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Benchmarking company performance from economic and environmental perspectives

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Abstract

Purpose – The purpose of this paper is to develop an approach to measuring the performance of motor vehicle manufacturers (MVMs) from economic and environmental (E&E) perspectives.

Design/methodology/approach – Eight measures are identified for benchmarking the performance from E&E perspectives. A new company performance index I_{MVM} is constructed to quantitatively generate the historical data of MVMs' company performance. Autoregressive integrated moving average (ARIMA) models are built to generate the forecast data of the I_{MVM}. The minimum Akaike information criteria value is used to identify the model of the best fit. Forecast accuracy of the ARIMA models is tested by the mean absolute percentage error.

Findings – The construction of the index I_{MVM} is benchmarked against three frameworks by six benchmark metrics. The I_{MVM} satisfies all of its applicable metrics while the three frameworks are incapable to satisfy their applicable metrics. Out of 15, 4 MVMs are excluded for benchmarking future performance due to their non-stationary time series data. Based on the forecast I_{MVM} data, GM is the best performer among the 15 samples in the FY2018.

Originality/value – This research highlights the environmental perspective during vehicles' production. The development of this approach is based on publicly available data and transparent about the methods it used. The data out of the approach can benefit stakeholders with insights by benchmarking the historical performance of MVMs as well as their future performance.

Keywords Benchmarking, Performance measure, Time series forecasting, Motor vehicle manufacturer

Paper type Research paper

1. Introduction

Growing concerns on the environmentally sustainable development call for data analysis from both economic and environmental (E&E) perspectives. For instance, to access the E&E performance of different countries, data analysis has been performed via analytical applications by the System of Environmental Economic Accounting. Unlike such data analysis which is at the national level or even broader global levels, this research focuses on E&E performance analysis at the company level.

The life cycle of a vehicle consists of three stages including production stage, use stage and end-of-life stage (Del Pero *et al.*, 2018). Production stage consists of mining, ingot production, material production, part production and vehicle assembly (Hakamada *et al.*, 2007). There are studies that state vehicles' production stage consumes a significant amount of natural resource and generates undesirable wastes. For instance, more than 95 percent of water consumption along the life cycles of Volkswagen's three car models is consumed in the production phase (Berger *et al.*, 2012).

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This research focuses on the production stage for motor vehicle manufacturers (MVMs). The term MVMs used in this research pertain to manufacturers that are primarily engaged in the design and manufacture of motor vehicles including passenger cars, commercial vehicles, buses and coaches. MVMs make a profit with input including materials, resources and energy, and output including vehicles, components and various pollutants. In 2018, some 91.5m vehicles were produced worldwide (Statista, 2019). Along with this production, a large volume of CO_2 has been emitted, which contributed around 73 percent to global greenhouse gas (GHG) (PBL Netherlands Environmental Assessment Agency, 2018). It is estimated that up to 16 percent of global man-made CO_2 emissions come from motor vehicles (International Organization of Motor Vehicle Manufacturers, 2019). In other words, CO_2 takes up about 12 percent of the total GHG. Environmental performance is an important dimension of organizational performance (Hart, 1995). MVMs are expected to take a long-term view in contributing toward the sustainable development rather than exclusively focusing on profitability. From the 1980s onwards, the vast majority of MVMs have adopted an active attitude toward the reduction of the environmental impact of their production processes (Orsato and Wells, 2007).

One technique of improving MVMs' performance is to identify existing gaps (Yasin, 2002) and to learn superior practices from their peers (Camp, 1989; Ramabadron *et al.*, 1997). Benchmarking is a management method aiming at finding performance gaps (Maleyeff, 2003). In addition, benchmarking is a very important instrument for the effective management of organizations to determine system performance (Ho and Wu, 2006). Many emerging business improvement methodologies, such as the total quality management (Deming, 1982) and knowledge management (Davenport and Prusak, 1998) involve an element of benchmarking and performance measurement (Moffett *et al.*, 2008). Benchmarking has been very widely deployed (Madsen *et al.*, 2017) within industries including manufacturing (Hong *et al.*, 2012), education (Lau *et al.*, 2018) and construction (Kim and Huynh, 2008).

Data at the company level such as profit generally are discrete in a series of particular time periods. These types of data are called time series data. Time series analysis can be used in business applications for forecasting a quantity into the future and explaining its historical patterns. Effective forecast of time series data can assist decision makers to better understand the trend of company performance in the complex business environment. Therefore, performance analysts use time series forecasting methods to quantitatively predict time series data's future values. However, current benchmarking studies focus more on individual benchmarking of certain individual measures from their previous performance.

Measuring and benchmarking the performance or MVMs with various measures is important and requires a very high level of effort. The use of conventional financial measures will provide straightforward company performance from an economic perspective. The advantages of these financial measures are that they are readily available and easy to use and understand (Joo *et al.*, 2009). However, there is one drawback, that is, it focuses more on benchmarking certain individual measure from historical performance of the same measure. Consequently, a comprehensive picture of MVMs' performance from E&E perspectives is missing.

In order to benchmark both of the historical performance and the future performance of MVMs from E&E perspectives, a time series data of this performance are crucial. Therefore, the main research question of this research arises as:

RQ1. How to measure the performance of MVMs from E&E perspectives?

The main research question is broken into the following sub-questions:

RQ1a. What measures can be applied to quantify the performance of MVMs from E&E perspectives?

RQ2b. Given the forecast horizon $h = 1$, how to generate the yearly time series data of this performance?

The remaining of this paper is organized as follows. Section 2 presents a literature review on company performance measures and on time series forecasting methods. Section 3 presents the methodology to develop the benchmark approach. First, a conceptual framework of company performance measurement from an economic perspective and from an environmental perspective is developed for MVMs. Then, an approach to measuring its historical (FY2008–FY2017) performance and future (FY2018) performance is developed. Section 4 generates data of historical performance and future performance with a case study in 15 MVMs. The effectiveness of the approach is shown for FY2017 with the mean absolute percentage error (MAPE) as an error criterion. Section 5 discusses the results out of the data analysis. Finally, the last section concludes this paper by indicating its limitation and four recommendations for further research.

2. Company performance measurement

Stakeholder theory suggests that companies should go beyond shareholders' interests to include other stakeholders (Keeble *et al.*, 2003; Pullman and Wikoff, 2017). In terms of company performance from E&E perspectives, key stakeholders of MVMs consist of customers, business partners, owners, employees, investors, government, non-government organizations (NGOs) and non-profit organizations (NPOs). The main concerns of stakeholders regarding company performance are listed in Table I. Based on different stakeholders' concerns and literature review, company performance measures from E&E perspectives are identified.

2.1 Economic measures from S_1, S_2, S_3 and S_6

There are several company performance measures that drive company performance from an economic perspective. As shown from the blue part in Figure 1, there are five measures that stakeholders concern about:

(1) Taking into account the concerns from S_1 customers, S_2 employees and S_3 business partners especially suppliers, a value-leverage perspective has been identified to measure the flow of products through the processes from an operation performance and financial economic perspective (Beelaerts van Blokland *et al.*, 2012). To express the value-leverage capabilities, there are three measures including turnover per employee (T/E), profit per employee (P/E) and research and development expenditure per employee (R&D/E).

(2) The measure operating cash flow margin matters to S_3 business partners. It is a measure of a company's liquidity. S_3 business partners are concerned whether they will be paid the amount promised to them at the date that was promised to them. If the value of operating cash flow margin is less than 1, S_3 may reason that

Label	Stakeholder	Concerns
S_1	Customers	Product price, product quality, after sales service, response time
S_2	Employees	Safe and healthy working condition, remuneration packages, quality of life, welfare measures
S_3	Business partners	Procurement policies, green supply chain management, information exchange
S_4	Financial organizations	Financial information, repayments, loans, environmental policies
S_5	NGOs or NPOs, Governments	Regional contribution activities, donations activities, product footprint, revenue and tax distribution, contribution to GDP, environment compliance, environmental preservation projects
S_6	Owners	Profitability, revenue, stock price, grievances and complaints, corporate governance, management of risk

Table I. Stakeholders of MVMs and their concerns from E&E perspectives

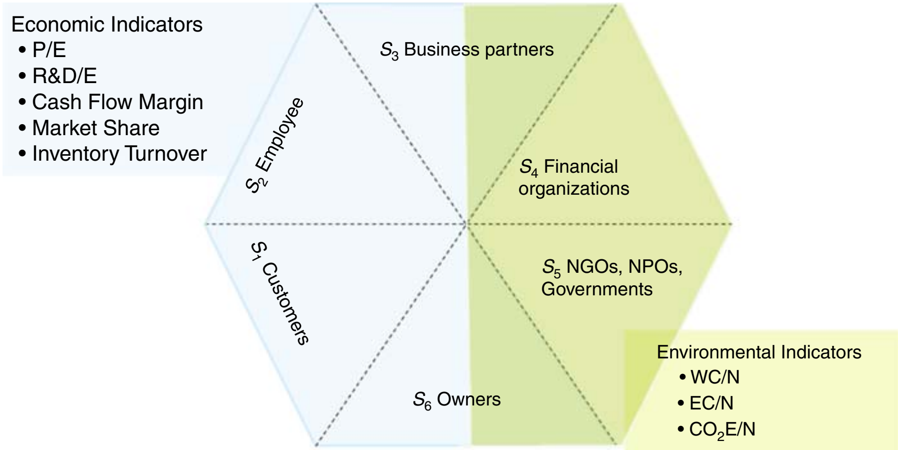

Figure 1.
Measures that stakeholders concern about from E&E perspectives

the company has generated less cash in the period than it needs to pay off its short-term liabilities.

(3) S_6 owners concern more about the measure market share. Increasing market share is the ultimate goal of any business marketing plan. It is mainly about taking competitive advantages to gain customers from established competitors. This measure is used to give a general idea of the percentage of a market (defined in terms of either units or sales) accounted for by a specific company over a specified time period (Kozmetsky and Yue, 1998).

(4) Another concern to S_6 owners as well as to S_3 suppliers is the inventory turnover. It is a financial measure used in accounting to understand how long it takes for a business to convert its inventory to cash. It reflects the overall efficiency of the supply chain, from S_2 suppliers to S_1 customers (Rabinovich *et al.*, 2003).

2.2 Environmental measures from S_3, S_4, S_5 and S_6

There are more and more MVMs participating in environmental preservation projects and releasing environmental policies regarding developing eco-friendly products (Audi AG, 2018), reducing over-consumption of energy and reducing GHG emissions. Stakeholder pressure is the main factor driving organizations toward more advanced environmental management (González-Benito and González-Benito, 2005). Investors and financial institutions are becoming increasingly concerned about company environmental policies (Chang *et al.*, 2015; Maxwell, 1873). In addition, suppliers are becoming more knowledgeable about products' environmental impact. A firm will be seriously damaged if suppliers withdraw from it (He *et al.*, 2011). NPOs, such as Greenpeace in the Netherlands (Greenpeace International, 2018), take inventive actions for reducing resource over-consumption and they take action against companies that damage the environment. Therefore, as shown from the green part in Figure 1, three measures are identified from an environmental perspective taking into account concerns mainly from S_3 business partners, S_4 financial organizations and S_5 governments, NGOs or NPOs.

