Global Financial Crisis Impact on SA Car Sales

Subjects: Mathematics, Applied
Contributor: Tendai Makoni , Delson Chikobvu

In both developed and developing nations, with South Africa (SA) being one of the latter, the motor vehicle industry is one of the most important sectors. The SA automobile industry was not unaffected by the 2007/2008 global financial crisis (GFC).

SA new car sales | Box–Jenkins methodology | global financial crisis (GFC)

1. Introduction

The automotive sector is a critical industry in most developed and developing countries [1]. After 1994 and the end of apartheid, South Africa (SA), a developing country, has seen rapid economic growth [2]. The average yearly gross domestic product (GDP) growth rate for SA rose from 3.6% between 2000 and 2003 to 5.1% between 2004 and 2007 [3].

More labor-intensive economic sectors, including manufacturing (particularly automotive), mining, trade, and construction, faced high unemployment rates during the global financial crisis (GFC) of 2007/2008 [4]. Global consumer demand declined, and, to make matters worse, SA began to experience severe energy shortages, which had an adverse effect on the manufacturing sector, particularly the automotive industry. The value added by SA's manufacturing decreased by 12.2% in 2009 [5]. Consequently, large decreases were experienced in the output of the automobile industry (34%), furniture industry (20%), and textile and apparel sector (14.6%). This had a negative impact on the country's economy.

The SA automobile sector generated 6.8% of the nation's GDP in 2018 (4.3% manufacturing and 2.5% retail) and directly employed about 110,000 people [6]. In 2019, the automobile industry contributed 300,000 jobs (100,000 directly in the manufacturing of vehicles and components and 200,000 indirectly). The sector contributed 6.4% to the national GDP and constituted 19% of the total manufacturing output [7].

According to [7], SA is the African continent's top vehicle manufacturer (54.3%), with 9 major original equipment manufacturers (OEMs) producing 600,000 vehicles per annum as of 2019; these serve both the domestic (40%) and export markets (60%). As one of SA's fastest-growing sectors, the automotive sector has long played a vital role in the country's economy. In 2021, it was regarded as the cornerstone of the national industrial foundation and the main manufacturing sector of the nation's economy. The automobile industry contributed 4.3% to GDP (2.4% manufacturing and 1.9% retail) in 2021 [8].

During the GFC, not only SA but other countries worldwide were affected by decreasing car sales. As per [9], the automotive industry, along with several other sectors, was significantly affected in 2008 and 2009. Tightening global financing conditions resulted in a nearly 25% drop in global vehicle sales from their peak in April 2008 to their trough in January 2009. Bai [10] reported that the financial and economic crisis had a strong negative effect on the automotive industry in Germany, with a 31% decline in passenger car sales and a 59% decrease in commercial vehicle sales by the end of 2009. The Chinese automotive industry experienced a 15% decline in its total automobile sales volume in 2009. In the first half of 2020, new car sales in European Union member states experienced an average decline of 36%, as reported by [11], due to yet another shock, namely, the COVID-19 pandemic.

Reliable automotive projections play a crucial role in strategic planning. SA reported a significant drop in new car sales between 2007 and 2008, reflecting the impact of the GFC on vehicle manufacturers worldwide [12]. The decline in new car sales and other sectors of the economy caused significant job losses, with damaging effects on workers' living standards. Its state-of-the-art car assemblies make SA the economic powerhouse of southern Africa. Understanding how SA's automotive industry was affected by the economic shock of the GFC provides valuable insights into similar economic shocks, including those experienced during the COVID-19 pandemic. These insights afford investors, customers, and other stakeholders an opportunity to understand the industry's vulnerabilities, challenges, and opportunities during similar economic shocks. When South Africa sneezes, the rest of the southern African economic region catches a cold. In other words, the economy of all of southern Africa is affected when SA's economy suffers.

