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Modelling and Forecasting the Impact of the COVID-19 Pandemic on South Africa's New Car Sales

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Abstract: The goal of this study is to use time series modeling to analyse and forecast, and to show how the COVID-19 pandemic impacted South Africa (SA)'s new car sales. An empirical approach employing the Box-Jenkins methodology to time series analysis is employed in this paper. A SARIMA $(0,1,1)(0,0,2)_{12}$ model, among other models, is found to give the best fit as measured by the root mean square error (RMSE), Akaike Information Criteria (AIC) and the Bayesian Information criterion (BIC). The analysis reveals a significant, average 84.5% decline in monthly new car sales following the pandemic's official declaration by the SA government. Future projections show that the prevailing rate of increase in new car sales has resulted in a recovery, and new car sales have reached pre-COVID-19 levels and even surpassed expected projected levels. The proposed methodology and findings are useful to the SA automotive industry to help develop motor vehicle sales plans and to help provide information to mitigate against unforeseen cash flow issues and better manage needs for car manufacturing, personnel, and financing of new car sales. The study uses a well-established statistical methodology to quantify the COVID-19 pandemic's impact on South Africa's car manufacturing industry. This study is one of the few empirical ones that look at how COVID-19 has affected the sales of new car sales in a developing nation, like SA. A post-mortem to determine/quantify how the COVID-19 pandemic affected the car manufacturing sector's business is essential to the country's future industrial and economic landscape.

Keywords: SA's new car sales; Box-Jenkins methodology; COVID-19 pandemic; forecasting.

1 Introduction

The National Association of Automobile Manufacturers of South Africa (NAAMSA) (2020) indicated that the automotive industry in South Africa (SA) contributed 6.8% of the country's gross domestic product (GDP) in 2018. According to [1], the manufacturing sector contributes 15% to the nation's GDP, with the automotive industry alone representing approximately 30% of this manufacturing output. In SA, the automobile industry was responsible for 457,000 jobs as per a 2019 report, both directly and indirectly [2]. According to [3], the car manufacturing industry accounts for 110,000 jobs, making it a vital sector of the economy. A post-mortem to determine/quantify how the COVID-19 pandemic affected the car manufacturing sector's business is essential to SA's future industrial and economic landscape. Valuable lessons are to be learned in preparation for the next economic shock.

According to [4], the World Health Organization (WHO) has classified COVID-19 as a worldwide pandemic in many nations, including SA. As with any other nation, the SA government, through its president Ramaphosa, introduced its first 21 days of economic lockdown measures responding to the COVID-19 pandemic on 27 March 2020. The nationwide lockdowns implemented by the government were to try and stop the spread of the disease. During the COVID-19 pandemic era, millions of people ran the risk of losing their employment, getting lower pay/salary/remuneration, and receiving fewer or no business incentives [5]. To make ends meet, consumers reduced/postponed expenditure on some goods, including the purchase of new cars. This significantly impacted all businesses, including the car industry [5].

Demand forecasting is crucial in the highly competitive auto industry. Car sales forecasting and demand forecasting are closely related, making it feasible to manage warehouse inventory more efficiently. Demand forecasting, which is the process of predicting future sales on historical data, is a crucial component of supply chain management that has a big impact on the choices made regarding planning, capacity, and inventory control [6-7]. To prevent waste/over-storage, every manufacturing organisation ought to store safety stock in the required quantities [8]. A precise forecasting technique

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generates the necessary safety stock, encourages the business to recognise competitive advantages, evaluate market demand trends, and decide on product development strategies [9].

Forecasts, as noted by [10], have long been indispensable for planning and implementing supply chain activities due to their substantial influence on decision-making processes. The growing customer expectations, shorter lead times, and the urgent need to manage limited resources compounded by the impact of supply chain disruptions and pandemics like COVID-19, have further heightened the criticality of accurate forecasts. Therefore, it is imperative to evaluate the effect of the COVID-19 pandemic on new car sales in SA, as highlighted by [11], given that a larger proportion of car manufacturing firms experienced substantial or severe disruptions in sales activity compared to other supply chains. The consequences of these supply chain disruptions and widespread shutdowns include reduced production, decreased consumer spending, and a significant decline in business investment, as consumers remain confined to their homes during emergency shutdowns [11].

[12] employed a SARIMA model, augmented with dummy variables to account for the impact of holidays and special days in their study on short-term electricity load modeling and forecasting in Brazil. This model was selected due to its capability to easily incorporate dummy variables, and in so doing, enhancing the accuracy of the results. SARIMA models offer an advantage over basic univariate models by considering various factors such as interventions, calendar variations, outliers, and other real aspects commonly observed in time series data [13]. Furthermore, [14] highlighted the reliability of both the no-change model and the ARIMA model in numerous forecasting contexts.

Other authors have praised the use of Sarima models including [15-17], among others. These models have consistently demonstrated their efficacy in capturing complex time series patterns and accounting for various factors, including seasonality thereby making them a reliable choice for modeling and forecasting purposes in diverse fields of research.

The automobile industry is a significant sector within many economies including SA, and changes in vehicle sales can provide understanding into the overall health of the economy. When vehicle sales are strong, it often indicates consumer confidence, increased spending, and economic growth ahead. On the other hand, declining vehicle sales can signal a slowdown in economic activity.

During the COVID-19 pandemic, vehicle sales were severely affected due to various factors. Economic lockdown measures including social distancing protocols, and general economic uncertainty, led to decreased consumer demand for vehicles. Many individuals postponed their vehicle purchases due to financial constraints or a lack of confidence in the economic outlook. Additionally, disruptions in the supply chain and manufacturing operations also impacted the availability of vehicles.

The decline in vehicle sales had broader implications for the economy as well. The automobile industry employs a significant number of people and contributes to various sectors including manufacturing, retail, transport and other services. Reduced vehicle sales resulted in job losses, reduced production, and lower revenue for businesses across the automotive value chain. This, in turn, had a negative ripple effect on related industries and the overall economy.

In the automotive sector, economic lockdowns impacted production, sales, exports and imports of economic goods. These key performance indicators of an economy influence economic demand [18]. According to [19], the economic lockdowns faced by trading entities made it difficult and expensive to import auto parts, thereby postponing the production of new vehicles. According to [20], the COVID-19 pandemic caused potential customers to delay buying new vehicles or keep their current vehicles for a longer period.