It is suggested that environmental management should be based on a systemic approach incorporating environmentally conscious strategy at every level of the organization (Jabbour, 2010). This research includes measures that are available from public documents. Therefore, studies that focus on variables that are not measurable from public documents are excluded.

Based on data availability from public documents, three measures were identified for MVMs, including water consumption divided by the number of vehicles produced (WC/N), energy consumption divided by the number of vehicles produced (EC/N) and CO_2 emissions divided by the number of vehicles produced (CO_2E/N) (Zeng *et al.*, 2018). Although other measures can be found from literature, they are excluded in this research due to their data unavailability. For instance, the adoption of eight environmental management variables may generate advantages in six measures in organizations of automotive companies (Jabbour *et al.*, 2013). However, the eight variables will not be used in this research because they are without available data from public documents. Different measures are proposed including information on kilograms of carbon dioxide emitted for the production, water consumption in liters for the production and information on the length of the transportation route (Plank and Teichmann, 2018). Because, it is not feasible to get accurate information on the length of the transportation route during vehicles' production, two measures are not eligible as measures in this research.

2.3 Time series forecasting

Time series forecasting can aid decision makers to plan for the future by understanding how changes in inputs affect outcomes. This method forecasts the future data on the basis of underlying patterns that are obtained from the historical data. There are several types of time series models such as moving average (AR) models and exponential smoothing models. As one of the time series forecasting methods, autoregressive integrated moving average (ARIMA) models can represent different types of time series such as pure AR models, pure moving average (MA) models and mixed AR and MA processes (Ramos *et al.*, 2015).

The ARIMA forecasting involves an iterative three-stage process of model selection, parameter estimation and model checking (Box *et al.*, 2015). It is important to evaluate forecast accuracy using genuine forecasts. The accuracy of forecasts can only be determined by considering how well a model performs on data that were not used when fitting the model (Hyndman and Athanasopoulos, 2018). Percentage errors have the advantage of being scale independent which makes it frequently used to compare forecast performance between different data sets. The main percentage errors are the mean percentage error and the MAPE.

2.4 Performance measurement of MVMs

For MVMs, several measurement frameworks have been developed as important methodologies for improving companies' competitiveness. There are three well-accepted frameworks including Dow Jones Sustainability World Index, Newsweek Green Rankings and Automobile Manufacturer Industry Scorecard.

2.4.1 Dow Jones Sustainability World Index. The World Index, or the Dow Jones Sustainability Indices (DJSI) World, first published in 1999, comprises global sustainability leaders as identified by Dow Jones Indexes, STOXX Ltd & SAM Group, 2013). It represents the top 10 percent of companies based on factors from environmental, social and governance developments. There are three dimensions totally with 24 criteria within this framework. The environmental factors include operational eco-efficiency, low carbon strategy, environmental reporting, climate strategy, product stewardship and environmental policy management systems. The weights of the 24 criteria were provided by RobecoSAM.

2.4.2 Newsweek Green rankings. Green Rankings 2017 is one of the most recognized environmental performance assessments of the world's largest publicly traded companies (Newsweek, 2017). This ranking was produced by the magazine Newsweek in partnership with Corporate Knights. The Global 500 from Green Rankings consists of an assessment of the 500 largest publicly traded companies in the world by revenue. Based on the data from Bloomberg, FactSet, Thomson Reuters and the Carbon Disclosure Project 19 motor vehicle companies were included in GLOBAL 500 2017, with the ranking rangeing from 16th to 366th.

2.4.3 Automobile manufacturer industry scorecard. In 2017, Moody's Investors Service developed a scorecard as the methodology for rating companies that are primarily engaged in the design and manufacture of passenger vehicles (Moody's Investors Service, 2017). Its methodology includes a scorecard which is a relatively simple reference tool that can be used in most cases to explain the factors that are generally most important in assigning ratings to issuers in the motor vehicle manufacture sector. All factors are financial measures except the "trend in Global Unit Share Over Three Years." However, this forward-looking measure brings a shortcoming, namely, key rating assumptions related to unanticipated changes such as general financial market conditions and industry competition can cause the rating to be incorrect.

2.4.4 Limitations of the three measurement frameworks. Despite that the three frameworks are currently well accepted, there are five limitations as follows:

(1) The measurement does not take into account environmental concerns. For instance, the Automobile Manufacturer Industry Scorecard fails to take environmental variables into account.

(2) The measurement is not designed especially for MVMs. For instance, the Global 500 from Newsweek Green Rankings uses the same methodology (with same criteria) for multiple industry sectors.

(3) The measurement involves experts' scoring to weigh variables, but fails to tackle the uncertainty and subjectivity inherent in experts scoring. For instance, methodologies for the DJSI World and the Automobile Manufacturer Industry Scorecard involve questionnaires to get weights. However, a step of handling the subjectivity of respondents is missing.

(4) The measurement keeps the importance levels/weights of variables/factors/measures approximated, fixed or totally the same for all companies. This is not applicable in reality because actual importance levels/weights of variables may vary substantially. Besides, companies in different application sectors may value the variables differently.

(5) The measurement is not constructed with clear methods for normalizing measures and aggregating measures.

3. Development of the performance measurement approach

Take the five limitations into account, this research aims to develop an approach with five requirements, namely, it is with an integration of measures from E&E perspectives; it is designed for MVMs by taking into the specific background into consideration; it is based on data which are available from public documents; it is mathematically constructed with transparency in generating time series data; and it provides a forecast value for benchmarking the future performance of MVMs in the following fiscal years.

An approach is developed for time series analyzing company performance for MVMs with three phases. In phase I, a conceptual framework of company performance for MVMs from E&E perspectives is developed. In phase II, an index of company performance (I_{MVM}) is constructed for generating the historical values of a time series. In phase III, the I_{MVM} forecast in FY2018 is analyzed based on ARIMA models. The three phases are shown in Figure 2.

3.1 Phase I: concept of company performance of MVMs from E&E perspectives

Performance benchmarking involves a comparison of measures (Adebanjo and Mann, 2008). It is crucial to choose those relevant E&E performance measures that meet the conditions for MVMs. Based on literature and measures' data availability, eight measures are identified

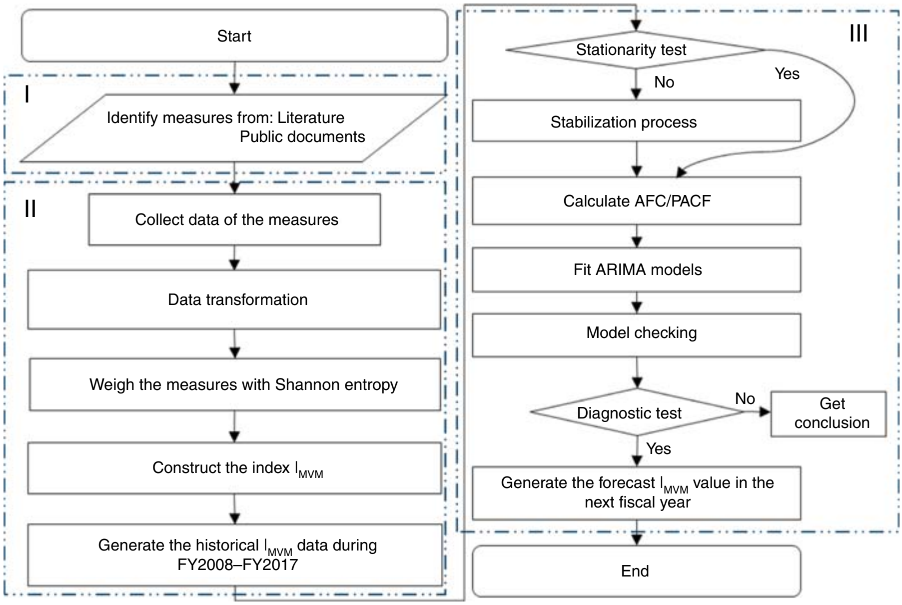

Figure 2.
An approach to generating time series data of company performance from E&E perspectives

as follows. Each measure is denoted with its impact direction. Impact "+" denotes the measure which satisfies "the larger its value is, the better the result gets" and impact "–" denotes the measure which satisfies "the smaller its value is, the better the result gets."

3.1.1 Measures from an economic perspective. Economic performance measures are identified as follows:

(1) Market Share. This metric is used to give a general idea of the size of a company in relation to its market, which can be defined by the sample company's production volume divided by the total production volume of all the sample companies (Kozmetsky and Yue, 1998; Tseng *et al.*, 2009). It is calculated as in the following equation. This measure is with the impact "+":

$$V_1 = \frac{N_i[\#]}{\sum_{i=1}^{n} N_i[\#]} \times 100\%, \tag{1}$$

where N is the motor vehicle production volume of company i; i the motor vehicle manufacturers ($i = 1, 2, \ldots, n$); and n the size of sample manufacturers.

(2) Cash Flow Margin. It is defined by the efficiency that a company converts its sales to cash. The higher the percentage, the more cash is available from sales. Some companies' fake transactions to ensure that sales numbers look good to the stock market. However, since only genuine sales can bring in cash flow, analysts can more accurately value the stock by operating cash flow (Chandler and Hanks, 1993). It is calculated as in the following equation. This measure is with the impact "+":

$$V_2 = \frac{\text{CFO}\,[\$]}{\text{NS}\,[\$]} \times 100\%, \tag{2}$$

where CFO is the cash flows from operating activities and NS the net sales.

(3) Continuity. Manufacturers are seeking to innovate with research partners to guarantee business continuity (Beelaerts van Blokland, 2010). The variable profit per capita was proposed to measure the continuity of a company. It involves attracting market demand for the vehicles or components (Beelaerts van Blokland *et al.*, 2012). In this research, the measure on a per-employee basis is used for continuity. Here, the term "Employee" refers to any person who is regularly employed by the company or consolidated subsidiaries or affiliated companies worldwide at a salary and is enrolled on the active employment rolls of the company or a subsidiary. It excludes part-time employees or apprentices. Continuity is calculated as in the following equation. This measure is with the impact "+":

$$V_3 = \frac{P[\$]}{E[\#]}, \tag{3}$$

where P is pretax operating profit and E the number of employees.

(4) Conception. It involves focusing on innovation within a company, and co-innovation with suppliers in the development process for new vehicles (Beelaerts van Blokland *et al.*, 2019). Innovation is a relevant aspect of corporate change and corporate success (Zegveld, 2004). The motor vehicle industry itself is asked to enhance technological innovations for improving the performances in terms of vehicles' safety, comfort and polluting emissions. Conception measures a company's ability of leveraging on its value system in order to develop new products (Beelaerts van Blokland, 2010). Despite that, a large-scale commercialization phase with innovative vehicles or motor components seems still far (Hildermeier, 2016; Lanzini, 2018), the motor vehicle industry is introducing in the market products with innovative technologies such as internet connection, AddiDrive Assist, electrical drive and vehicle networking technology. In this research, it is calculated as in the following equation. This measure is with the impact "+":

$$\mathrm{V}_4 = \frac{\mathrm{R\&D}[\$]}{\mathrm{E}[\#]}, \tag{4}$$

where R&D is the R&D expenditure.

