economies

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Assessing and Forecasting the Long-Term Impact of the Global Financial Crisis on Manufacturing Sales in South Africa

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Abstract: Sales forecasting is a crucial aspect of any successful manufacturing organisation as it provides the foundation for investment, employment development, and innovation. The Global Financial Crisis (GFC) had a negative impact on the manufacturing sector in South Africa (SA) and the rest of the world. The objective of this paper is to analyse the trend of manufacturing sales before, during, and after the GFC and to quantify the impact of the GFC on the total manufacturing sales in SA. The time-series-based Box–Jenkins methodology is used to achieve the objective. The study used Statistic South Africa's data on monthly total manufacturing sales in SA from January 1998 to December 2022. Total manufacturing sales exhibit strong seasonality. The ACF, PACF, and EACF plots, as well as the AIC, BIC, RMSE, and MAE, suggest the SARIMA$(2,1,2)(2,1,1)_{12}$ model as the best model for explaining and forecasting manufacturing sales in SA. The SA manufacturing sector was negatively impacted by the GFC, as evidenced by the comparison between actual data and projections based on a historical path prior to the GFC. Manufacturing sales are recovering from the GFC but have not reached potential levels that could have been achieved without the crisis. The SA manufacturing sector may take time to reach the expected/projected sale levels that could have been achieved in the absence of the GFC.

Keywords: South Africa; manufacturing sales; forecasting; global financial crisis

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Citation: Makoni, Tendai, and Delson Chikobvu. 2023. Assessing and Forecasting the Long-Term Impact of the Global Financial Crisis on Manufacturing Sales in South Africa. *Economies* 11: 158. https://doi.org/10.3390/economies11060158

Academic Editor: Ralf Fendel

Received: 4 April 2023
Revised: 18 May 2023
Accepted: 26 May 2023
Published: 30 May 2023

1. Introduction

The manufacturing sector is an essential component of any nation's economy, as it creates numerous high-quality employment opportunities and contributes significantly to the gross domestic product (GDP). The manufacturing sector has connections to other industries and has ripple effects in those industries (Industrial Development Corporation (IDC) (2013)). Several studies, including those by the European Commission (EC) (2012), McKinsey Global Institute (2012), and Naudé and Szirmai (2012), have concluded that the manufacturing sector is a cornerstone of many national economies, representing a crucial sector for generating structural change, productive jobs, and sustainable economic growth. The South African manufacturing sector is no exception, as it plays an important role in the country's economic growth. The expansion of the manufacturing sector suggests significant benefits to the economy.

The 2007–2009 financial crisis, or the Global Financial Crisis (GFC), was a severe worldwide economic crisis that occurred during that era. The crisis is considered by many economists and analysts as the worst financial crisis the world has experienced since the Great Depression of the 1930s (Kapoor 2012).

During the GFC, SA's economy experienced a slowdown in growth, a decline in exports, investment, and consumer spending. This was due to a decrease in demand for South African commodities, such as minerals and metals, and a decrease in foreign investments. The impact of the GFC on SA's economy was also felt through increased unemployment and inflation rates. Steytler and Powell (2010) highlighted that the unemployment rate in SA had risen to 25.2% by the first quarter of 2010 as a result of the GFC. Overall, while the exact impact of the GFC on SA's economy may vary depending on the specific indicators and time period analysed, it is widely acknowledged that the GFC had a significant negative impact on the country's economic performance.

Due to the GFC, the manufacturing sector's real gross value added (GVA) in SA shrank by 10.6% in 2009 after increasing at an average annual rate of 4.2% during the commodity boom between 2000 and 2008 (Mnguni and Simbanegavi 2020). The World Bank (2018) noted that the decline in SA's domestic output from 2007 to 2009 was due to a confluence of global, domestic, and commodity-specific shocks, as well as shocks to global demand. This demonstrates how the GFC negatively impacted SA's economy.

In response to the GFC, the South African government implemented a range of policies and interventions to stimulate economic growth and promote recovery. These included such measures as increased government spending, tax incentives for businesses, and infrastructure development projects.

According to the Deloitte Manufacturing Competitiveness Report (2013), after the GFC, around 1.7 million people were employed in the manufacturing sector in South Africa (SA), which is currently the second-largest economic sector and contributed 15.3% to the Gross Domestic Product (GDP) in 2011. The report also revealed that, in terms of value, food and drink (25%), iron, steel, metal (20%), motor vehicles (10%), and wood products (8%) are the top manufacturing industries in SA, highlighting the diversity of the sector's sub-units.

In SA, between 2008 and 2014, the manufacturing sector shed 331,000 jobs, by far the largest of any sector (Statistics South Africa 2016). The job losses were influenced by the GFC that was experienced between 2007/2009 (Bhorat and Rooney 2017). This again demonstrates how the GFC of 2007–2008 had a detrimental impact on the manufacturing sector.