To prevent asset losses and asset degradation from overstocking, automotive manufacturers need to properly manage their production distribution and procurement processes. [21] asserts that it is challenging to anticipate automobile sales during a pandemic, such as COVID-19, because demand drastically changes in a very short period making planning very difficult. However, proper planning is still needed to aid the recovery from a pandemic, and this can be achieved using quantitative methods that can accurately predict future sales. [22] concluded that quantitative methods are more flexible in application and are more precise in generating quality results useful for strategic planning purposes. These quantitative methods will help retailers in creating acceptable future sales strategies cognisant of the competitive market and intense rivalry, the need to lower inventory costs, boost productivity and get ready for any unforeseen increases or decreases in demand.

According to [23], reliable forecasts are essential for ensuring and enabling effective production procedures, optimising inventory levels, and enhancing market performance as a whole. Inaccurate car sales forecasting can result in inventory shortages, high labour expenses, overstocking, bankruptcy, unmet customer needs, and resultant collateral damage to the manufacturer's reputation [24]. To support strategic management and sustainable development, the forecast gives managers a comprehensive picture of the potential sales as a strong foundation for decision-making. Again, for SA, new car manufacturers can thrive in the fiercely competitive, unstable modern market in which accurate demand forecasting is always crucial.

[25] projected car sales in SA using both the seasonal autoregressive integrated moving average (SARIMA) and Holt-Winters models but did not consider pandemics like COVID-19. It is important to consider the COVID-19 impact on car sales. This paper aims to come up with a statistical model for SA new car sales, based on the Box-Jenkins technique, with the ability to quantify the impact of the COVID-19 pandemic on new car sales. The Box-Jenkins technique for time series analysis is selected for forecasting in this study because it logically justifies forecasting and enhances the accuracy of new car sales predictions. Since more automobile consumers are altering their purchasing and consumption behaviors, a forecasting model will assist automotive manufacturers in keeping up with shifting consumer demand and preferences. Additionally, policymakers may put important steps in place to address the crisis caused by the COVID-19 pandemic in the automotive purchase. Some pandemic business disruption insurance is not unthinkable. As firms recover from a pandemic, statistical models are capable of generating accurate short-and-long-term car sales forecasts that allow firms to identify market demand patterns going forward, and improve market performance, minimising losses, thinking of and determining product development strategies, and planning manufacturing processes and marketing policies in more efficient ways.

Although there are many models for predicting automobile sales, this study is one of the few empirical ones that looks at how the COVID-19 pandemic has affected the sales of new cars in a developing nation, like SA. In this regard, the research focuses on assessing how South African new car manufacturers were impacted and determining whether the sector recovered from the pandemic's effects. Thus, in addition to suggesting a Box-Jenkin sales forecasting framework capable of measuring the impact of the COVID-19 pandemic and related crises on new car sales, the study contributes to the body of knowledge on forecasting new car sales during global pandemics and other crises or economic shocks. This paper's forecast model can assist new car manufacturers around the world, and SA in particular, in reducing the risk of not knowing unquantifiable losses and ultimately enhancing their contractual capacity. The article aims to make a valuable contribution by applying time series models to the car retail environment, specifically in accurately forecasting future car sales in the event of unforeseen shocks to the automobile industry. This proactive approach aids in preparing for future disruptions, implementing effective risk mitigation strategies, and enhancing policy-making. The significance of this contribution arises from the existing gap in statistical time series models that address the impact of sudden shocks on the automobile industry in SA.

Moreover, the article provides valuable insights for stakeholders and customers, offering a comprehensive understanding of aggregated new car sales patterns in South Africa. It also serves as a foundational piece for future research endeavours, facilitating the quantification of the impact of interventions in SA's automobile industry and potentially contributing insights to similar industries beyond the country's borders. Assessing the impact of COVID-19 on aggregated new car sales offers a holistic and resource-efficient approach, providing policymakers and stakeholders with clear, macro-level insights to inform strategic decisions and industry-wide interventions, and this further aids in understanding the broader implications of the pandemic on the automobile industry.

2 Literature review

[26] emphasised the significance of demand forecasting, especially for firms introducing new products with shorter life cycles at a higher frequency. The study employed ARIMAX and three machine learning methods based on deep neural networks (DNNs) to assess their performance. Surprisingly, the results revealed that the simple ARIMAX model outperformed the more advanced DNNs. This finding underscores the pivotal role of traditional models like S/ARIMA in forecasting accurately.

In their study on forecasting incoming calls to telemarketing centers in the United States for planning and budgeting purposes, [16] conducted a comparison between Holt-Winters (HW) models and ARIMA models with intervention analysis. Their findings revealed that the ARIMA model with intervention analysis outperformed the HW models in capturing the dynamics of the time series under investigation. This conclusion highlights the superior performance of the ARIMA model when applied to specific time series data.

Descriptive quantitative methods were employed by [27] to evaluate the impact of the COVID-19 pandemic on the SA automobile industry. According to the study's findings, new car sales began to noticeably decline in March 2020, with April 2020 recording the worst negative decrease. Although their study did not show whether or not automobile sales have returned to pre-COVID-19 pandemic levels, the present analysis is considering this and further projects future sales that are crucial for planning purposes post-COVID-19 pandemic.

[28] compared the forecasting ability of Holt-Winters and SARIMA models while modelling Indian motorcycle sales, and it was concluded that the Holt-Winters model produced more precise and accurate forecasts than the SARIMA model. The model results were said to be helpful to the Indian motorcycle and parts manufacturers to build an effective strategy, and also of benefit to the government, since the sales feed into the country's GDP.

[29] used the Box-Jenkins methodology for time series analysis and concluded that sales forecasting is a crucial component

when running businesses successfully. The authors forecasted the total car sales in India using an autoregressive integrated moving average (ARIMA) model. The ARIMA(1,1,0) model was suggested and their findings could guide the motor vehicle companies to cover expenses and decide salaries and wages for the employees, as well as stocking inventory levels. The same approach was used by [30] in India to model and predict automobile sales. There was a significant impact of new car sales on the economy through trade flows. The forecasts indicated a gradual increase in future car sales in the country, a positive sign for the economy.