(5) Inventory Turnover. It is defined by a ratio showing how many times a company has sold and replaced inventory during a given period. Inventory turnover can be calculated as sales divided by average inventory. It also can be calculated as the cost of goods sold divided by average inventory. Sales include a mark-up over cost, so its calculation inflates inventory turnover. For greater accuracy, inventory turnover is calculated as the cost of goods sold divided by average inventory (Zeng and Beelaerts van Blokland, 2018). It is calculated as in the following equation. This measure is with the impact "+":

$$V_5 = \frac{\mathrm{COGS}_t[\$]}{0.5 \times (I_t + I_{t-1})[\$]}, \tag{5}$$

where COGS is the cost of goods sold; t the fiscal year ($t = 0, 1, \ldots, T$); and I the inventory size.

3.1.2 Measures from an environmental perspective. Environmental performance measures are identified as follows:

(1) Water consumption per vehicle produced. Access to affordable water has been identified as one of the most important issues at risk through companies' activities.

Water consumption can be regarded as the indicator of the company's impact on water resources (Harik *et al.*, 2015). This figure is made up of freshwater consumption internal catchment, and freshwater consumption externally sourced (including rainwater used, ground water, surface water from lakes, rivers, ocean). For companies which do not report direct the data of water consumption, such as Nissan Motor Company, this figure can be measured by the difference between the amount of water intake (or water input or water withdraw) and water discharge. The water intake amount includes drinking water (tap water), industrial-use water, underground water (spring/well water) and rainwater (Harik *et al.*, 2015). It is calculated as in the following equation. This measure is with the impact "−":

$$V_6 = \frac{\mathrm{WC}\left[m^3\right]}{N_i[\#]} = \frac{\mathrm{WI}\left[m^3\right] - \mathrm{WD}\left[m^3\right]}{N_i[\#]}, \tag{6}$$

where WC is the water consumption; WI the water input; and WD the water discharge.

(2) Energy consumption per vehicle produced. The increasing use of energy-saving techniques is a recent trend in motor vehicle manufacture. Nevertheless, the motor vehicle manufacturing consumes a large volume of energy during the production process (Afgan and da Graça Carvalho, 2000). This figure is made up of the electricity, the energy from renewable energy sources, heating (including district heating), combustion gases for production processes and externally supplied refrigeration (source: G4–EN3 Power consumption within the organization). It is calculated as in the following equation. This measure is with the impact "−":

$$V_7 = \frac{\mathrm{EC[MWh]}}{N_i[\#]}, \tag{7}$$

where EC is the energy consumption.

(3) CO_2 Emissions per vehicle produced. This figure is made up of direct CO_2 emissions (Scope 1) and the indirect CO_2 emissions (Scope 2). Direct CO_2 emissions are from business activities, as defined by the GHG Protocol (examples: combustion of fuel oil at manufacturing plants). Indirect CO_2 emissions are from a company's use of energy, as defined by the GHG Protocol (examples: purchased electrical energy used by a manufacturing plant or office (source: G4–EN15 and G4–EN16 Direct and Indirect GHG emissions). It is calculated as in the following equation. This measure is with the impact "−":

$$V_8 = \frac{\mathrm{CE}[t]}{N_i[\#]}, \tag{8}$$

where CE is the CO_2 emissions.

3.2 Phase II: construct an index I_{MVM} and generate its historical data

In order to measure the integration of multidimensional measures, performance analysts use composite indicators. A composite indicator is defined as an index which is "formed when individual indicators are compiled on the basis of an underlying model of the multidimensional concept" (Joint Research Centre European Commission, 2008). Constructing indices mainly involves phases of selecting measures, weighting measures, normalizing measures to make them comparable and aggregating measures into one single index.

3.2.1 Normalize measures based on a min-max method. In this section, the index (I_{MVM}) is constructed with the eight measures from Phase I. In order to transfer measures with different measurement units into dimensionless measures, a normalization phase should be done. A linear method based on min-max algorithm is used by the following equation. After this normalization for all measures, the higher normalized value a manufacturer has, the better performance a manufacturer has in terms of the measure:

$$x'^t_{ij} = \begin{cases} 1+\frac{x^t_{ij}-\ \min x^t_j}{\max x^t_j-\ \min x^t_j} & \text{for measures with impact "+"} \\ 1+\frac{\max x^t_j-x^t_{ij}}{\max x^t_j-\ \min x^t_j} & \text{for measures with impact "−"} \end{cases}, \tag{9}$$

where j is the individual measures, $j = 1, 2, \ldots, m$; x^t_{ij} the value of measure j for manufacturer i in t; min x^t_{ij} the minimum value of measure j for manufacturer i in t; max x^t_{ij} the maximum value of measure j for manufacturer i in t; x'^t_{ij} the normalized value of x^t_{ij}, $x'^t_{ij} \in [1, 2]$.

3.2.2 Weigh measures based on Shannon entropy. Conduct the data transformation in Equation (9) for measures with negative values or not satisfied for logarithm application. Calculate the entropy value of measure j as Equation (10) and get weights for each measure as Equation (11):

$$e_j = -k \times \sum_{i=1}^{n} p_{ij} \times \ \ln p_{ij}, \ \ k = (\ln n)^{-1}, \tag{10}$$

$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j}, \ \ d_j = 1-e_i, \tag{11}$$

where p_{ij} is the relative frequency of x_{ij}; d_j the degree of diversification; and w_j the weight of measure j for manufacturer i, w_j (0, 1) and $\sum w_j \ = \ 1$.

3.2.3 Aggregate measures into a single index. The method in Phase VI is a geometric mean for aggregating individual measures into the single index I_{MVM}. Construct a multiplicative function in Equation (12), where $I_{MVM_i^t}$ is the company performance index for motor vehicle manufacturer i in the fiscal year t, w_j stands for the final weights of measure j. The historical data of I_{MVM} can be generated with measures as inputs based on the following equation:

$$I_{MVM_i^t} = f\left[x'^t_{ij}, w_j\right] = \prod_{j=1}^{8} \left(x'^t_{ij}\right)^{w_j}. \tag{12}$$

3.3 Phase III: time series forecasting of $I_{MVM_i^t}$

The I_{MVM} time series data by FY (during FY2008 to FY2017) is used to forecast its future data in FY2018. There are seven steps as follows:

(1) Examine the data. Plot the data and examine its patterns and irregularities. Clean up outliers and deal with missing values if needed. Take a logarithm of a series to help stabilize a strong growth trend. For certain economic and financial series, a logarithmic transformation process is required to stabilize the volatility of the time series.

(2) Decompose the data. Time series decomposition is a mathematical procedure to split a time series into three components including seasonality, trends and random fluctuations.

Decomposition is often used to remove the seasonal effect from a time series and provide a cleaner way to understand trends.

(3) Check stationarity. If it is unclear to tell stationarity from the data plot, a unit root test can be performed. The augmented Dickey–Fuller (ADF) test is a formal statistical test for stationarity. The null hypothesis assumes that a unit root is present in a series which means the series is non-stationary. The alternative hypothesis assumes that the series is stationary. Normally, non-stationary series can be corrected by difference transformations.

(4) Identify the order of AR (auto-regressive) and/or MA (moving average) terms. Besides the order of differencing d, there are another two parameters for ARIMA models. The autocorrelation function (ACF) plot displays correlation between a series and its lags. ACF plots can help in determining the order of the MA (q) model. The partial autocorrelation (PACF) plot displays correlation between a variable and its lags that are not explained by previous lags. PACF plots are useful when determining the order of the AR(p) model. By examining the ACF and PACF plots, the order of the MA (q) model and the order of the AR(p) model can be tentatively identified.

(5) Fit ARIMA models. Models with some extent of non-stationary in the AR part or moving average part should be excluded. Compare model errors and fit criteria. Two most widely used criteria are Akaike information criteria (AIC) and Bayesian information criteria (BIC). These criteria are closely related and can be interpreted as an estimate of how much information would be lost if a given model is chosen. The less the AIC or BIC value is, the better fitness the model is. In this research, the criterion AIC is used as the fit criterion considering AIC encourages the goodness of data fitting and tries to avoid overfitting.

(6) A diagnostic analysis of the identified model. Check residuals to see if the residual of the resulting model which is with the least AIC value is white noise. The residuals should have no patterns and be normally distributed.

(7) Calculate forecast values using the identified model. In this research, data in FY 2008–FY2016 are used for fitting the ARIMA model. Data in FY2017 are used for testing the errors between the forecast value and the real value. The value in FY2018 will be forecast by the model.

4. Case study

4.1 Sample cases

The case sampling is done by two steps. Step 1 is referring to the top 50 MVMs listed in the International Organization of Motor Vehicle Manufacturers (OICA). OICA represents the common interests of the global auto industry. Step 2 is filtering the MVMs that are without available data for measures V_1 to V_8 during the FY 2008–2017. As shown in Table II, the sampling processes result in 15 MVMs, including Toyota, Audi, Hyundai, GM, Ford, Nissan, Honda, FCA, Renault, PSA, Daimler, BMW, Mazda, Mitsubishi and Tata. The other 33 MVMs cases are not included as a case study manufacturer due to insufficient information in terms of their environmental performance.

4.2 Data collection

A data set that consists of available data for all the eight measures from the 15 MVMs needs building. Data are collected from multiple sources: annual reports from MVMs including financial reports, sustainability reports, environmental reports and corporate social responsibility reports; and professional websites for stock market information. The time span is a ten-year period from FY2008 to FY2017. In order to make the data comparative, the currency is all adjusted to US dollars. The units of the three environmental measures have been unified as follows which are in line with the unites in Equations (6)–(8):

(1) The unit of water consumption has been unified into cubic meters (m^3). Out of 15, 14 manufacturers report data in m^3 while Hyundai in ton. 1.0 ton of water = 1.0160469 metric ton of water = 1.0160469 m^3 of water.

(2) The unit of energy consumption has been unified into megawatt hour (MWh). Ten manufacturers report data in megawatt hour while Daimler in gigawatt hour, Ford in kilowatt hour, Honda in terajoule, FCA and Toyota in gigajoule. 1.0 Kilowatt hour = 1.0×10^{-6} Gigawatt hours = 1.0×10^{-3} Megawatt hours. 1.0 Terajoule = 1.0×10^{3} Gigajoules = 277.7778 Megawatt hours.

(3) The unit of CO_2 emissions has been unified into metric ton (*t*). Out of 15, 13 manufacturers report data in metric ton while FCA and Toyota in ton. 1.0 ton of CO_2 emissions = 1.0×160,469 metric ton of CO_2 emissions.

4.3 Generate the historical data of the index I_{MVM}

4.3.1 Normalize measures based on a min-max method. Get the normalized values of eight measures by Equation (9). Take the data in FY2017 as an example. As shown in Table III, the normalized values range from 1 to 2. The higher normalized value an MVM has, the better performance the MVM has.

4.3.2 Weigh the eights measures by Shannon entropy. Weights vary from FY to another. The value of the entropy is calculated for each of the eight measures in each FY by Equation (10). Accordingly, the weights of the eight measures are calculated by Equation (11) and listed in Table IV.