The manufacturing sector in SA is stagnant primarily due to the emergence of a plentiful supply of cheap labour in such nations as India, Indonesia, China, and Vietnam, as well as a skills shortage. This prevents the sector from moving up the value chain and producing sophisticated manufactured goods (Bhorat and Rooney 2017). Accurate manufacturing sales data can be beneficial in analysing market demands, leading to the identification of areas of skills deficiency in the South African manufacturing industry, which can aid in improving the sector's productivity and competitiveness.

As the manufacturing industry becomes increasingly global and competitive, optimising operational functions is crucial for manufacturing companies. Accurate sales forecasting is helpful in achieving this goal. In today's world, where competitive margins are narrowing, the ability to make informed decisions based on accurate forecasts is essential, as highlighted by Pao and Sullivan (2017). Precise sales forecasting enables manufacturing companies to make informed decisions, such as allocating or diverting existing inventory and adjusting future production levels. This allows for optimal utilisation of resources and aids in improving operational efficiency.

The objective of this paper is to analyse the trend of manufacturing sales before, during, and after the GFC to quantify the impact of the GFC on the total manufacturing sales in SA. The time-series-based Box–Jenkins methodology is used to achieve the objective. Accurate manufacturing sales are crucial for manufacturing companies, as they aid in producing the desired quantities of goods and services at the appropriate time, making timely arrangements for raw materials, and estimating the anticipated revenue to be generated. As noted by Hyndman and Athanasopoulos (2018), the Box–Jenkins time-series models are easy to interpret, and the interpretation can provide valuable insights into the underlying process that generates the data. The contribution of this paper is the use of quantitative techniques to forecast and quantify the impact of the GFC on total manufacturing sales in SA and to provide valuable insights to the manufacturing industry in developing strategies to mitigate the negative impact of future economic crises.

The originality of work in this paper should be viewed within the context of applying an already established statistical methodology to provide new insights into the complex relationship between global financial events and local market conditions and by demonstrating the impact of a shock on the manufacturing sector in SA. The time-series approach is used as a tool for understanding and predicting economic trends from existing data. The current research aims to fill an important gap, investigating the effect of an external shock, the GFC, on the manufacturing sector in SA. This study is also a reference for similar research on the impact of the financial crisis on other industries in SA or other countries.

The GFC had significant economic implications for countries worldwide, including SA. As mentioned, one of the critical sectors impacted by the crisis was the manufacturing industry, which is a significant contributor to the country's economy. However, there is a lack of understanding of the magnitude of the impact of the GFC on the manufacturing industry in SA, and it is unclear whether the industry has fully recovered from the crisis. This knowledge gap hinders policymakers and industry stakeholders from developing effective strategies to mitigate any lingering negative effects of the GFC and in dealing with other impacts of future economic shocks on the sector. There is a need to investigate and quantify the impact of the GFC on the manufacturing industry in SA to determine the extent of the recovery and to inform policy-making and the industry when making decisions.

Investigating and projecting the long-term effects of the GFC on manufacturing sales in SA is crucial for understanding the impact and then informing policy decisions going forward. By using a time-series approach, one can analyse the trend of manufacturing sales before, during, and after the GFC to identify the extent of the shock and to forecast the future trajectory of the industry. The analysis is essential for determining if the manufacturing industry in SA is fully recovered from the GFC and to do any necessary or further mitigations thereof and for developing effective strategies to deal with similar shocks in the future.

2. The Literature Review

After noting the need for accurate fresh food product sales, Dellino et al. (2015) applied ARIMA, ARIMAX, and transfer function models to forecast fresh food supply chain sales in Italy based on sales data from 19 small and medium-sized retailers and 156 different fresh products. The ARIMAX model performed better than the ARIMA and indicated an increase in future fresh food products. Karimian and Siavashi (2021) noted poor decision-making by retailers that led to a loss of revenue in Sweden. They used the ARIMA and Long Short-Term Memory (LSTM) models to predict retail sales in Sweden and found that LSTM was superior to ARIMA as it captured nonlinear patterns in retail sales.

Permatasari et al. (2018) utilised ARIMA models to forecast the number of newspapers sold in Surakarta, as precise forecasts for newspaper sales are crucial for optimising the production and distribution strategies of publishers and distributors. The researchers chose ARIMA models due to their capability of capturing the temporal dependence and seasonality of the newspaper data. For short-term forecasting of newspaper sales, an acceptable ARIMA (1,1,0) model gave a good fit to the newspaper sales. The authors recommended the use of the ARIMA approach by newspaper publishers and distributors as a means of improving their operations and profitability.