[31], who noted that the automobile industry makes a sizable contribution to the Indian economy, looked at how the COVID-19 pandemic affected the sector using a time series modelling approach. The most effective model for car sales was an ARIMA (2, 1, 3) model. To determine the extent to which the COVID-19 pandemic affected the Indian automobile sector, forecasts were created for the period January 2020 to December 2021 and compared with actual car sales during the pandemic. The conclusions confirmed the COVID-19 pandemic had a detrimental impact on Indian automobile sales. The current study uses a similar Box Jenkins Methodology approach to forecast new car sales in SA, because of its flexibility and accuracy in forecasting. SA is an important player in African economies and indeed in the World economy.

3 Methodology

The [32] methodology approach is employed in modelling and forecasting SA car sales. The SARIMA models are capable of generating accurate car sales forecasts; and are adopted in this paper.

3.1 ARIMA (p,d,q) and SARIMA (p,d,q) (P,D,Q)$_s$ models

An ARIMA (p,d,q) model can be expressed as:

$$\phi(B)\,\nabla^d Y_t = \theta(B)\varepsilon_t, \tag{1}$$

where $\nabla^d = (1-\mathrm{B})^{\mathrm{d}}$, is a non-seasonal difference operator component to achieve stationarity, d is the order of the difference, B is the backward shift operator where $B^{\mathrm{k}} Y_{\mathrm{t}} = Y_{\mathrm{t-k}}$, k is the time lag, Y_{t} are new car sales, $\phi(B)$ and $\theta(B)$ are ordinary Autoregressive (AR) and Moving Average (MA) model components represented by polynomials of orders p and q respectively, and ε_{t} represents the error term at time t, which captures the random fluctuations in the data.

To cater for seasonal data, the ARIMA model is improved to a SARIMA(p,d,q) (P,D,Q)$_s$, which can be expressed as:

$$\Phi_P(\mathrm{B}^s)\phi(B)\,\nabla_s^D \nabla^d Y_{\mathrm{t}} = \Theta_{\mathrm{Q}}(\mathrm{B}^s)\theta(\mathrm{B})\,\varepsilon_{\mathrm{t}}, \tag{2}$$

where $\Phi_P(\mathrm{B}^s)$ and $\Theta_{\mathrm{Q}}(\mathrm{B}^s)$ are the seasonal AR and MA components of order P and Q, respectively. $\nabla_s^D = (1-\mathrm{B}^s)^D$ is the seasonal difference operator component, s denoting the seasonal period.

3.2 SARIMA model with COVID-19 dummy variable

Since the COVID-19 pandemic resulted in a period of disruption or change in the new car sales, a dummy variable $\mathrm{D_t}$ or a pulse intervention can capture the impact of the pandemic. This paper uses the Dummy variable approach to capture the impact of the COVID-19 pandemic on new car sales. In SA, a temporary economic movement restriction was introduced during the COVID-19 pandemic period, commencing on 27 March 2020. However, the impact of the COVID-19 extended beyond the initial period in April 2020 and continued to have effects over an extended duration as some companies closed down. The effects may still be lingering to this day. Therefore, the period of a dummy variable $\mathrm{D_t}$ can be defined as 1 from April 2020 onwards, while all months preceding April 2020 are denoted as zero. The dummy variable can be expressed as follows:

$$\mathrm{D_t} = \begin{cases} 1, & \text{if } \mathrm{t} \geq \text{April 2020} \\ 0, & \text{if } \mathrm{t} < \text{April 2020}, \end{cases} \tag{3}$$

where t represents the months. The SARIMA model that incorporates the COVID-19 pandemic dummy variable impact can then be expressed as:

$$\Phi_{\mathrm{P}}(\mathrm{B^s})\phi(\mathrm{B})\,\nabla_{\mathrm{s}}^{\mathrm{D}}\nabla^{\mathrm{d}}\mathrm{Y_t} = \Theta_{\mathrm{Q}}(\mathrm{B^s})\theta(\mathrm{B})\,\varepsilon_{\mathrm{t}} + \beta\mathrm{D_t}, \tag{4}$$

where β is the coefficient of the dummy variable ($\mathrm{D_t}$) representing the impact of COVID-19 pandemic, $\mathrm{D_t}$ is the dummy variable that takes a value of 1 during/post the COVID-19 pandemic period and 0 otherwise.

Automotive companies are also encouraged to consider rolling forecasts. Rolling forecasts play a crucial role in enhancing financial and operational management, expediting decision-making processes, and allocating more time to value-added activities, as highlighted by [33]. SARIMA models provide the flexibility to generate rolling forecasts by updating the model parameters with new data, allowing for an extended forecast horizon. This iterative process enables continuous updates and incorporation of the latest information, ensuring accurate and up-to-date predictions in a changing data environment.

The SARIMA model, when applied to new car sales forecasting, enables organisations to adapt to dynamic changes and anticipate both risks and opportunities in a volatile business environment, as emphasised by [34]. This adaptive forecasting approach facilitates effective reactions to market fluctuations and supports automotive companies in identifying emerging business prospects and improving negotiation effectiveness [35].

The results from the SARIMA model will be compared to an Exponential smoothing (ETS) and Naïve models.

3.3 Exponential smoothing (ETS)

Exponential smoothing (ETS) is one of the most popular methods used in forecasting analysis. The Holt-Winters' Additive Method (A,Ad,A) is one of the ETS techniques and can be expressed as:

$$\left.\begin{aligned} \hat{y}_{t+h} &= l_t + hb_t + s_{t+h-m} \\ l_t &= \alpha(y_t - s_{t-m}) + (1-\alpha)(l_{t-1} + b_{t-1}) \\ b_t &= \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1} \\ s_t &= \gamma(y_t - l_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m}, \end{aligned}\right\}, \quad (5)$$

where γ, α and β are the smoothing parameters (seasonal, level and trend) taking values between 0 and 1. y_t, l_t, b_t, s_t and m represent the new car sales, the smoothed level, trend change, seasonal smooth, and the number of seasons per year, respectively, at time t. The forecasted new car sales at time $t + h$, denoted as $\hat{y}_{t+h}$, represent the forecasted values for the forecasting horizon (h).

3.4 Naïve method

[36-37] have both recommended the Naïve method as a benchmark for comparing different forecasting models. They emphasize its effectiveness and widespread use for model comparison purposes. The Naïve method is recognised as a valuable reference point against which other models can be evaluated. A Seasonal Naïve method that caters for highly seasonal data can be expressed as follows:

$$y_t = y_{t-s} + \varepsilon_t , \quad (6)$$

where s is the seasonal period. y_{t-s} is the historical value of new car sales at time $t - s$.