4.3.3 Aggregate measures into I_{MVM} and generate its historical data. Aggregate the eight measures into one single index, namely, the company performance index I_{MVM} by Equation (12). As shown in Table V, the data represent for the values of company performance index for each MVM during FY2008–FY2017.

4.3.4 Check stationarity of historical data during FY2008–FY2016. To demonstrate how to develop the autoregressive model, data from Toyota is used as an example. The data consist of nine observations. As shown in Figure 3, these data from Toyota have no missing values, no outliers or seasonality. Basically, there is an increasing trend in these data. It is unclear to test the stationarity from the plot. As shown in Figure 4, the same conclusion can be obtained for data in first order difference data. Therefore, an augmented ADF test is performed with the null hypothesis that a unit root is present in a time series.

Table II. Sample cases from top 50 MVMs based on OICA

Data availability	MVM
Yes	Toyota, Volkswagen, Hyundai, GM, Ford, Nissan, Honda, Fiat, Renault, PSA, Daimler, BMW, Mazda, Mitsubishi and Tata
No	Suzuki, SAIC, Changan, BAIC, Dongfeng Motor, Geely, Great Wall, Fuji, Chery, Anhui JAC Automotive, Iran Khodro, Isuzu, Mahindra, FAW, SAIPA, BYD, Brilliance, Guangzhou Auto Industry, Hunan Jiangnan, Chongqing Lifan Motor CO., AvtoVAZ, China National Heavy Duty Truck, Haima Cars, Ashok Leyland, Paccar, Shannxi, South East (Fujian), Changfeng, GAZ, Rongcheng Huatai, Xiamen King Long, Proton, Zhengzhou Yutong, Chengdu Dayun and Eicher

Normalized value	V'_1	V'_2	V'_3	V'_4	V'_5	V'_6	V'_7	V'_8
Toyota	2	2	1.199	1.524	1.286	1.721	1.582	1.539
Audi	1.072	1.53	1.185	2	1.21	1.75	1.547	1.618
Hyundai	1.357	1	1.061	1.337	1.241	1.676	1.839	1.602
GM	1.911	1.446	1.219	1.835	1.281	1.694	1.675	1.602
Ford	1.587	1	1.09	1.813	1.429	1.76	1.65	1.615
Nissan	1.491	1.379	1.199	1.524	1	2	1.726	1.824
Honda	1.407	1.181	1.199	1.524	1.256	1.297	1.533	1.098
FCA	1.348	1.425	1.045	1.095	1.239	1.836	1	1.931
Renault	1.228	1.464	1.018	1.349	1.244	1.708	1.733	2
PSA	1.21	1.278	1.029	1.255	1.291	1.788	2	1.939
Daimler	1.142	1.184	1.173	1.732	1.157	1.519	1.206	1
BMW	1.16	1.034	1.337	1.949	1.201	1.954	1.636	1.935
Mazda	1.042	1.033	1.029	1.491	1.206	1.48	1.622	1.879
Mitsubishi	1.005	1.477	2	1.628	1.02	1.488	1.645	1.916
Tata	1	1.276	1	1	2	1	1.548	1.566

Table III. The normalized value of measures in FY2017

FY	Weight	V_1	V_2	V_3	V_4	V_5	V_6	V_7	V_8
2008	e_j	0.992	0.993	0.995	0.993	0.992	0.994	0.988	0.994
	w_j	0.138	0.116	0.087	0.126	0.13	0.102	0.203	0.098
2009	e_j	0.992	0.99	0.993	0.993	0.993	0.995	0.996	0.99
	w_j	0.141	0.167	0.125	0.121	0.118	0.086	0.074	0.168
2010	e_j	0.992	0.993	0.992	0.994	0.993	0.993	0.993	0.994
	w_j	0.148	0.119	0.147	0.11	0.12	0.121	0.133	0.101
2011	e_j	0.99	0.992	0.992	0.993	0.994	0.991	0.995	0.994
	w_j	0.168	0.141	0.133	0.114	0.108	0.157	0.085	0.094
2012	e_j	0.99	0.994	0.99	0.993	0.995	0.993	0.995	0.995
	w_j	0.181	0.113	0.187	0.123	0.089	0.125	0.094	0.088
2013	e_j	0.99	0.993	0.992	0.994	0.994	0.993	0.994	0.996
	w_j	0.184	0.131	0.146	0.118	0.104	0.121	0.118	0.077
2014	e_j	0.992	0.992	0.993	0.994	0.995	0.993	0.994	0.996
	w_j	0.156	0.153	0.133	0.118	0.099	0.144	0.112	0.084
2015	e_j	0.992	0.99	0.992	0.993	0.995	0.995	0.992	0.995
	w_j	0.151	0.174	0.146	0.123	0.09	0.089	0.144	0.083
2016	e_j	0.991	0.993	0.993	0.993	0.994	0.995	0.995	0.994
	w_j	0.17	0.144	0.138	0.137	0.11	0.099	0.09	0.111
2017	e_j	0.989	0.993	0.993	0.993	0.994	0.995	0.995	0.993
	w_j	0.206	0.122	0.128	0.135	0.105	0.096	0.084	0.124

Table IV. The weights of the eight measures during FY 2008–FY2017

As shown in Table VI, the p-value is 0.6023 with the ADF result from the original data. This indicates that the null hypothesis should be accepted, that is, these original data from Toyota are non-stationary. In this case, a differential processing is needed. Generally, the differencing process starts with the order of $d=1$.

The ADF test on first order difference (diff1) data accepts the null hypotheses of non-stationarity. This suggests that diff1 is insufficient and should not be included in the model. In the second-order difference data, the p-value is 0.01 which is below the value 0.05. Therefore, the null hypothesis is rejected which means the second order difference data can be considered to be stationary.

The same test is performed to data of the other 14 MVMs. The test results are listed in Table VII. The data of FCA, PSA, Mitsubishi and Tata are non-stationary, no matter by its

Table V.
The values of I_{MVM} for each case during FY2008–FY2017

FY	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Toyota	1.578	1.546	1.57	1.397	1.61	1.607	1.712	1.764	1.594	1.613
Audi	1.557	1.511	1.614	1.504	1.719	1.552	1.698	1.649	1.526	1.421
Hyundai	1.326	1.373	1.492	1.488	1.537	1.457	1.5	1.469	1.354	1.59
GM	1.427	1.338	1.53	1.518	1.61	1.549	1.457	1.647	1.595	1.59
Ford	1.408	1.379	1.499	1.456	1.535	1.498	1.539	1.595	1.509	1.462
Nissan	1.484	1.465	1.453	1.5	1.516	1.425	1.553	1.61	1.567	1.475
Honda	1.573	1.54	1.397	1.415	1.402	1.341	1.406	1.383	1.366	1.306
FCA	1.277	1.3	1.295	1.315	1.346	1.292	1.387	1.272	1.329	1.33
Renault	1.421	1.441	1.394	1.365	1.405	1.359	1.473	1.525	1.436	1.402
PSA	1.46	1.413	1.409	1.295	1.329	1.318	1.368	1.429	1.431	1.386
Daimler	1.206	1.142	1.252	1.223	1.237	1.17	1.173	1.186	1.296	1.238
BMW	1.481	1.446	1.469	1.38	1.584	1.467	1.514	1.484	1.433	1.446
Mazda	1.316	1.265	1.27	1.316	1.258	1.371	1.304	1.436	1.317	1.279
Mitsubishi	1.102	1.111	1.253	1.416	1.475	1.378	1.487	1.41	1.476	1.443
Tata	1.387	1.613	1.374	1.433	1.217	1.168	1.251	1.252	1.288	1.215

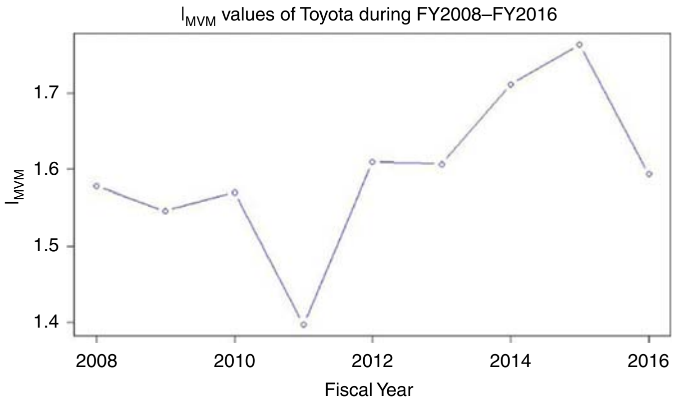

Figure 3.
The plot of data from Toyota

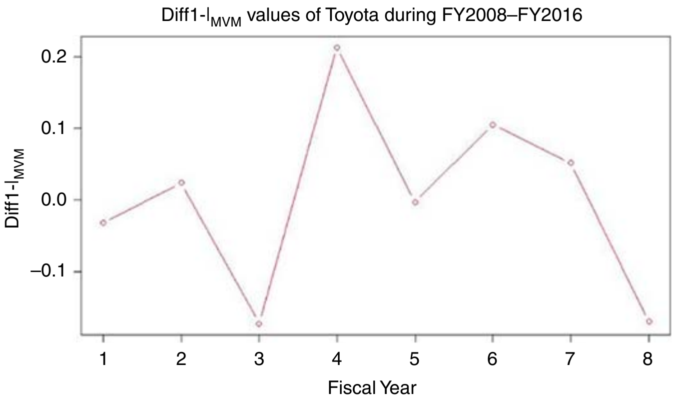

Figure 4.
The plot of data (diff1) from Toyota

original data, its first order difference data, second order difference data first order difference (diff1) data or its logarithm data. These kinds of sequence data are relatively rare in economic finance. One possibility is that the sequence data size is too small or the observations are inaccurate. These data are insufficient to reflect regularities. Therefore, the four MVMs are excluded from the following data analysis.

