\ \text{In}\ (1 - \lambda_{r0+1})$, where LR $(r_0; r_0 + 1)$ is the likelihood ratio test statistic for testing whether rank = r0 versus the alternative hypothesis that rank = r0 + 1. For example, the hypothesis that rank = 0 versus the alternative that rank = 1 is tested by the likelihood ratio test statistic LR $(0; 1) = -T \ln (1 - \lambda_{r0+1})$.

The trace test is used to evaluate whether the rank of the matrix is equal to r0, with the null hypothesis indicating that the rank is indeed equal to r0. On the other hand, the alternative hypothesis assumes that r0 < rank <= n, where n is the maximum possible number of cointegration vectors. If the null hypothesis is rejected in the first test, a follow-up test is conducted to test the null hypothesis that the rank is equal to r0 + 1, while the alternative hypothesis assumes that r0 + 1 < rank <= n. The likelihood ratio test statistic is, $LR(\text{r0}; n) = -T \sum_{r_0+1}^{n} \text{In}(1-\lambda_i)$, where LR(r0;$n$) is the likelihood ratio statistic for testing whether rank = r versus the alternative hypothesis that rank < = n. For example, the hypothesis that rank = 0 versus the alternative that rank < = n is tested by the likelihood ratio test statistic $\text{LR}(0; \text{n}) = -T \sum_{r_0+1}^{n} \text{In}(1-\lambda_i)$. According to Johansen (1995), The name "trace test" comes from the distribution of the test statistic, which is the trace of a matrix constructed using functions of Brownian motion or standard Wiener processes.

The result of the cointegration test for the economic variables and AS in both trace statistics and eigenvalues of all variables are non-zero, and there are more cointegration vectors among the variables. Therefore, results indicated a long-run association between the economic variables such as GDP, IR, and UR on AS in Malaysia.

Table 3: Cointegration Test Result (Johansen Test)

Variables	Eigenvalue	Trace Statistics	0.05 Critical Value	Maximum Eigenvalue	0.05 Critical Value
AS	0.824245	83.45236 (0.00000)**	55.24578	48.68267 (0.0001)	30.81507
GDP	0.503130	34.76970 (0.0530)**	35.01090	19.58395 (0.1840)	24.25202
IR	0.399795	15.76970 (0.1331)**	18.39771	14.29335 (0.1242)	17.14769
UR	0.031362	0.892199 (0.3449)**	3.841465	0.892199 (0.3449)	3.841465

Note: Trace test indicates 1 cointegration eqn (s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
** MacKinnon-Haug-Michelis (1999) p-values

Long Run Association of Economic Factors on Automotive Sales (Bound Test)

A bound test was derived from the ARDL model to confirm the long-run relationship between independent variables consisting of GDP, IR, and UR on AS, which represent dependent variables, and the results are shown in Table 4. The result of F-statistics conducted by lower and upper bound represents I(0) and I(1), respectively. This result is interpreted by referring to Narayan (2005), whose result found that the computed F-statistics value of 2.138812 is less than the lower bound, and the null hypothesis is accepted that no cointegration exists between the independent variables. In a nutshell, no long run was connected to AS among the three variables.

The ARDL model with the ECT is acquired to indicate the responsive direction where there is a steady, meaningful long-run equilibrium, and the results are shown in Table 4. The result of the Error Correction Term (ECT) derived from the ARDL model found out the coefficient of the ECT is -0.810579, and the probability is statistically significant at a 5 percent level, indicating that long-run equilibrium exists in the relationship between AS from each variable. In addition, the coefficient on the ECT at 81.0579 percent (Coefficient value: -0.810579) with a Probability value of 0.0140 shows equilibrium agencies remove the last percentage of disequilibrium in each period, which means the speed is very rapid. After conducting ECT, serial correlation and CUSUM tests should be checked again to determine the Chi-Square value.