3.5 Decomposing the time series, stationarity test and data transformation

Before checking for the presence of the unit root, the data will be decomposed to reveal some of the properties of the series. The Augmented Dickey-Fuller (ADF) test is then used to determine the stationarity or otherwise of the monthly automobile sales. Stationary testing is necessary in the time series identification stage of modeling. The ADF model and test is given as:

$$\Delta Y_t = \alpha + \delta T + \beta Y_{t-1} + \sum_{i=1}^{k} \gamma_i \Delta Y_{t-i} + \varepsilon_t, \quad (7)$$

where $\Delta Y_t = Y_t - Y_{t-1}$, T stands for the deterministic trend, ΔY_{t-i} is the lagged initial difference to account for a serial correlation in ε_t error term. γ_i , δ, β and α are model parameters (constants) that need to be estimated. The null hypothesis of the model to test for a unit root is reduced to testing for $H_0{:}\,\beta = 0$.

The Box-Cox transformation graphics will be used to suggest all suitable and feasible data transformations to aid in making the data variance stationery.

3.6 Model identification, parameter estimation and selection

The Autocorrelation Function (ACF), Partial Autocorrelation Function (PACF), and Extended Autocorrelation Function (EACF) are all used to estimate the tentative orders of the ARIMA/SARIMA models. All the model parameters are estimated using the maximum likelihood estimate (MLE) technique. The Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) are commonly used criteria for model selection. The model with the lowest value of AIC and BIC is considered the most plausible and preferred among the candidate models. After selecting the model based on AIC and BIC, diagnostic checks are conducted to assess the adequacy of the re-estimated model in describing the entire sample period.

3.7 Model diagnostic testing

The Ljung-Box test will be applied to check for autocorrelation on the model residuals. A good model should have no correlation in the residuals. A histogram and the Q-Q plot are used to determine the Normality of the model residuals. The forecasting capacity of the model is evaluated using the root mean square error (RMSE), which is of the following form:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t - \widehat{Y_t})^2}, \quad (8)$$

where Y_t are the actual car sales, $\widehat{Y_t}$are the forecasted care sales and n is the total number of years in the forecasting period.

4 Results

The Statistics South Africa's Motor trade sales reports, which are accessible at https://www.statssa.gov.za, were utilised to compile monthly SA new car sales data for the period from April 2009 to November 2022. The preintervention period for model estimation is defined as April 2009 to February 2020. The data from April 2009 to February 2019 is used as the training data, while the data for the period March 2019 to February 2020 is reserved for model validation purposes. The selected pre-intervention period represents the time before the COVID-19 pandemic economic lockdown. A model is then estimated using this sample. Subsequently, the same model is re-estimated over the entire sample period, spanning from April 2009 to November 2022. In this case, $\mathrm{D_t} = 1$ is incorporated to account and quantify the impact of the economic lockdown during the COVID-19 pandemic. During this period, the dummy variable $\mathrm{D_t}$ is assigned a value of zero. R 4.2.2 software was used for all data analysis. The following R packages were used, TSA, tseries and forecast.

4.1 Data and descriptive statistics

The summary statistics for the monthly SA car sales (Y_t) are shown in Table 1.

Minimum	Maximum	Median	Mean	Std. Deviation	Skewness	Kurtosis
27554	65163	49180	47880.13	9036.24	-0.34	-0.74

Table 1: Descriptive statistics of Y_t (April 2009 to February 2020)

With a minimum and maximum monthly sale of R27554 million and R65163 million, respectively, the average monthly sales of motor vehicles in SA are R47880.13 million. Figure 1 displays the time series plot of Y_t.

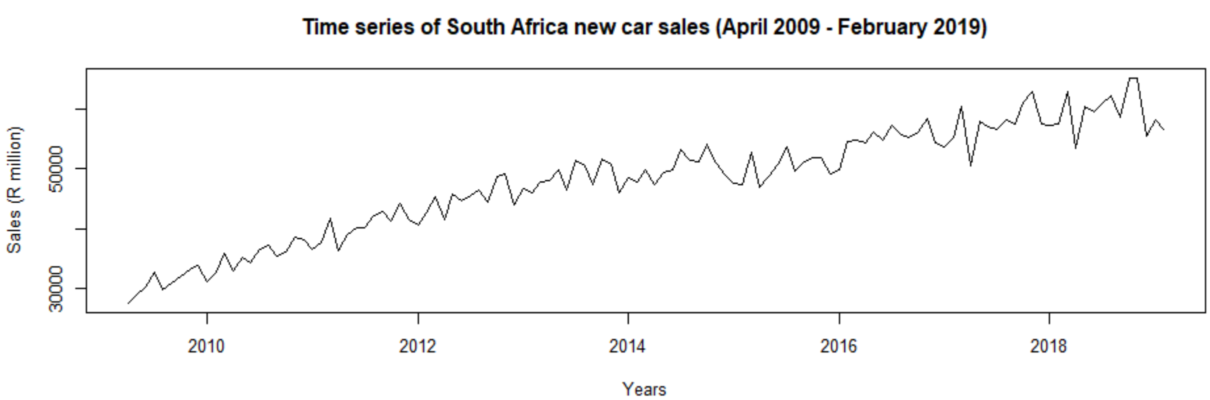

Fig.1: Time series plot of Y_t

The dataset is not stationary as evidenced by the upward trend and is associated with increasing variation with time. The new car sales behavior of a growing or steady trend is domineering. To identify the key elements of the data, a deconstructed time series is built.