4.3.5 Choose the order of ARIMA models. Besides the order of differencing d, the order of the MA (q) model and the order of the AR(p) model need to be tentatively identified. Take the data from Toyota as an example. The second order differentiation data can be considered to be stationary. So the $d = 2$. As seen from Figure 5, order of MA term q can be 1. Similarly, as

Data	Dickey–Fuller	Lag order	p-value	Significant (Yes/No)
Original	−1.9215	2	0.6023	No
Data(diff1)	−0.99007	1	0.922	No
Data(diff2)	−5.0366	1	0.01	Yes

Table VI. Augmented Dickey–Fuller Test results for Toyota during FY2008–FY2016

Case	p-value from original data	Significant (Yes/No)	p-value from data (diff1)	p-value from data (diff2)	p-value from data ln()	Significant (Yes/No)
Toyota	0.6023	No	–	0.01	–	Yes
Audi	0.99	No	–	0.01	–	Yes
Hyundai	0.9221	No	–	0.045	–	Yes
GM	0.691	No	–	0.01	–	Yes
Ford	0.702	No	–	0.01	–	Yes
Nissan	0.99	No	0.02561	–	–	Yes
Honda	0.01	Yes	0.01	–	–	Yes
FCA	0.99	No	–	0.4154	–	No
Renault	0.99	No	–	–	Ln(diff2)–0.0412	Yes
PSA	0.7909	No	0.1662	0.6325	Ln(diff2)–0.1662	No
Daimler	0.99	No	–	0.02741		Yes
BMW	0.9491	No	–	–	Ln(diff2)–0.03001	Yes
Mazda	0.9505	No	0.04479	–	–	Yes
Mitsubishi	0.6334	No	0.6334	0.5933	Ln(diff1)–0.6416	No
Tata	0.953	No	0.7951	0.8651	Ln(diff1)–0.8027	No

Table VII. Augmented Dickey–Fuller test results for fifteen MVMs during FY2008–FY2016

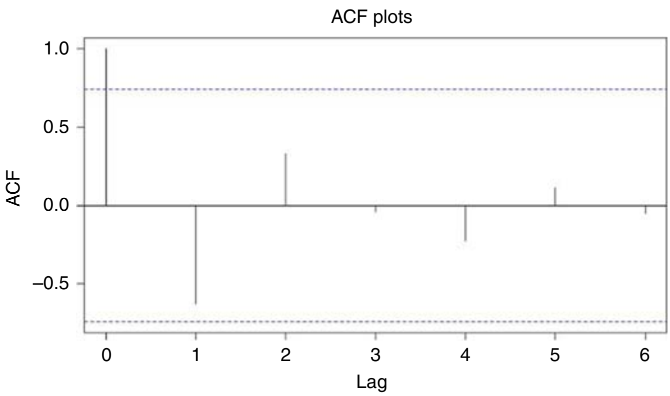

Figure 5. The ACF plot from data (diff2) of Toyota

shown in Figure 6, the order of AR term can be $p = 1$. So, the parameters ($p = 1$, $d = 2$, $q = 1$) is used to fit models with the original data from Toyota.

4.3.6 Fit ARIMA models and identify the model with the least AIC value. For fitted ARIMA models, AR orders (1 through 2) are run against MA orders (1 through 2). The differentiating order d is identified as 1 or 2. Therefore, a total of seven models can be fitted for each MVM. The AIC values are calculated for each potential fitted model in Table AI. The AIC with "N.A." indicates that there is some extent of non-stationary in the auto-regressive part of the model. These models are excluded despite the AIC value is less. The minimum value of AIC is used to identify the model of the best fit for 11 MVMs (4 out of 15 MVMs are excluded due to non-stationary data). The models of the best fit are marked in italic. Take Toyota as an example. The model ARIMA (2,2,0), which incorporates second-order difference data and uses an autoregressive term of second lag, has been identified as the ARIMA model of the best fit. The model can be written as following equation where "E" stands for error:

$$\hat{Y}_t = 1.0083\hat{Y}_{t-1} - 0.4323\hat{Y}_{t-2} + E, \tag{13}$$

4.3.7 A diagnostic analysis of the identified model. For Toyota, the model ARIMA (2, 2, 0) has been identified with the least AIC value. To test its effectiveness, the model residuals need examining by ACF and PACF plots. Its ACF residual plot is shown in Figure 7.

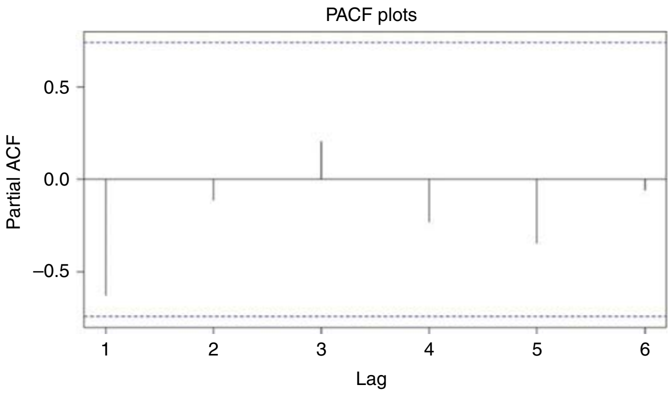

Figure 6.
The PACF plot from data (diff2) of Toyota

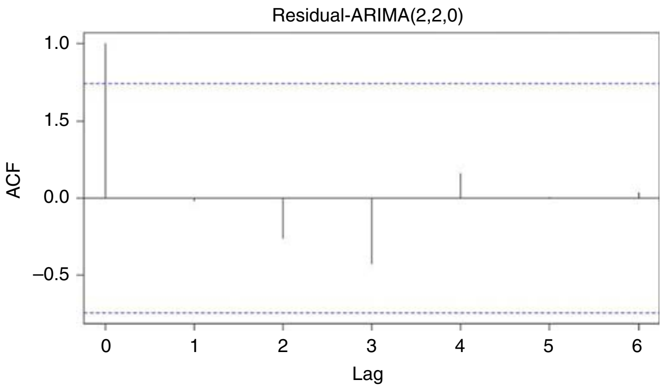

Figure 7.
The ACF plot from ARIMA (2, 2, 0) of Toyota

Since lag = 1, all the residuals are located within a 95 percent confidence interval. Therefore, this fitted model AMRMA (2, 2, 0) is validated as stationary. In other words, this model can be used to forecast the future I_{MVM} value in FY2018. Do diagnostic analysis to other cases and get the validated models for each MVM in Table VIII.

4.3.8 The forecast I_{MVM} value in FY2017 and FY2018. The forecast horizon h ahead for predictions is made to be two, that is, in FY2017 and in FY2018. The forecast accuracy by ARIMA models in FY2017 is tested. The forecast accuracy is tested by MAPE in this research. It is calculated as in the following equation. The forecast values $\hat{y}_t$ from the models are compared and shown as a percentage of the actual value y_t. Both over and underestimations were considered of same relevance, which means that only the absolute value of the errors is considered. Denote $a = 10$ and $b = 9$ since data during FY2008 and FY2016 is taken for developing the models. The identified model is used to forecast the I_{MVM} value in FY2018:

$$\mathrm{MAPE}_i^{2017} = \frac{1}{a-b}\sum_{t=b+1}^{a}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \times 100\%, \tag{14}$$

where MAPE_i^{2017} is the mean absolute percentage error between the historical I_{MVM} value and the forecast I_{MVM} value in FY 2017 for the MVM i; a the size of time series period; b the in-sample size of time series period; y_t the historical I_{MVM} value; and $\hat{y}_t$: the forecast I_{MVM} value.

As shown in Figure 8, the blue area shows the fit provided by the model for Toyota. The light blue area and dark blue area cover the forecast with confidence intervals of 95 and 80 percent, respectively, based on the values in Table IX. The MAPE_i^{2017} value in FY2017 and the forecast I_{MVM} value for the other ten MVMs are calculated. The results are listed in Table X.

Case	Fitted model	Case	Fitted model
Toyota	ARIMA (2, 2, 0)	Honda	ARIMA (2, 1, 0)
Audi AG	ARIMA (2, 2, 1)	Renault	ARIMA (1, 2, 0)
Hyundai	ARIMA (1, 2, 0)	Daimler	ARIMA (1, 2, 0)
GM	ARIMA (1, 2, 1)	BMW	ARIMA (1, 2, 0)
Ford	ARIMA (2, 2, 1)	Mazda	ARIMA (2, 1, 1)
Nissan	ARIMA (0, 1, 1)		

Table VIII. Validated models for 11 cases

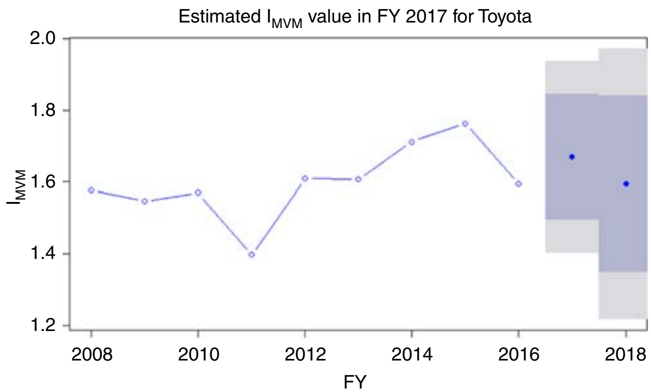

Figure 8. The forecast I_{MVM} value in FY2017 and FY2018 of Toyota

5. Discussion

This research develops an approach to measuring the performance of MVMs from E&E perspectives. An index I_{MVM} is constructed as the performance from E&E perspectives. Its historical data during FY2008 to FY2017 is generated by Equation (12). In addition, its future data in FY2018 are generated by ARIMA models of the best fit. Benchmarking has been recognized as one of the most widely known improvement techniques or tools in the world (Al Nuseirat *et al.*, 2019). The data out of this research can contribute to benchmarking the historical performance (during FY2008–FY2017) of MVMs relative to their competitors as well as the forecast performance in FY2018.

5.1 Benchmark the I_{MVM} against other frameworks

To benchmark the DJSI World, Newsweek Green Rankings and the Automobile Manufacturer Industry Scorecard by Moody's Corporation, six items are listed. A benchmark between I_{MVM} and the three indices is presented in Table XI. The development of the index I_{MVM} does not involve subjective scoring methods, so the third benchmark item is not applicable for I_{MVM}. In conclusion, the index I_{MVM} satisfies all five applicable benchmark items while the three indices are incapable to satisfy their applicable benchmark items.

5.2 Benchmark the environmental performance of MVMs during FY2008–FY2017

Benchmarking performance involves a comparison of metrics while best practice benchmarking involves "studying the practices of those organizations that are higher performers and adapting their 'better practices' to another organization" (Adebanjo and Mann, 2008). This section benchmarks constructs an environmental performance index (EPI). Based on the outcome, the best performer and the worst performer from an

	FY2017	FY2018
y_t	1.613	–
$\hat{y}_t$	1.670749	1.594689
Low value (95%)	1.402644	1.217096
High value (95%)	1.938853	1.972283
Low value (80%)	1.495445	1.347794
High value (80%)	1.8460533	1.841585
MAPE (%)	3.58	–

Table IX. The forecast I_{MVM} value in FY2017 and FY2018 of Toyota

Ranking	MVM	y_{2017}	$\hat{y}_{2017}$	MAPE[2017] (%)	$\hat{y}_{2018}$
1	GM	1.59	1.66873	4.95	1.674856
2	Toyota	1.613	1.670749	3.58	1.594689
3	Nissan	1.475	1.566981	6.24	1.566981
4	Renault	1.402	1.465	4.49	1.5423
5	Audi	1.421	1.435871	1.04	1.534884
6	Ford	1.462	1.69445	15.9	1.479001
7	BMW	1.446	1.4244	1.49	1.4522
8	Daimler	1.238	1.327363	7.22	1.422476
9	Honda	1.306	1.368987	4.82	1.369841
10	Mazda	1.279	1.435871	12.47	1.334884
11	Hyundai	1.59	1.292567	18.71	1.196974
	Average	1.438	1.486	7.356	1.47

Table X. I_{MVM} forecast values in FY2017 and FY2018

Benchmark Item	A	B	C	I_{MVM}
(1) The index takes into account environmental concerns	✓	✓	×	✓
(2) The index is designed especially for motor vehicle manufacturers (rather than for multiple industry sectors)	✓	×	✓	✓
(3) The index tackles the uncertainty and subjectivity inherent in weighting variables if the experts' scoring method is used as the weighting method	×	NA	×	NA
(4) The index makes the variables weights adjustable for different manufacturers rather than fix the weights of variables the same for all manufacturers	×	✓	×	✓
(5) All of the variables in the index can be measurable based on public available data	×	✓	×	✓
(6) The index is constructed with clear methods for normalizing variables and aggregating variables	✓	✓	✓	✓

Notes: A: Dow Jones Sustainability World Index, B: Newsweek Green Rankings, C: Automobile Manufacturer Industry Scorecard. ✓: the framework satisfies the metric, ×: this framework dissatisfies the metric, NA.: this metric is not applicable for this framework

Table XI. A benchmark between I_{MVM} and other indices

environmental perspective are identified. A benchmark is performed regarding their environmental performance.