The accurate forecasting of automotive sales helps dealers to dynamically change their marketing tactics and, in the case of a financial crisis, to make wise decisions for both the wider economy and the transportation sector. According to [13], accurate sales predictions strengthen the competitive edge of vehicle manufacturers in their efforts to optimize their production planning processes. Sales forecasting is crucial for the implementation of sustainable business strategies in the automotive sector. Any financial crisis or economic instability in a country influences purchase decisions related to cars and car products [14].

2. Long-Term Impact of the Global Financial Crisis on New Car Sales in South Africa

Common methods used for new car sales forecasting include time series, linear regression, machine learning, and grey forecasting methods. Autoregressive moving average (ARMA) and grey prediction are often the forecasting methods of choice [14]. In SA [15], monthly car sales are mostly forecast by using both the SARIMA and Holt–Winters models. In terms of short-term seasonal auto sales forecasting accuracy, the Holt–Winters model performed better than the SARIMA model.

In Indonesia [16], the ARIMA (2,1,2) and ARIMA (1,1,0) models were used to forecast new car and motorcycle sales, respectively. The results were important in assessing the effect of cars and motorcycles on traffic jams and accidents, as well as air pollution, in order to draft better policies.

The naïve method (NM), simple moving average (SMA), weighted moving average (WMA), simple linear regression (SLR), exponential smoothing (ES), Holt–Winter linear trend, autoregression (AR), ARMA, and ARIMA models were used in India [1] to compare the forecasted demand for vehicles. The Holt–Winter linear trend model was considered the most suitable. However, the modeling was conducted without considering shocks such as a GFC; therefore, the latter is considered in the current research. Shakti et al. [17] used an $SARIMA(0,1,1)(0,1,1)_{12}$ model to predict 5-year tractor sales for the Mahindra Tractors Company in India. The forecasted average increase in future sales meant an improvement in the country's GDP, and thus the economy. Such forecasts are at best true/correct if no shocks, such as the GFC experienced during 2007/2008, occur.

Pherwani and Kamath [18] concluded that sales forecasting is a crucial element in successful business management. The authors forecasted the total car sales in India using an ARIMA (1,1,0) model and concluded that their findings could guide motor vehicle companies to cover expenses and decide both employee wages and stocking inventory. The same Box–Jenkins methodology was used by [19] in India to model and predict automobile sales because of their significant impact on the economy through trade flows. However, the authors did not consider the impact of the GFC on car sales in their study. The current research aims to fill an important gap by investigating the effect of this external shock (the GFC) on new car sales, forecasting and providing information/data-based recommendations for inventory management, and other business operations in the automotive industry.

Chen [20] predicted Chinese automotive demand with the Box–Jenkins approach (an ARIMA model) using monthly data. The conclusion was that the ARIMA model generates better forecasts that could aid government in drafting automobile industry policies, as well as automobile enterprises in planning their output. Qu et al. [14] adopted the support vector regression (SVR) model to predict the monthly sales of automobiles in the Chinese car segment. The proposed grey wolf optimizer–support vector regression (GWO-SVR) model fitted the data well. Unlike the Box–Jenkins approach, the GWO-SVR approach is computationally expensive; it requires a significant number of computational resources and time to train and tune the model, especially when dealing with large amounts of data [21], such as with new car sales. The GWO-SVR also lacks interpretability as it uses machine learning techniques that do not provide clear insights into the underlying relationships between variables. Conversely, the ARIMA is a well-established time series model that provides interpretable coefficients that can help explain the relationship between variables.

Kaya and Yildirim [22] used an eight-layer deep neural network (DNN) model to forecast automobile sales. Several variables, such as the consumer confidence index (CCI), the exchange rate, the GDP, and the consumer price index (CPI), were considered. The authors recommend the use of their approach on various sales prediction problems. However, DNN models can be more challenging to use due to their high cost and the need for optimal architecture and hyper-parameter tuning, as noted by [23][24]. Furthermore, DNN models are more suitable to use with a large, homogeneous dataset with multiple observations, according to [25]. For a single variable such as new car sales, SARIMA models can lead to a higher forecasting accuracy and are therefore the preferred choice in this research.