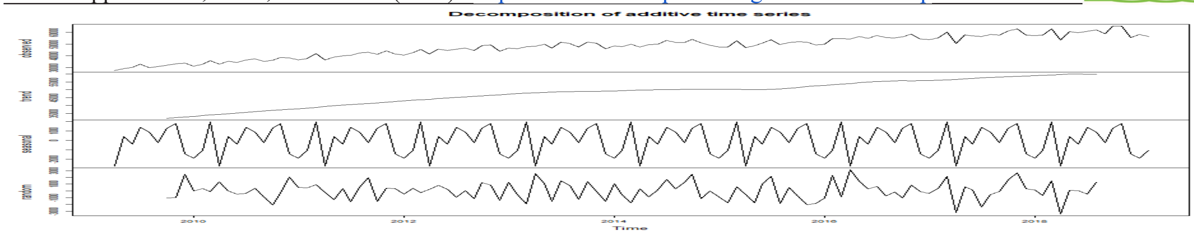

Fig.2: Decomposed time plot of Y_t

The components of Figure 2 include (from top to bottom) the original series, a steadily rising trend component, a fluctuating or seasonal component, and a random component. The new car sales have a high seasonality and a distinct increasing trend, as seen by the time plot. The pattern of oscillations moving upwards and downwards indicates a strong correlation, implying that a SARIMA model may be well-suited to analyse this data. However, on the ETS part, the Holt-Winters (A, Ad, A) model is recommended to address the presence of random fluctuations, approximately linear trend, and recurring seasonal patterns in the data. The best and most appropriate data transformation to apply and achieve Normality is chosen using the Box-Cox method. Figure 3 presents the Box-Cox results.

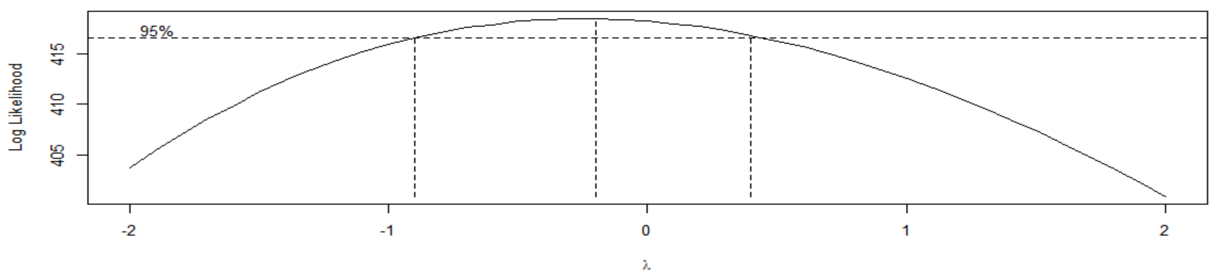

Fig.3: Box–Cox plot of SA new car sales (Y_t).

A logarithm transformation is recommended because the Box-Cox method demonstrates that the maximum loglikelihood of the transformation parameter lambda (λ) is very close to zero. Equation nine gives a logarithm transformation formula as the appropriate transformation to tame the variance.

$$Z_t = \log(Y_t) \quad (9)$$

Figure 4 shows a plot of the logarithm transformed new car sales (Z_t).

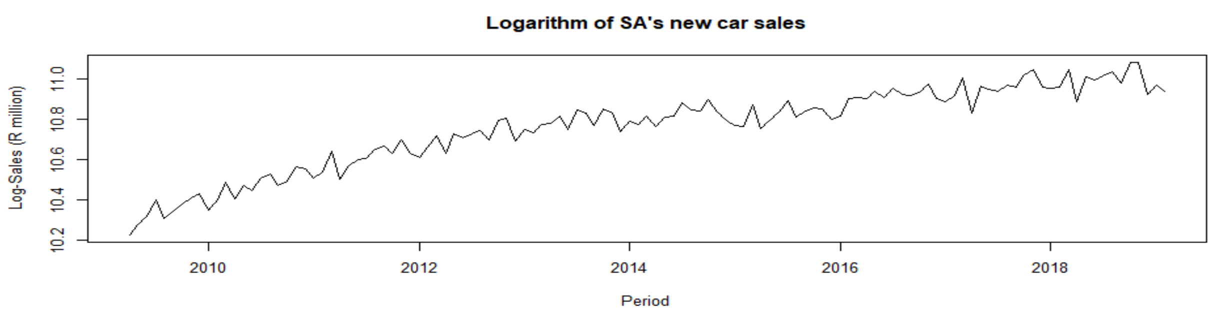

Fig.4: Time series plot of Z_t.

Figure 4 shows a smoothed series that is variance stationery but trend non-stationary. The logarithm transformed new car data (Z_t) is subjected to an ADF test to determine stationarity. The ADF test results are shown in Table 2.

Table 2: ADF test results of Z_t.

Dickey-Fuller	Lag order	p-value
-1.9626	4	0.5921

According to Table 2's findings, the series Z_t are not trend stationary, as shown by the p-value of 0.5921. As a result, we are unable to rule out the null hypothesis that there is a unit root in the data. Z_t was subjected to an ordinary first difference. An ADF test is employed and Table 3 confirms the result

Table 3: ADF test of first difference of Z_t.

Dickey-Fuller	Lag order	p-value
-5.3727	4	0.01

The results shown indicate that the data is stationary after the first ordinary difference at say, 5% level of significance, as shown by the p-value of 0.01.

4.2 Model Identification

To identify p, d, and q for the preliminary model, the ACF and PACF of the first difference of Z_t are performed. The ACF and PACF results are shown in Figure 5.

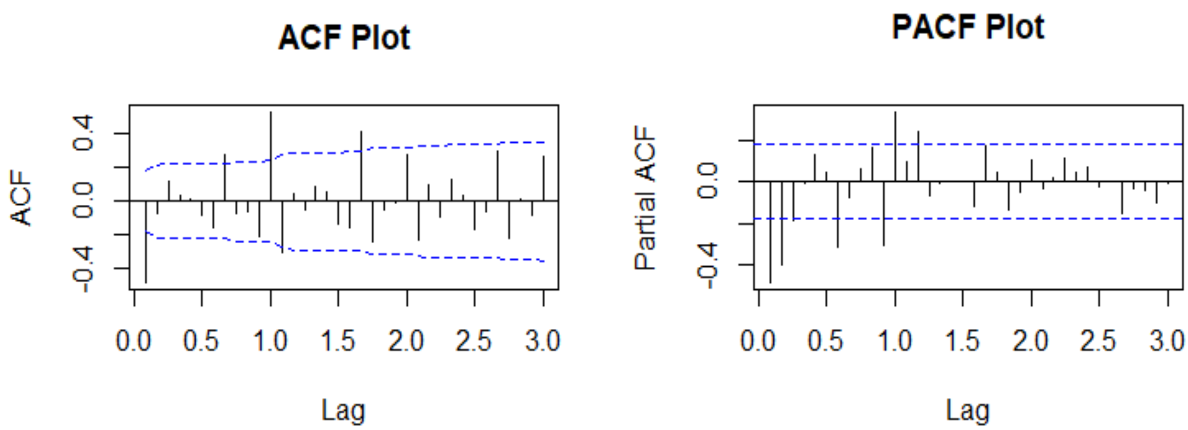

Fig.5: ACF and PACF plots of the ordinary differenced Z_t series.