5.2.1 Construct an environmental performance index I_{ENVI}. The normalized values of the three measures (V_6-V_8) are the same as the ones when constructing the I_{MVM}. However, the weights of the three measures are different from the ones when constructing the I_{MVM}. Calculate the weights of the three measures in Equations (10) and (11). Finally, the three environmental measures into a single index I_{ENVI} are aggregated as $I^{t}_{ENVI.i} = f[x'^{t}_{ij}, w_j] = \prod_{j=6}^{8} (x'^{t}_{ij})^{w_j} = x'^{t\,w_{v6}}_{i6} \times x'^{t\,w_{v7}}_{i7} \times x'^{t\,w_{v8}}_{i8}$. The weights of the three measures and the aggregated EPI values are listed in Tables AII and AIII, respectively.

5.2.2 The best performer and the worst performer in terms of environmental performance. The purpose of benchmarking is to systematically measure and compare performance with the best-in-class to determine what should be improved for achieving superior performance (Anand and Kodali, 2008; Motwani *et al.*, 2006). As is seen in Table AIII, Audi was the best performer in terms of its environmental performance. During FY2008–FY2017, its average value of EPI was the highest among all the 15 MVMs. Audi aims to be a leader in electric cars which can reduce carbon footprint. In April 2017, Audi's new all-electric concept vehicle, the e-tron Sportback, made its debut. Audi aims that one in three Audi cars sold by 2025 is to be an electric model. This indicates that Audi might have even better performance regarding environment protection with less CO_2 emissions and energy consumption.

Daimler was identified as the worst performer in terms of average environmental performance during FY2008–FY 2017. Daimler is one of the biggest suppliers of premium cars and commercial vehicles with a global reach. Its industrial divisions include Mercedes-Benz Cars, Daimler Trucks, Mercedes-Benz Vans and Daimler Buses. In FY 2017, Daimler spent €8.7bn on activities including researching and developing the EQ electric brand in Mercedes-Benz Cars, emission standards and fuel efficiency in Daimler Trucks, the fulfillment of future emissions standards and measures to further reduce fuel consumption in Daimler Buses. The Mercedes-Benz Citaro is further reducing its fuel consumption with its new electro-hydraulic steering system. This is large because of its range including Daimler Trucks and Daimler Buses in this research. Generally speaking, compared with car manufacturing, the truck manufacturing and the bus manufacturing consume more energy, more water and generate more pollutants. The demand for clean and economical transport is growing all over the world. That might boost the development of Daimler Trucks and Daimler Buses. Considering the high level of research and development expenditure on fuel-efficient and environmentally friendly drive systems, Daimler Group will probably have higher normalized values of the three environmental measures in the following years.

5.3 Economic performance and environmental performance during FY2008–FY2017

5.3.1 Construct an economic performance index $I_{ECON.}$. With the same methods of constructing the index $I_{ENVI.}$, an economic performance index I_{ECON} is constructed in this section. The weights of the five measures (V_1–V_5) are calculated and listed in Table AIV. The aggregated value of the index I_{ECON} is listed in Table AV.

5.3.2 I_{ENVI} performance vs I_{ECON} performance. The average values of the 15 MVMs are pitched in Figure 9. As shown, it is visible that the I_{ECON} values had a downward trend since FY2008 which can be explained by the economic crisis between 2008 and 2009. In 2010, most MVMs revived and the economic performance increases due to the rapid economic recovery. Nevertheless, it remains unstable until FY2013 when there was a continuous increasing trend.

In terms of the environmental performance, generally the average values increase. It is obvious that data at several points showing a contraction between I_{ECON} values and I_{ENVI} values. For example, in FY2010, there was a peak of the I_{ENVI} value, while a valley of the I_{ECON} value. Similar phenomena showed up in FY2011, FY2012, FY2015, FY2016 and FY2017. This may be reasoned by the fact that a struggling economy leads to a decline in vehicles' production volume which results in less resource consumption and less CO_2 emissions.

5.4 Performance matrix on environmental performance index vs company performance I_{MVM}

The generated I_{MVM} values and the values of the EPI are combined in a matrix. The I_{MVM} values are presented for each MVM on the horizontal axes. The values of the EPI values are presented on the vertical axes. A common practice is to compare with average (Deming, 1986). The average levels by the average score on I_{MVM} values (1.424) and by the average score on the EPI values (1.603) are added. The combined result is presented in Figure 10.

As shown in Figure 10, MVMs are distributed in four quadrants which is formed by two average levels. MVMs located in Quadrant I are with high EPI values and high I_{MVM} values. On the contrary, MVMs located in Quadrant III are with low EPI values and low I_{MVM} values. MVMs located in Quadrant II are with high EPI values but low I_{MVM} values. MVMs located in Quadrant IV are with high I_{MVM} values but low EPI values.

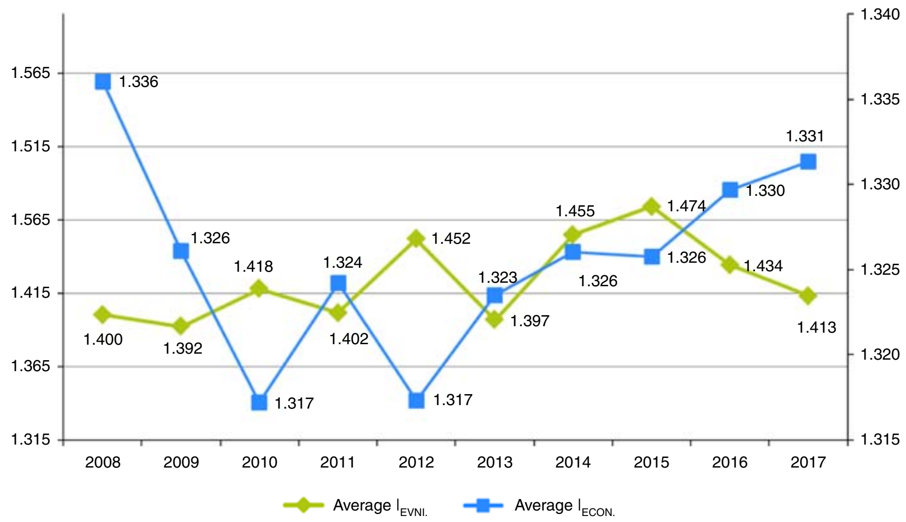

Figure 9.
Average values of the index I_{ECON} and the index I_{ENVI} during FY2008–FY2017

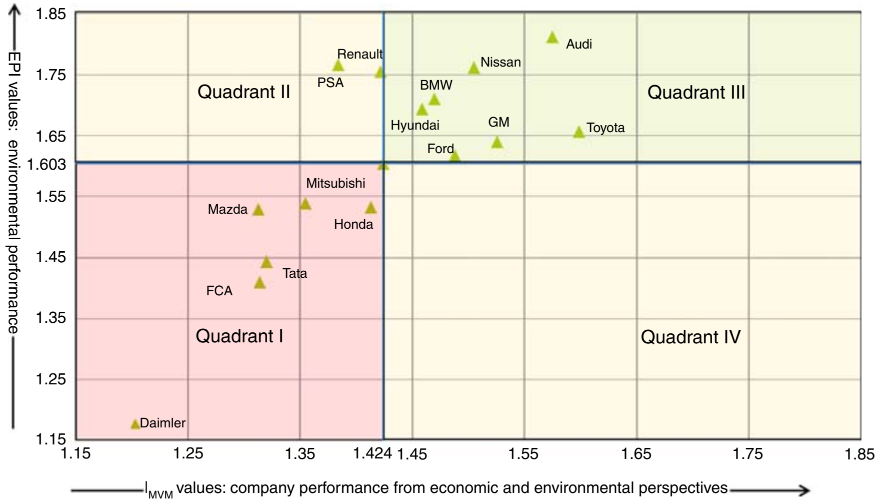

Figure 10.
Performance matrix on environmental performance index vs company performance index (FY2008–FY2017)

5.4.1 MVMs located in quadrant I. MVMs located in Quadrant I failed to perform well in neither environmental performance nor company performance. There are six MVMs in this quadrant, including Daimler, FCA, Tata, Mazda, Mitsubishi and Honda. Daimler had both the lowest EPI value (1.195) and the lowest I_{MVM} value (1.212). FCA remains dedicated to a culture of sustainability aimed at balancing its environment responsibilities, including making its contribution by supporting the United Nations Sustainable Development Goals. More than 2bn cubic meters of water were saved at FCA plants in FY2017. Besides, FCA implemented about 5,000 environment projects at their plants around the world, reducing its carbon footprint and leading to about €68m in savings. Globally, plants of FCA reduced CO_2 emissions by 2.2 percent in FY 2017. Its Verrone transmission plant earned the prestigious international "Lean and Green Management Award" based on its optimum integration of environmental and energy issues and innovative manufacturing solutions. Despite these efforts, FCA had the second least EPI value (1.409).

5.4.2 MVMs located in quadrant III. MVMs located in this quadrant are Audi, Toyota, GM, Nissan, Ford, BMW and Hyundai. They came up high both in EPI values and I_{MVM} values. As shown in Figure 10, Audi had the highest EPI value (1.811) and Toyota had the highest I_{MVM} value (1.599). Toyota's approach to water conservation is its two-measure plan which consists of "a comprehensive reduction in the amount of water used, and water purification and returning it to the earth." Toyota is famous for its lean production system, which makes Toyota outstanding decreasing the waste generated from vehicles' production. Toyota comes up with innovative vehicles that reduce the overall carbon footprint. One of the most outstanding cars is the Prius model which is also celebrated as the world's first mass-market hybrid vehicle. This allows Toyota to have better environmental performance.

5.4.3 MVMs located in quadrant II or in quadrant IV. In Figure 10, two MVMs including PSA and Renault are with high EIP values but low I_{MVM} values. This indicates that PSA and Renault had both better environmental performance (1.765 and 1.754, respectively), but neither of them had better company performance (1.384 and 1.422, respectively) compared with the average level among the 15 MVMs. It is obvious that Renault had the highest normalized value of CO_2 Emissions per vehicle produced (2.0) among all the fifteen MVMs. As a pioneer in Europe, Renault is building on nine years of expertise in the design, production and sale of electric vehicles. In FY2015, Renault was the best performing brand in Europe in electric vehicles sales, with a market share of 23.6 percent. In FY2017, Renault set a new record of roughly 36,300 units all-electric car sales. Today, almost one electric vehicle in every four sold in Europe is a Renault. By 2022, Renault will have a range of 8 electric vehicles and 12 electrified vehicles, as part of the Group's strategic "Drive The Future" plan.