In order to provide accurate forecasts for the future wholesale price of vegetables in Indian grocery stores, Shukla and Jharkharia (2013) employed the ARIMA model. The ARIMA (2,0,1) model was deemed useful by farmers and wholesalers in making informed sale decisions. It was concluded that the ARIMA (2,0,1) model's accuracy could aid farmers, traders, and retailers in making informed decisions regarding pricing and inventory management.

Sharma and Burark (2015) observed the need for accurate forecasts for sorghum prices in Ajmer Market, as they help farmers, traders, and buyers to make informed decisions about the production, marketing, and purchasing of sorghum. They used the Box–Jenkins approach to time-series analysis and predicted future sorghum prices in Rajasthan's Ajmer Market. The most effective model for predicting the price of sorghum in Rajasthan's Ajmer market was an ARIMA (1,1,2) model. The model captured the underlying data patterns and dynamics of sorghum prices. Rizkya et al. (2019) used an ARIMA model after highlighting the significance of demand forecasting for nail products produced by one of the building material industries in Medan markets in Indonesia. The most accurate model for predicting nail unit sales was found to be an ARIMA (3,0,2) model, which also suggested future expansion in the production of nails.

Due to the popularity of the methodology, and after noting the need for an accurate forecasting model for the Fast-Moving Consumer Goods (FMCG) market sales in Sri Lanka, Dassanayake et al. (2011) used a SARIMA $(1,1,0)(0,1,0)_{12}$ model, which provided a high level of accuracy. An increase in FMCG sales based on their model's forecasts was concluded, indicating a positive outlook for the FMCG industry in Sri Lanka. Wanjuki et al. (2021) used a SARIMA model, which accounts for the seasonal component in a given time series of data, to fit and forecast the food and beverage price index (FBPI) in Kenya. The SARIMA $(1,1,1)(0,1,1)_{12}$ was found to give the best fit for the data, and predictions from the model indicated that the FPBI is unstable with an overall upward tendency.

In recent years, the ARIMA/SARIMA model has been increasingly used in various industries for time-series analysis and forecasting. In the manufacturing sector, this model has proven to be effective in predicting future sales and demand. For example, Akhavan-Tabatabaei et al. (2019) applied a SARIMA model to provide accurate forecasting tools for the petrochemical company's monthly sales in Iran and to optimise production, inventory management, and marketing strategies. The study showed that the SARIMA model provided accurate forecasts, which helped the company to better allocate resources and plan production schedules. Similarly, Nisar et al. (2020) utilised the ARIMA model to forecast the monthly sales of a textile manufacturing company in Pakistan. The results indicated that the model provided reliable forecasts, which allowed the company to optimise its production processes and inventory management. Overall, the ARIMA/SARIMA model has proven to be a valuable tool for manufacturing companies in making informed decisions based on accurate sales forecasts. The Box–Jenkins approach is used to forecast manufacturing sales in this paper because of its proven superiority in generating accurate forecasts, as demonstrated in previous studies, such as those by Dellino et al. (2015) and Permatasari et al. (2018).

This study uses the Box–Jenkins approach to time-series analysis to describe and predict manufacturing sales. The methodology is selected because of its ability to model data with a seasonality element and to generate good forecasting results.

3. Methodology

The methodology used in this study is based on the Box and Jenkins (1970) approach to time-series analysis. This approach involves several steps, including model identification, parameter estimation, and diagnostic testing. The stationarity of the manufacturing series is assessed using the Augmented Dickey–Fuller (ADF) test. After ensuring stationarity, model identification is conducted using such tools as the Autocorrelation Function (ACF), Partial Autocorrelation Function (PACF), and Extended Autocorrelation Function (EACF). The model parameters are estimated using the maximum likelihood estimator (MLE) and diagnostic tests, such as the Ljung–Box test, normality plots, Akaike information criterion (AIC), Bayesian information criterion (BIC), root mean square error (RMSE), and mean absolute error (MAE), are used to evaluate the model's performance.

3.1. Data

SA's monthly total manufacturing sales for the period January 1998 to December 2022 are obtained from Statistics South Africa's Manufacturing website. The production and sales reports available on https://www.statssa.gov.za/ (accessed on 20 February 2023) are used. Data for the period from January 1998 to November 2008 was considered as the training data, whilst forecasts from December 2008 to December 2023 were created as expected for the future total manufacturing sales for comparison with the actual total manufacturing sales in order to assess the impact of the GFC on SA manufacturing industry. All the data analysis was conducted using R 4.2.2 software package, TSA and forecast packages, in particular, were developed by Hyndman and Khandakar (2008).