Models like the SARIMA $(0,1,1)(0,0,1)_{12}$ and SARIMA$(0,1,1)(0,0,2)_{12}$ are suggested by ACF and PACF plots. Additionally, the EACF is plotted to further validate the suggested models.

Table 4: The EACF of the ordinary differenced Z_t series.

AR/MA	0	1	2	3	4	5	6	7	8	9	10	11	12	13
0	x	o	o	o	o	o	o	x	o	o	x	x	x	o
1	x	x	o	o	o	o	o	x	o	o	o	x	x	x
2	x	x	o	o	o	o	o	x	o	o	o	x	x	x
3	x	o	o	o	o	o	o	o	o	o	o	x	x	o
4	x	x	o	o	x	o	o	o	o	o	o	x	o	o
5	x	x	o	o	x	o	o	o	o	o	o	x	o	o
6	o	x	o	x	o	x	o	o	o	o	o	x	o	o
7	x	x	x	x	o	o	o	o	o	o	o	x	o	o

The EACF results suggest such a SARIMA $(0,1,1)(0,0,1)_{12}$ and SARIMA$(0,1,1)(0,0,2)_{12}$ model. Together with other proposed models, the suggested models are fitted. The AIC and BIC are used to determine the best fitting model.

Table 5: Fitted models' AIC, BIC and RMSE. (Note: The final model considered is bold.)

Model	AIC	BIC	RMSE (In- sample)	RMSE (Validation)
SARIMA $(0,1,1)(0,0,2)_{12}$ model with drift	**-408.33**	**-394.48**	**0.0401**	**0.0276**
SARIMA $(0,1,1)(0,0,1)_{12}$ model with drift	-404.53	-393.00	0.0411	0.0263
SARIMA $(1,1,1)(1,1,1)_{12}$ model without drift	-385.17	-371.86	0.0340	0.0332
SARIMA $(1,1,1)(0,0,2)_{12}$ model with drift	-407.32	-390.69	0.0399	0.0268
SARIMA $(0,1,1)(2,0,0)_{12}$ model with drift	-388.85	-375.00	0.0434	0.0325
Holt-Winters (A, Ad, A) model	-223.70	-173.67	0.0308	0.1182
Seasonal Naïve model	-	-	0.0519	0.0415
Naïve model	-	-	0.1071	0.0793

The SARIMA $(0,1,1)(0,0,2)_{12}$ model with a drift parameter outperformed the baseline models, including the Holt-Winters (A, Ad, A) model (γ =1e-04 , $\alpha = 0.2248$ and β =1e-04), naïve, and seasonal naïve models, exhibiting superior performance in terms of the lowest AIC and BIC values, as well as the lowest in-sample RMSE, as indicated in Table 5 results. Table 6 lists the parameters for the SARIMA $(0,1,1)(0,0,2)_{12}$ model.

Table 6: SARIMA $(0,1,1)(0,0,2)_{12}$ model parameters.

Parameter	Coefficient	Standard Error (SE)	Test statistic	P-value
θ_1	-0.6924	0.0674	-10.2683	<0.0001
Θ_1	0.6064	0.0981	6.1808	<0.0001
Θ_2	0.2167	0.0897	2.4171	0.0156
c	0.0062	0.0020	3.0723	0.0021

All of the model parameters shown in Table 6 are statistically significant at the 5% level of significance. Considering the model parameters, the SARIMA $(0,1,1)(0,0,2)_{12}$ model is written as:

$$Z_t = Z_{t-1} + \varepsilon_t + 0.6924\varepsilon_{t-1} - 0.6064\varepsilon_{t-12} - 0.4199\varepsilon_{t-13} - 0.2167\varepsilon_{t-24} - 0.15\varepsilon_{t-25} \quad (10)$$

4.3 Model testing

The Ljung-Box test was used to determine whether any autocorrelation existed in the SARIMA $(0,1,1)(0,0,2)_{12}$ model residuals, and the results indicated that there was none (χ^2 = 7.2471, df = 3, p-value = 0.644). The Q-Q plot and histogram in Figure 6 are used to check the Normality of the model residuals.

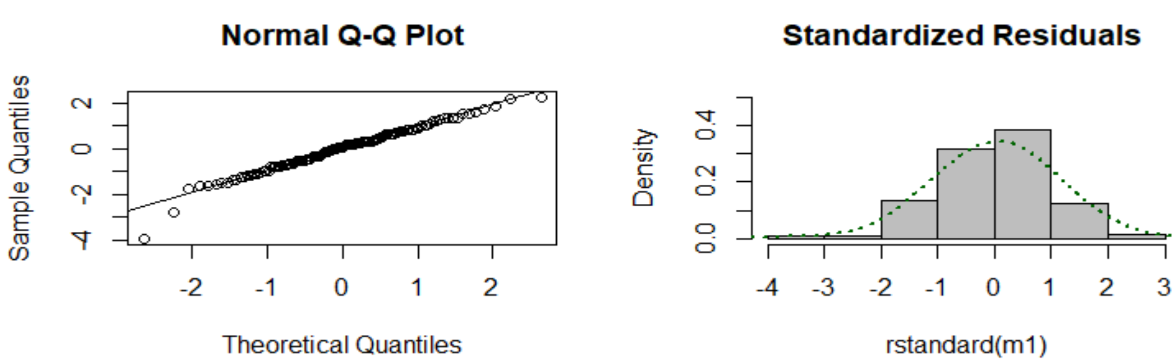

Fig.6: Q-Q plot and histogram of SARIMA(0,1,1)(0,0,2)$_{12}$ model residuals.

The model residuals appear to be Normally distributed based on the Q-Q plot and residuals histogram. The SARIMA$(0,1,1)(0,0,2)_{12}$ model is shown to be the model that fits well to SA's monthly car sales; and as a result, the model is used to predict sales of motor vehicles.

4.4 In-and-out of sample projections (forecasts)

Figure 7 compares the in sample actual and fitted car sales (after reversing the logarithm transformation).