5.4.4 Movement of the I_{MVM} values from the period FY2008–FY2017 with the values in FY2018. In this section, the movement of I_{MVM} values from the period FY2008–2017 with FY2018 is analyzed. There are 11 MVMs in this analysis because there are 4 MVMs without forecast I_{MVM} values in FY2018. As shown in Figure 11, the average I_{MVM} values from the period FY2008 to FY2017 for the 11 MVMs are placed along the horizontal axis. The average level ($x = 1.451$) for the 11 MVMVs is marked in blue. The forecast I_{MVM} values in FY2018 for the 11 MVMs are placed on the vertical axis. The average level ($y = 1.452$) for the 11 MVMVs is marked in orange. During FY2008–FY2017, there are seven MVMs including Toyota, GM, Nissan, Ford, BMW, Audi and Hyundai that had better performance than the average level. However, in FY2018, BMW, Audi and Hyundai will drop below the average level. The slight increase of the average level from 1.451 to 1.452 indicates a better company performance for the 11 MVMs in FY2018.

MVMs that are located in the diagonal line ($y = x$) in red means that the average I_{MVM} values from the period FY2008 to FY2017 is equal to the forecast I_{MVM} values in FY2018. It means that MVMs located above the diagonal line means they will improve their company performance in FY2018. On the contrary, MVMs that are located below the diagonal line means they will have a drop in their company performance in FY2018. Five MVMs including GM, Nissan, Renault, Mazda and Daimler will have better company performance

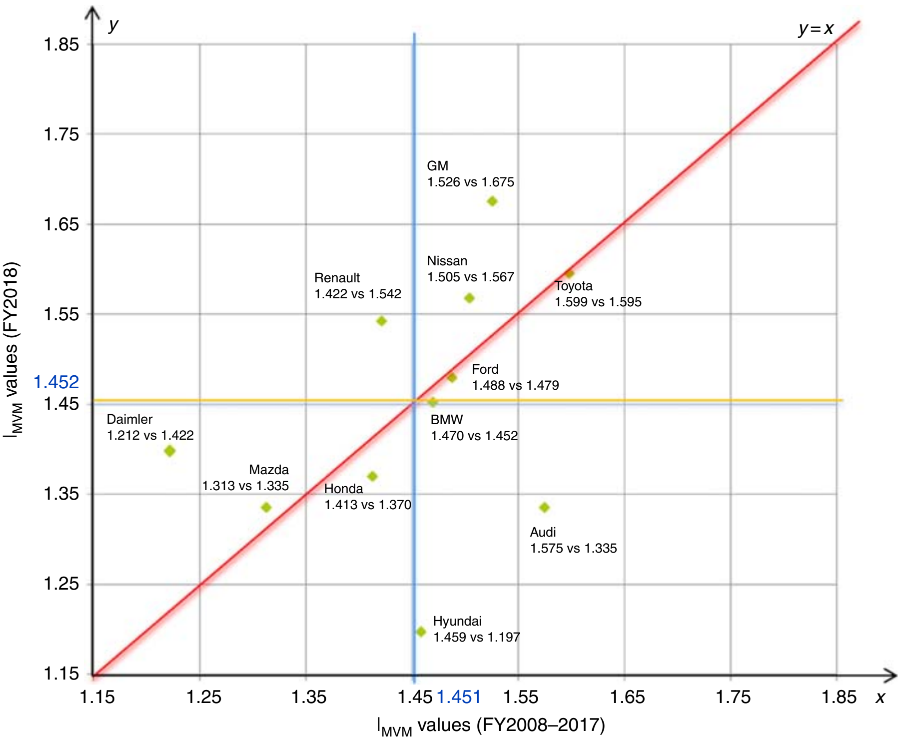

Figure 11.
Movement of the I_{MVM} historical data to its forecast data

in FY2018. A big improvement is clearly observed in Daimler. Despite of the lowest I_{MVM} value (1.212) in the past, its forecast value in FY2018 moves to 1.422.

Five MVMs including Ford, BMW, Audi, Honda and Hyundai will move backwards regarding their company performance. As shown in Figure 11, Hyundai has the biggest drop from 1.459 in the past to 1.197 in FY2018. However, as seen in Table IX, for Hyundai, the MAPE between the actual I_{MVM} value in FY2017 (1.59) with the forecast I_{MVM} value in FY2017 (1.29) is 18.71 percent which is higher than the average MAPE (7.356 percent). This large MAPE makes the forecast I_{MVM} value in FY2018 less convincing. Company performance of Audi will move forward from 1.575 to 1.335. As seen in Table IX, the MAPE in FY2017 is 1.04 percent which makes the forecast I_{MVM} value in FY2018 convincing. Therefore, Audi needs to look into its specific performance measures and benchmark with better performers.

5.5 Benchmark the performance of MVMs from E&E perspectives in FY2018

On the basis of the I_{MVM} forecast value in FY2018, a ranking by manufacturer is determined from the best (benchmark) to the worst MVMs. As shown in Figure 11, totally, there are six MVMs that have better performance than the average level (1.470), including GM, Toyota, Nissan, Renault, Audi and Ford. There are four MVMs that have worse performance than the average level, including Daimler, Honda, Mazda and Hyundai. GM has the highest I_{MVM} forecast value (1.674856). This indicates that GM will be assigned as the best performing MVM in FY2018 in terms of heading toward company performance from E&E perspectives. On the contrary, Hyundai will be assigned as the worst performing MVM in FY2018 due to its lowest I_{MVM} forecast value (1.196974).

In order to explore why GM and Hyundai have different results and identify the weak spots or opportunities for improvement, this section makes a benchmark on the measures between the worst performer Hyundai with the best performer GM. Figure 12 shows the normalized forecast values of the eight measures from Hyundai and GM, respectively. V'_1 is for normalized forecast value of Market Share. V'_2 is for normalized forecast value of Cash Flow Margin. V'_3 is for normalized forecast value of Continuity. V'_4 is for normalized forecast value of Conception. V'_5 is for normalized forecast value of Inventory Turnover. V'_6 is for normalized forecast value of Water Consumption per vehicle produced. V'_7 is for normalized forecast value of Energy Consumption per vehicle produced. V'_8 is for normalized forecast value of CO_2 emissions per vehicle produced. Note: the higher normalized forecast value GM or Hyundai has, the better performance GM or Hyundai will have in terms of the measure.

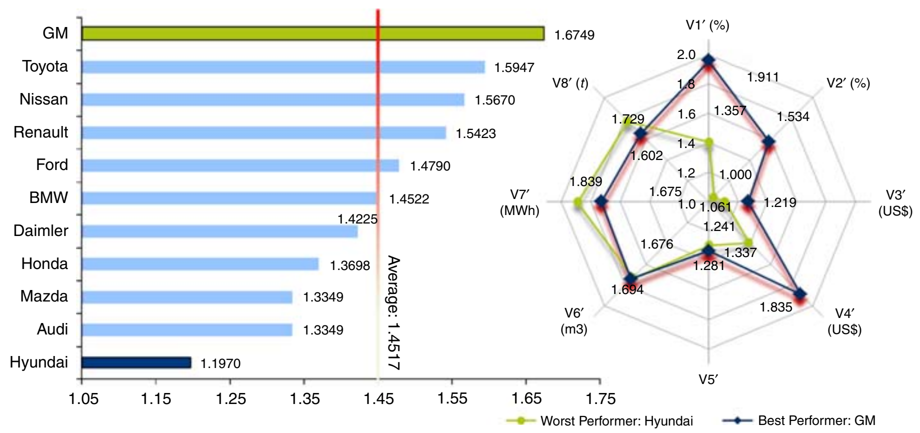

Figure 12.
Forecast data of the performance from E&E perspectives in FY2018

5.5.1 Relative weaknesses in Hyundai for performance improvement. Benchmarking provides reasons of good performance and explanation for poor performance for remedial action (Tseng *et al.*, 2014). This section discusses the different performance between the best performer and the worst performer. As shown in Figure 12, the biggest difference between Hyundai and GM is in the measure Market Share which reaches a gap of 0.554. Despite of a wider plan by GM to slash car production in North America and halt production of several low-selling brands in November 2018, GM is still the largest American automobile manufacturer based on production volume. The market has been a source of frustration for Hyundai since the South Korean automaker was slow to respond to a consumer shift toward sports utility vehicles. Hyundai was forced to cut production at its factory in the USA and export fewer vehicles to the USA to reduce inventories of less-favored sedans.

5.5.2 Relative weaknesses in GM for performance improvement. It is interesting to see that Hyundai has better performance in terms of energy consumption performance. Hyundai excels GM on the normalized forecast value of this measure by 0.164. The same to CO_2 emissions performance where Hyundai excels GM by 0.126. In other words, in terms of the environmental perspective, GM did not perform well in FY2017. In October 2017, GM publicly announced that its vehicle lineup would feature 20 electric car models by the year 2023. It indicates that GM might have higher normalized values of Energy Consumption and CO_2 Emissions in the following years, which could enhance their principles regarding the environment. Hyundai becomes the first company in the world to mass-produce hybrid, plug-in hybrid and all-electric vehicles with a single dedicated eco-car platform. The Hyundai ix35 is the world's first mass-produced hydrogen fuel cell electric vehicle. By FY 2017, more than 700 units Hyundai ix35 was sold in 17 countries. In September 2017, Hyundai first unveiled the Nexo, a second generation fuel cell electric vehicle that has reduced charging time to just five minutes. The Nexo is powered by electric energy produced by a reaction between hydrogen and oxygen. It, therefore, does not discharge any exhaust gases or other substances that could pollute the environment.

6. Conclusions

This research developed an approach to measuring the performance of MVMs from E&E perspectives. The integration of eight measures from E&E perspectives answered the first sub-question. An index I_{MVM} and ARIMA models of the best fit are constructed to generate the time series data of this performance. This answered the second sub-question as well as the main research question.

The effectiveness of the approach was shown with its forecast accuracy for FY2017 with the MAPE as an error criterion. The data out of the models contribute to benchmarking the historical performance (during FY2008–FY2017) of MVMs relative to their competitors. In addition, the forecast performance in the following fiscal years is presented and benchmarked as well.

6.1 Contribution

This research has contributed to the literature of performance management and measurement with an approach to quantitatively measuring company performance from E&E perspectives. Five requirements have been listed for the approach as follows: it is with an integration of measures from E&E perspectives; it is designed for MVMs by taking into the specific background into consideration; it is based on data which is available from public documents; it is mathematically constructed with transparency in generating time series data; and it provides a forecast value for benchmarking the future performance of MVMs in the following fiscal years.

Based on the index I_{MVM}, a ranking by MVM from E&E perspectives can be generated. The construction of the index I_{MVM} has been benchmarked against the methodologies from

DJSI World, Newsweek Green Rankings and Automobile Manufacturer Industry Scorecard with six benchmark metrics. The index I_{MVM} satisfies all applicable benchmark metrics while the three indices are incapable to satisfy their applicable benchmark metrics. The forecast data for FY2018 is generated by ARIMA models of the best fit.