Short Run Association of Economic Factors on Automotive Sales (Wald Test)

The short-run relationship between each economic variable and the Malaysian automotive industry was tested using the Wald test of the ARDL model (Table 4). The results indicated that the Chi-Square statistic had a probability of exceeding the significance level of 5 percent. There is no significant value, failure to reject null, and a short-run association between economic variables and AS. The details of the short-run association found a short-run effect by AS lag 2, GDPG lag 2, IR lag 1, IR lag 2, and UR lag 1 at 5 percent significance level. However, GDP lags 1 and UR lags 2 showed the probability of significance at 0.05, and it can be concluded that GDP has no short-run association with AS changes in one year. The UR is also not associated with AS in the two years.

Table 4: Diagnostics Test of ARDL Model and Hypothesis Test Results

Diagnosis Tests	Results	Decisions
Serial correlation LM Test H_0: There is no Serial Correlation H_A: There is a Serial Correlation	F- statistics = 0.134349 Prob. F = 0.8749 Prob. Chi-Square = 0.8534 R-squared = 0.317093 Durbin-Watson stat = 1.856289	Prob. F-value (0.8749) >0.01 Do not reject Ho. Thus, residuals have no serial correlations.
Long run association: Bond Test H_0: There is no long-run association. H_A: There is long-run association. I(0) I(1) 10% 2.37 3.2 5% 2.79 3.67 2.5% 3.15 4.08 1% 3.65 4.66	F- statistics = 2.138812	Less than lower bond I(0) Fail to reject Ho. There is no long-run association by explanatory variables on AS.
Error Correction Term (ECT) Test	Coefficient = -0.810579 Probability = 0.0140	Significant at 5 percent level. Long-run association exists
Short-run association: Wald Test H_0: There is a short-run association. H_A: There is no short-run association.	F-Statistics (probability)=0.7295 Chi-Square (probability)= 0.7257 Variables Coefficient Prob. C 1.44 0.7665 D(AS(-2)) -0.12 0.6711 D(GDPG(-1)) 5.13 0.0072 D(GDPG(-2)) 0.22 0.9068 D(IR(-1)) - 2.59 0.4601 D(IR(-2)) - 2.11 0.5455 D(UR(-1)) -3.05 0.9093 D(UR(-2)) 47.72 0.0545 ECT(-1) -0.87 0.0109	0.7295 > 0.05, fail to reject Ho, There is a short-run association between explanatory variables and dependent variables. There is a short-run effect by AS lag 2. No short-run effect by GDPG lag 1. There is a short-run effect by GDPG lag 2. There is a short-run effect by IR lag 1. There is a short-run effect by IR lag 2. There is a short-run effect by UR lag 1. No short-run effect by UR lag 2.

Conclusion

In conclusion, economic variables (GDP), unemployment, and IR are the main economic impact determinants that affect the automotive industry in Malaysia. The effective unemployment recommendation, one of the negative impacts on the automotive industry, can improve the demand for AS to become more positive. The first objective of this study is to identify whether the economic variables affect AS in the Malaysian economy. The results showed that AS in Malaysia has no impact from the economic variables with long-run relationship and cointegrated between AS, GDP, IR, and UR. However, a positive short-run relationship existed between GDP with lag 2 or in two years. No relation was found in lag 1 on

AS using correlation analysis, and it represents the highest beta compared to the other variables. This means GDP is the major factor in AS within Malaysia's two-year cycle. Furthermore, the relationship between the IR and AS showed a significant short-run association with a negative effect, and the IR negatively affected AS in Malaysia for one to two years. The UR and AS showed negative short-run effects in one year, and it could be concluded that unemployment affects AS through interrelation with GDP growth in Malaysia. Among all the economic factors, GDP showed an effect within two years. The country's economic growth had a more explanatory effect on AS in Malaysia within a short time. Moreover, the same pattern of negative effect was found in the UR, which might be the cofactors with GDP growth on AS. The findings could contribute to managing the automotive industry both in the long and short run by looking at the economic factors in the country. Based on our findings, the government must focus on reducing the negative impact of IR and UR during the pandemic outbreak of COVID-19 which would weaken the production and demand of the automotive industry. In future research, a more thorough analysis could be carried out, including a detailed analysis of the automotive industry in each vehicle category, such as passenger vehicles, industry-used vehicles, etc.

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Conflict of Interest

All authors declared that they have no conflicts of interest.

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