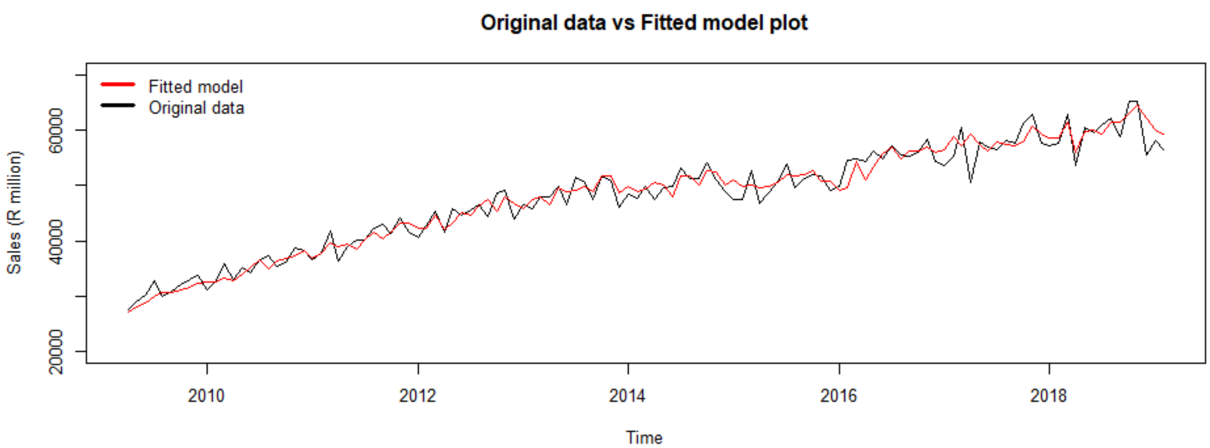

Fig. 7: Original versus fitted values.

The fitted values and the original values do not significantly differ as shown in Figure 7. The model is doing a good job.

For planning, marketing, and policy-making purposes, forecasts of future auto sales in SA are crucial to the government and all parties involved in the automotive industry. Out-of-sample projections for the next 46 months are generated using the SARIMA $(0,1,1)(0,0,2)_{12}$ model. Forecasted new car sales after reversing the logarithm transformation, had COVID-19 pandemic and intervention not occurred and actual new car sales are displayed in Figure 8.

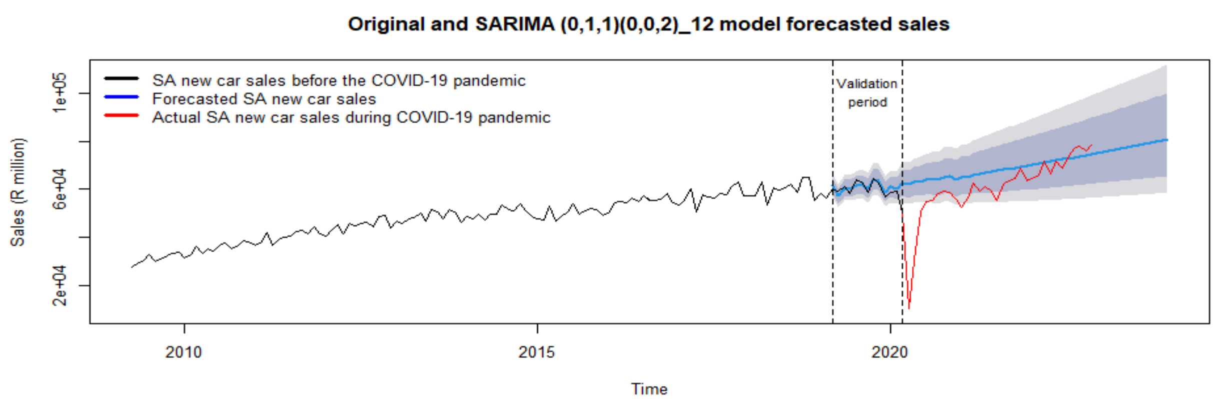

Fig.8: Actual new car sales during the COVID-19 pandemic and forecasted sales.

In Figure 8, the period between the black dashed vertical lines represents the model validation period. During this period, the observed and forecasted new car sales show an insignificant difference, indicating that the model fitting well to the data. Additionally, the dark grey coloured area in the figure represents the 80% confidence limit, while the lighter grey coloured area represents the 95% confidence limits. The SA automotive sector felt the effects of the COVID-19 pandemic, as expressed by the difference between the blue line (forecasted future new car sales had the COVID-19 not occurred) and the red solid line (actual new car sales). According to Figure 8, if the COVID-19 outbreak had never occurred, new car sales would have been as projected by past behaviour patterns. Figure 8 shows that the rate of increase in new car sales has recovered to such an extent that the level of new car sales has reached the pre-COVID-19 pandemic projected levels and even surpassed these figures slightly. The uplifting of the COVID-19 pandemic restrictions did help the situation as seen by a significant increase in new car sales. The anticipated new automobile sales will continue to assist SA automakers in preparing their businesses for future changes in the industry brought on by future pandemics like the COVID-19.

4.5 Assessing the impact of COVID-19 pandemic on new car sales

A SARIMA $(0,1,1)(0,0,2)_{12}$ model, which incorporates a COVID-19 pandemic dummy variable Dt is estimated using the entire dataset (April 2009 to November 2022) following the recommendation of Enders (1990). This approach would allow for the assessment and quantification of the impact of COVID-19 pandemic on new car sales. The final equation for the model is then expressed as follows:

$$Z_t = Z_{t-1} + \varepsilon_t + 0.3852\varepsilon_{t-1} - 0.1932\varepsilon_{t-12} - 0.0745\varepsilon_{t-13} - 0.1372\varepsilon_{t-24} - 0.0528\varepsilon_{t-25} - 1.8634D_t \qquad (11)$$

The disparity between the estimates of Equations (10) and (11) can be attributed to the variation in sample size and the inclusion of the pandemic effect captured by the dummy variable in the SARIMA model. A larger sample size has the potential to yield more dependable and precise estimates of the model parameters, enhancing the overall performance of the model. A greater sample size enables the model to better grasp the underlying patterns and dynamics within the data, thus potentially resulting in more accurate estimations of the pandemic's influence on the monthly logged new car sales.