Fantazzini and Toktamysova [26] used multivariate models, drawing on economic variables, and Google online search data to forecast Germany's monthly car sales. The conclusion was that the models, which included Google search data, outperform other competing car models. Such models can, however, be very complicated and subjective. In multivariate models, variable selection is difficult and subjective, which may lead to overfitting and poor forecasting performance. Thus, the use of ARIMA models that do not require the selection of relevant predictors becomes important.

Kim et al. [27] forecasted offline retail sales during the COVID-19 pandemic period in South Korea by comparing ARIMA to several ETS methods. The conclusion was that the SARIMA $(2,0,2)(1,0,0)_{12}$, ARIMA $(1,0,1)(0,0,0)_{12}$, and ARIMA $(2,0,3)(0,0,1)_{12}$ models were the best fit for retail sales in fashion, cosmetics, and sports categories, respectively, when compared to the naïve seasonal and Holt–Winter additive models. The forecasts showed that sales in the fashion retail category were increasing gradually, with sales in the cosmetics and sports retail categories increasing at a faster rate. The S/ARIMA models were better forecasting models than the ETS models, hence their adoption in the current research.

The simple and flexible Box–Jenkins approach is used in this entry to forecast new car sales in SA. Its suitability relies on its accuracy in forecasting, as well as its flexibility and adaptability to a wide range of time series data, such as new car sales. Brito et al. [28] concluded that the SARIMA models are more flexible in their application and more accurate in generating quality results.

References

1. Jain, P.; Arora, P. Analysis of Time Series Forecasting Techniques for Indian Automotive Industry. J. Emerg. Technol. Innov. Res. 2021, 8, d831–d840.
2. Committee of Central Bank Governors in SADC. SADC Bankers.Org: Recent Economic Developments. 2009. Available online: http//www.sadcbankers.org/SADC/SADC (accessed on 2 February 2023).
3. Madubeko, V. The Global Financial Crisis and its Impact on the South African Economy. 2010. Available online: https://core.ac.uk/download/pdf/145049071.pdf (accessed on 5 February 2023).
4. Rena, R.; Msoni, M. Global Financial Crises and Its Impact on the South African Economy: A Further Update. J. Econ. 2014, 5, 17–25.
5. National Treasury. Budget Review. 2010. Available online: https://www.treasury.gov.za/documents/national%20budget/2010/review/Budget%20Review.pdf (accessed on 5 February 2023).
6. Automotive Export Manual. 2019. Available online: https://aidc.co.za/wp-content/uploads/2021/08/AutomotiveExportManual2019.pdf (accessed on 3 February 2022).