This rigorous study of company performance measurement and benchmarking from E&E perspectives provides valuable insights which are not obvious directly from the raw data for MVMs to improve their performance. The comprehensive benchmarking results on both the eight individual performance measures and the overall performance are relevant to decision making in the societal context. For organizations such as OICA and the European Environment Agency, the historical data generated by the I_{MVM} can contribute with available statistics and useful insights for decision making. For practitioners in MVMs, data out of the forecast approach can aid them to identify manufacturers' relative weaknesses for performance improvement. For stakeholders such as asset management organizations, these data help them identify manufacturers with positive environmental policies for sustainability themed investments.

6.2 Limitations

Despite all efforts and cautions taken to develop the forecasting method in this paper, there are two main limitations:

(1) A step of cleaning extreme values is missing. This indicates that the maximum or minimum value of the measures is not removed. The data set of the eight measures during the FY2008–FY2017 for the 15 samples is small. Considering each available data is valuable for generating a time series data, this research did not clean extreme values.

(2) The effectiveness of the ARIMA models can be compared with forecast results from other forecasting methods. In order to test forecast accuracy, more error criteria such as the root mean square error can be referred to.

6.3 Recommendations for further research

For further research, four main recommendations are given as follows:

(1) Consistent and transparent data of the right measures are encouraged to be released on periodic reports by manufacturers. The time series data of the performance from E&E perspectives can be added to manufacturers' reports. With these data as a benchmark metric, manufacturers will feel motivated to achieve a balanced relationship between their environmental performance and economic performance.

(2) Better forecasting performance can be expected with extensive data. More reliable data are needed not only in a yearly basis but also in shorter periods of time. During the data preprocessing, several concerns need to be taken into account to deal with missing data and inconsistent data.

(3) For more reliable and precise forecast values, more detailed investigations are required. For instance, a comparison of forecasting capability can be concluded with different forecasting methods such as exponential smoothing methods, recurrent neural network methods and support vector regression methods.

(4) The production of electric vehicles or hybrid vehicles is getting more attention both in industry and in academia. It can be interesting to conduct correlation analysis between sustainable cars production and the relevant environmental performance.

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Further reading

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Appendix 1

Case	Model	Value					
Toyota	ARIMA (1, 2, 1)	ARIMA (1, 2, 0)	ARIMA (0, 2, 1)	*ARIMA (2, 2, 0)*	ARIMA (0, 2, 2)	ARIMA (1, 2, 2)	ARIMA (2, 2, 1)
AIC	9.8554	9.5936	11.4782	6.5011	10.4035	10.4484	10.2594
Audi	ARIMA (1, 2, 1)	ARIMA (1, 2, 0)	ARIMA (0, 2, 1)	ARIMA (2, 2, 0)	ARIMA (0, 2, 2)	ARIMA (1, 2, 2)	*ARIMA (2, 2, 1)*
AIC	9.4583	9.4606	14.4914	N.A.	12.6915	12.6915	5.0678
Hyundai	ARIMA (1, 2, 1)	*ARIMA (1, 2, 0)*	ARIMA (0, 2, 1)	ARIMA (2, 2, 0)	ARIMA (0, 2, 2)	ARIMA (1, 2, 2)	ARIMA (2, 2, 1)
AIC	1.2380	−0.2600	3.8988	N.A.	2.9941	3.1908	3.2376
GM	*ARIMA (1, 2, 1)*	ARIMA (1, 2, 0)	ARIMA (0, 2, 1)	ARIMA (2, 2, 0)	ARIMA (0, 2, 2)	ARIMA (1, 2, 2)	ARIMA (2, 2, 1)
AIC	10.5333	10.8904	10.4147	1.7116	10.7439	11.7233	N.A.
Ford	ARIMA (1, 2, 1)	ARIMA (1, 2, 0)	ARIMA (0, 2, 1)	ARIMA (2, 2, 0)	ARIMA (0, 2, 2)	ARIMA (1, 2, 2)	*ARIMA (2, 2, 1)*
AIC	3.5397	3.5552	5.6987	N.A.	5.1134	4.5248	−3.2409
Nissan	ARIMA (1, 1, 1)	ARIMA (1, 1, 0)	*ARIMA (0, 1, 1)*	ARIMA (2, 1, 0)	ARIMA (0, 1, 2)	ARIMA (1, 1, 2)	ARIMA (2, 1, 1)
AIC	−1.4362	−0.8296	−3.0179	N.A.	−3.0731	−1.1269	1.9755
Honda	ARIMA (1, 1, 1)	ARIMA (1, 1, 0)	ARIMA (0, 1, 1)	*ARIMA (2, 1, 0)*	ARIMA (0, 1, 2)	ARIMA (1, 1, 2)	ARIMA (2, 1, 1)
AIC	−4.4397	−2.9865	−4.1863	−15.4561	−5.3659	−4.4734	−13.3862
Renault	ARIMA (1, 2, 1)	*ARIMA (1, 2, 0)*	ARIMA (0, 2, 1)	ARIMA (1, 2, 0)	ARIMA (2, 2, 0)	ARIMA (0, 2, 2)	ARIMA (1, 2, 2)
AIC	−0.0451	−0.9895	−0.9509	−15.4561	N.A.	0.8986	−1.4914
Daimler	ARIMA (1, 2, 1)	*ARIMA (1, 2, 0)*	ARIMA (0, 2, 1)	ARIMA (2, 2, 0)	ARIMA (0, 2, 2)	ARIMA (1, 2, 2)	ARIMA (2, 2, 1)
AIC	−0.1456	−1.9034	3.3447	−0.3844	3.1949	1.3630	N.A.
BMW	ARIMA (1,2,1)	*ARIMA (1,2,0)*	ARIMA (0,2,1)	ARIMA (1,2,0)	ARIMA (2,2,0)	ARIMA (0, 2, 2)	ARIMA (1, 2, 2)
AIC	4.1136	4.6753	7.2819	1.0323	5.5841	4.2307	6.3976
Mazda	ARIMA (1, 1, 1)	ARIMA (1, 1, 0)	ARIMA (0, 1, 1)	*ARIMA (2, 1, 0)*	ARIMA (0, 1, 2)	ARIMA (1, 1, 2)	ARIMA (2, 1, 1)
AIC	−4.4397	−2.9865	1.9076	−15.4561	−0.0242	−4.4734	−4.8845

Table AI. AIC values for 11 cases during FY2008–FY2016

Appendix 2

Measure	2017	2016	2015	2014	2013	2012	2011	2010	2009	2008
V_6	0.312	0.33	0.281	0.424	0.333	0.407	0.467	0.341	0.264	0.252
V_7	0.287	0.301	0.456	0.33	0.333	0.307	0.253	0.374	0.225	0.505
V_8	0.402	0.369	0.263	0.247	0.334	0.286	0.28	0.284	0.511	0.243

Table AII. Weights of the three environmental measures during FY2008–FY2017

Appendix 3

Case	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Average
Toyota	1.623	1.678	1.743	1.406	1.77	1.754	1.766	1.63	1.58	1.607	1.656
Audi	1.759	1.878	1.911	1.463	1.973	1.941	1.955	1.784	1.807	1.638	1.811
Hyundai	1.437	1.702	1.673	1.52	1.714	1.831	1.808	1.84	1.751	1.652	1.693
GM	1.555	1.584	1.696	1.469	1.691	1.724	1.708	1.701	1.608	1.652	1.639
Ford	1.442	1.547	1.632	1.467	1.697	1.693	1.695	1.683	1.637	1.67	1.616
Nissan	1.611	1.706	1.648	1.668	1.858	1.85	1.858	1.802	1.763	1.849	1.761
Honda	1.967	1.961	1.439	1.58	1.427	1.464	1.436	1.428	1.331	1.273	1.531
FCA	1.262	1.447	1.37	1.309	1.478	1.469	1.471	1.244	1.466	1.575	1.409
Renault	1.714	1.757	1.811	1.555	1.788	1.78	1.774	1.774	1.756	1.829	1.754
PSA	1.781	1.863	1.821	1.499	1.774	1.764	1.756	1.732	1.756	1.908	1.765
Daimler	1.157	1.08	1.271	1.329	1.28	1.117	1.178	1.108	1.231	1.202	1.195
BMW	1.618	1.65	1.748	1.332	1.809	1.791	1.802	1.748	1.736	1.851	1.709
Mazda	1.384	1.413	1.454	1.809	1.438	1.503	1.356	1.632	1.622	1.673	1.528
Mitsubishi	1.004	1.201	1.317	1.572	1.749	1.743	1.706	1.711	1.678	1.696	1.538
Tata	1.389	1.725	1.458	1.791	1.328	1.38	1.333	1.347	1.326	1.357	1.443

Table AIII. Values of the index I_{ENVL} during FY2008–FY2017

Appendix 4

Measure	2017	2016	2015	2014	2013	2012	2011	2010	2009	2008
V_1	0.270	0.243	0.221	0.237	0.270	0.262	0.253	0.230	0.210	0.231
V_2	0.159	0.206	0.254	0.232	0.191	0.163	0.213	0.185	0.248	0.194
V_3	0.203	0.198	0.214	0.202	0.213	0.270	0.200	0.229	0.187	0.145
V_4	0.207	0.196	0.180	0.179	0.173	0.177	0.172	0.171	0.180	0.212
V_5	0.161	0.158	0.132	0.151	0.153	0.128	0.163	0.186	0.176	0.218

Table AIV. Weights of the five economic measures during FY2008–FY2017

Appendix 5

Table AV. Values of the index I_{ECON} during FY2008–FY2017

Case	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Average
Toyota	1.592	1.602	1.564	1.604	1.569	1.599	1.607	1.611	1.599	1.587	1.593
Audi	1.365	1.363	1.333	1.339	1.323	1.330	1.352	1.363	1.355	1.343	1.347
Hyundai	1.541	1.517	1.510	1.532	1.526	1.538	1.529	1.523	1.538	1.552	1.531
GM	1.541	1.517	1.510	1.532	1.526	1.538	1.529	1.523	1.538	1.552	1.531
Ford	1.381	1.327	1.342	1.342	1.344	1.351	1.333	1.316	1.353	1.381	1.347
Nissan	1.310	1.314	1.303	1.321	1.324	1.324	1.325	1.329	1.325	1.327	1.320
Honda	1.318	1.300	1.304	1.307	1.309	1.310	1.304	1.300	1.312	1.322	1.309
FCA	1.234	1.237	1.220	1.234	1.211	1.229	1.234	1.233	1.228	1.220	1.228
Renault	1.265	1.263	1.238	1.251	1.223	1.243	1.255	1.257	1.252	1.242	1.249
PSA	1.221	1.211	1.199	1.205	1.186	1.200	1.205	1.203	1.206	1.202	1.204
Daimler	1.265	1.251	1.245	1.246	1.248	1.245	1.250	1.252	1.258	1.261	1.252
BMW	1.302	1.279	1.290	1.280	1.303	1.286	1.282	1.281	1.297	1.312	1.291
Mazda	1.156	1.135	1.133	1.130	1.126	1.129	1.131	1.128	1.139	1.144	1.135
Mitsubishi	1.330	1.375	1.376	1.363	1.406	1.365	1.379	1.403	1.373	1.361	1.373
Tata	1.219	1.200	1.190	1.179	1.137	1.165	1.175	1.165	1.173	1.162	1.176

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