The estimated parameter for the COVID-19 dummy variable in Equation (11) is -1.8634. This suggests that the pandemic had a significant negative effect on the monthly log-transformed new car sales, leading to a reduction/loss of approximately 84.5% [exp(-1.8634)] in new car sales for the whole period, from the period of the first lockdown onwards. The result highlights the detrimental impact of the COVID-19 pandemic on the automotive industry, causing a noticeable decline in new car sales in SA.

5. Discussion

The South African automotive industry experienced an initial sharp decline in new car sales on the onset of the Covid-19 pandemic and the economic lockdown response that followed in the aftermath, all in an effort to slow down the spread of the pandemic. However, the industry demonstrated resilience by bouncing back after a few months, thus indicating that the impact was temporary. A parallel study conducted by [38] on US vehicle sales echoed these same results and conclusions. They observed an initial decline in US vehicle sales on the onset of the Covid-19 pandemic, with the series eventually reverting back to higher sales levels. The rapid recovery suggested the industry's robustness. [39] affirmed comparable conclusions, confirming that the worldwide automotive industry, specifically in terms of car production and sales, faced initial detrimental impacts due to the Covid-19 pandemic with a subsequent recovery shortly after. They advocated for stakeholders to proactively identify strategies to mitigate the adverse effects of the pandemic on the automotive industry.

To overcome the challenges posed by the Covid-19 pandemic, the automotive industry may adopt various strategic measures. Remote work in the sales department and collaboration are two key strategies that involve implementing remote work policies, virtual collaboration tools, and digital communication platforms. These measures ensure smooth business operations, especially during periods of lockdown. Moreover, the industry may prioritise digital transformation and e-commerce. Car manufacturers may accelerate their digital transformation efforts and invest in e-commerce platforms. This includes improving online sales channels, creating virtual showrooms, and providing contactless purchasing options. These initiatives are designed to effectively engage customers not only during lockdowns but also in the evolving landscape beyond the pandemic.

The Covid-19 pandemic led to supply chain disruptions due to economic lockdowns in some instances, contributing to a decline in supply and the sale of new cars in SA. Similarly, the impact of the COVID-19 crisis on the automotive sector in Central and Eastern Europe was evident in supply chain disruptions and a substantial decrease in demand [40]. These findings align with the conclusions drawn in the current study of an initial decline and followed by a gradual recovery taking a few months. The diversification of the supply chain is a crucial strategy that car manufacturers may choose to adopt. Car manufacturers may proactively identify alternative suppliers in different geographic regions for critical components and establish partnerships with suppliers in these different geographic locations. Geographic regions may be affected different at different times. The Covid-19 virus in known to be more active in winter months. The northern and southern hemispheres experience their winters in different months of the year. This strategic move aims to minimise disruptions and enhance the resilience of the supply chain.

[41] assessed the post-impact of the Covid-19 pandemic on the Chinese automotive industry, examining its effects across different categories of cars. The study concluded that a substantial negative impact on Chinese car sales overall was evident, again aligning with the current study's conclusion of an initial abrupt decline with a gradual recovery soon after. These insights are valuable for both South African and international car companies, offering guidance for effective production, operations, and supply chain management decisions in the face of similar future shocks. The results emphasise the importance of readily available strategies to cope with unforeseen challenges, such as embracing digital solutions and possibly discounts on car sales during such episodes. This entails prioritising technology adoption, online parts ordering, and e-marketing to enhance industry resilience, ensuring preparedness for the expected coming recovery. The industry will thus be better equipped to withstand and recover from potential challenges of similar pandemics in the future. Those car industries that are better prepared will most likely survive and recover the fastest.

6 Conclusions and recommendations

The COVID-19 pandemic was a direct economic threat as much as it was a hazard to public health. Through widespread economic lockdowns, many nations, including SA, took drastic actions to halt the spread of COVID-19 virus, which had a substantial impact on the world's supply networks. This resulted in the closure of automotive manufacturing facilities worldwide as well as in SA. Due to the automotive industry's importance to the SA economy, the nation's GDP and tax was significantly negatively affected. This paper uses the Box Jenkins SARIMA$(0,1,1)(0,0,2)_{12}$ model to predict and forecast new car sales so as to determine how the COVID-19 pandemic has/would affect new car sales in SA going forward. The AIC, BIC and RMSE values for this model are found to be the lowest hence confirming it as the best fitting model. Actual new automobile sales for the period from March 2020 to November 2022, which includes the COVID-19 era, were compared with the projected new car sales from the SARIMA$(0,1,1)(0,0,2)_{12}$ model, assuming the pandemic had not occurred. According to the comparison, actual new automobile sales during the first COVID-19 wave fell dramatically short of projected expectations. By the end of the year 2020, however, there was a small improvement in actual new car sales compared to expectations/projections. Further work could investigate whether SA automotive Industry has shrugged off the devastating impact of the 2008/9 Global Financial Crisis. The estimated parameter for the COVID-19 dummy variable indicated a significant negative impact of the pandemic on the monthly log-transformed new car sales. After the declaration of the COVID-19 pandemic in SA, there was a notable decrease of approximately 1.86% in monthly log-transformed new car sales, as indicated by the parameter associated with the dummy variable for the period of the lockdowns and beyond. This finding underscores the adverse consequences of the COVID -19 pandemic on the automotive industry, manifesting in a noticeable decline in new car sales in SA.

The proposed methodology and findings are useful to the SA automotive industry to help develop motor vehicle sales plans, and to help avoid unforeseen cash flow issues and better manage needs for manufacturing, personnel, and financing of new car sales. The model will help automobile makers in giving useful data/information, leading to improvements planning for the future in value chains. The government's support for the automotive industry could lead to the introduction of creative policies including the use of technology to accept consumer orders, disaster or pandemic insurances (e.g. ensuring salaries of work employees for a given period of the pandemic), strategic alliances between producers, middlemen, and delivery services, and creative inventory management to minimise stock-outs. The car sector, and indeed other sectors as well, could investigate how to take precautions and to cushion themselves as humanly as is possible against future pandemics which are sure to come.

Potential study's limitations include the exclusive focus on aggregated new car sales, without delving into the forecasting of a specific car model/brand. For future research, the authors will explore the use of disaggregated data and will employ a hierarchical forecasting model approach. This approach would offer more detailed insights and facilitate the generation of tailored recommendations for individual car manufacturers or car brands

Conflicts of Interest Statement

The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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