7. Automotive Export Manual. 2021. Available online: https://naacam.org.za/wp-content/uploads/2021/04/AutomotiveExportManual2021.pdf (accessed on 5 February 2023).
8. Automotive Export Manual. 2022. Available online: https://naamsa.net/wp-content/uploads/2022/05/Automotive-Export-Manual-2022.pdf (accessed on 3 February 2022).
9. European Central Bank (ECB). Monthly Bulletin December 2010. Developments in the Euro Area and Global Car Industries. 2010, pp. 1–218. Available online: https://www.ecb.europa.eu/pub/pdf/mobu/mb201012en.pdf (accessed on 5 April 2023).
10. Bai, X. The Effects of the 2007–2009 Economic Crisis on Global Automobile Industry. Applied Economics Theses. Paper 2. 2012. Available online: https://core.ac.uk/download/pdf/230661682.pdf (accessed on 5 April 2023).
11. Török, L. The Link Between Car Sales and the Economic Crisis in the European Union at the Time of the COVID-19 Epidemic. Int. J. Econ. Bus. Adm. 2020, 8, 1033–1042.
12. Kasekende, L.; Ndikumana, L.; Rajhi, T. Impact of the Global Financial and Economic Crisis on Africa; Working Papers Series No 96; African Development Bank: Tunis, Tunisia, 2009; pp. 1–29.
13. Wachter, P.; Widmer, T.; Klein, A. Predicting Automotive Sales Using Pre-Purchase Online Search Data Proceedings of the 2019 Federated Conference on Computer Science and Information Systems; Ganzha, M., Maciaszek, L., Paprzycki, M., Eds.; ACSIS: Kobe, Japan, 2019; Volume 18, pp. 569–577.
14. Qu, F.; Wang, Y.-T.; Hou, W.-H.; Zhou, X.-Y.; Wang, X.-K.; Li, J.-B.; Wang, J.-Q. Forecasting of Automobile Sales Based on Support Vector Regression Optimized by the GreyWolf Optimizer Algorithm. Mathematics 2022, 10, 2234.
15. Makatjane, K.D.; Moroke, N.D. Comparative study of Holt-Winters Triple Exponential Smoothing and Seasonal ARIMA: Forecasting short term seasonal car sales in South Africa. Risk Gov. Control. Financ. Mark. Inst. 2016, 6, 71–82.
16. Irhami, E.A.; Farizal, F. Forecasting the Number of Vehicles in Indonesia Using Auto Regressive Integrative Moving Average (ARIMA) Method. J. Phys. Conf. Ser. 2021, 1845, 012024.
17. Shakti, S.P.; Hassan, M.K.; Zhenning, Y. Annual Automobile Sales Prediction Using ARIMA Model. Int. J. Hybrid Inf. Technol. 2017, 10, 13–22.
18. Pherwani, N.; Kamath, V. Using ARIMA Model to Forecast Sales of an Automobile Company. Int. J. Sci. Technol. Eng. 2017, 4, 77–82.
19. Srigandan, S.; Venkatesh, A.; Srinivasan, S.; Vasudevan, N. Car sales forecasting using ARIMA model. Int. J. Sci. Innov. Eng. Technol. 2017, 1, 1–6.
20. Chen, D. Chinese automobile demand prediction based on ARIMA model. In Proceedings of the 2011 4th International Conference on Biomedical Engineering and Informatics (BMEI), Shanghai,

China, 15–17 October 2011.

21. Rizzi, A.M. Support Vector Regression Model for BigData Systems. 2016. Available online: https://arxiv.org/pdf/1612.01458.pdf (accessed on 6 April 2023).
22. Kaya, S.K.; Yildirim, Ö. A prediction model for automobile sales in Turkey using Deep Neural Networks. J. Ind. Eng. 2020, 31, 57–74.
23. Chen, Z.; Cao, Y.; Liu, Y.; Wang, H.; Xie, T.; Liu, X. A comprehensive study on challenges in deploying deep learning-based software. In Proceedings of the 28th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering, New York, NY, USA, 8–13 November 2020; pp. 750–762.
24. Paleyes, A.; Urma, R.G.; Lawrence, N.D. Challenges in deploying machine learning: A survey of case studies. ACM Comput. Surv. 2020, 55, 1–29.
25. Makridakis, S.; Hyndman, R.J.; Petropoulos, F. Forecasting in social settings: The state of the art. Int. J. Forecast. 2020, 36, 15–28.
26. Fantazzini, D.; Toktamysova, Z. Forecasting German car sales using Google data and multivariate models. Int. J. Prod. Econ. 2015, 170, 97–135.
27. Kim, H.-J.; Kim, J.-H.; Im, J.-B. Forecasting Offline Retail Sales in the COVID-19 Pandemic Period: A Case Study of a Complex Shopping Mall in South Korea. Buildings 2023, 13, 627.
28. Brito, G.R.A.; Villaverde, A.R.; Quan, A.L.; Pérez, M.E.R. Comparison between SARIMA and Holt–Winters models for forecasting monthly stream flow in the western region of Cuba. SN Appl. Sci. 2021, 3, 671.