3.2. ARIMA/SARIMA Model

Non-seasonal ARIMA models are typically written as ARIMA (p,d,q), where p, d, and q are the non-seasonal autoregressive (AR), non-seasonal differencing, and non-seasonal moving average (MA) components, respectively. Typically, seasonal ARIMA (SARIMA) models are referred to as SARIMA (p,d,q) $(P,D,Q)_s$, where s denotes the number of seasons, and P, D, Q denote the seasonal AR, seasonal differencing, and seasonal MA components, respectively.

An ARIMA (p,d,q) model can be expressed in vector form as follows:

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

where $\nabla^d = (1-B)^d$ is a non-seasonal difference operator component; ε_t is a white noise process; μ is a constant term; B is the backward shift operator, where $B^d Y_t = Y_{t-d}$; Y_t are manufacturing 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. 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 follows:

$$\Phi_P(B^s)\phi(B)\nabla_s^D \nabla^d Y_t = \Theta_Q(B^s)\theta(B)\varepsilon_t + \mu, \tag{2}$$

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

3.3. Data Transformation

The manufacturing series data transformation is suggested by the Box–Cox transformation. Box and Cox (1964) introduced the Box–Cox transformation, a method for transforming non-normal dependent variables into a normal shape. The Box–Cox transformation is given by the following:

$$y(\lambda) = \begin{cases} \frac{y^\lambda - 1}{\lambda}, \ if\ \lambda \neq 0, \\ \ln(y), \ if\ \lambda = 0. \end{cases} \tag{3}$$

where y denotes the original non-normal manufacturing sales, and λ is a transformation parameter estimated using say the maximum likelihood estimation (MLE) method, which determines the degree and direction of the transformation.

3.4. Argumented Dicky-Fuller (ADF) Test

The stationarity of the manufacturing sales is examined through the ADF test developed by Dickey and Fuller (1979), which is expressed as follows:

$$\Delta Y_t = \alpha + \delta T + \beta Y_{t-1} + \sum_{i=1}^{k} \phi_i \Delta Y_{t-i} + \varepsilon_t, \tag{4}$$

where $\Delta Y_t = Y_t - Y_{t-1}$, T is for the deterministic trend; ΔY_{t-i} is the lagged initial difference to cater for autocorrelation in the error term (ε_t). ϕ_i, δ, β and α are model parameters to be estimated. The Akaike Information Criterion (AIC) and the Bayesian Information Criteria (BIC) are both employed in determining the appropriate number of lags to be considered in the ADF test. The ADF test for a unit root's null hypothesis is reduced to testing for $H_0 : \beta = 0$.

3.5. Maximum Likelihood Estimator (MLE)

There are many different parameter estimation methods, but the commonly used MLE of the parameter ψ is defined as follows:

$$\hat{\psi}_n = \arg\max_{\psi \in \Psi} L_n(Y;\psi) = \arg\max_{\psi \in \Psi} \mathcal{L}_n(\psi), \tag{5}$$

where $\hat{\psi}_n$ is the nth parameter to be estimated, and Y is the manufacturing series. Solving the derivative of the log-likelihood (Equation (5)) gives the parameter estimates.

3.6. Model Selection and Accuracy Measures

The ACF, PACF, and EACF arguments are used to identify the tentative optimal SARIMA model. The auto.arima() function in the R forecast package, which utilises a heuristic search approach based on a combination of unit root tests, model selection criteria, and optimisation algorithms, confirmed the same optimal SARIMA model. Model selection is made based on the AIC and BIC. A model with the lowest AIC and BIC is considered the best. The AIC and BIC can be written as follows:

$$AIC = -2\log(L) + 2(p+q+k+1), \tag{6}$$

and

$$BIC = -2\log(L) + 2(p+q+k+1)\log(n), \tag{7}$$

where L is the likelihood function; $k = 1$ if $c \neq 0$ (c = constant term); $k = 0$ if $c = 0$; p is the order of the AR part, and q is the order of the MA and n is the number of observations. The RMSE and the MAE used to assess the forecasting accuracy of the fitted models are defined as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(Y_t - \hat{Y}_t\right)^2}, \tag{8}$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|Y_t - \hat{Y}_t\right| \tag{9}$$

where Y_t denotes the original manufacturing sales; $\hat{Y}_t$ are the projected manufacturing sales, and n is the projected period.

4. Results

4.1. Descriptive Statistics and Model Identification Processes

Table 1 presents the descriptive statistics of the monthly total manufacturing Y_t in rands.

Table 1. Descriptive statistics of SA total manufacturing sales (Y_t).

Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
39,275,290	153,975,510	82,029,512	27,892,621	0.7	−0.19

Table 1 shows that the minimum and maximum monthly sales in SA are ZAR 39,275,290 million and ZAR 153,975,510 million, respectively, with a monthly average of ZAR 82,029,512 million for manufacturing sales. Figure 1 depicts the time-series plot of total manufacturing sales.

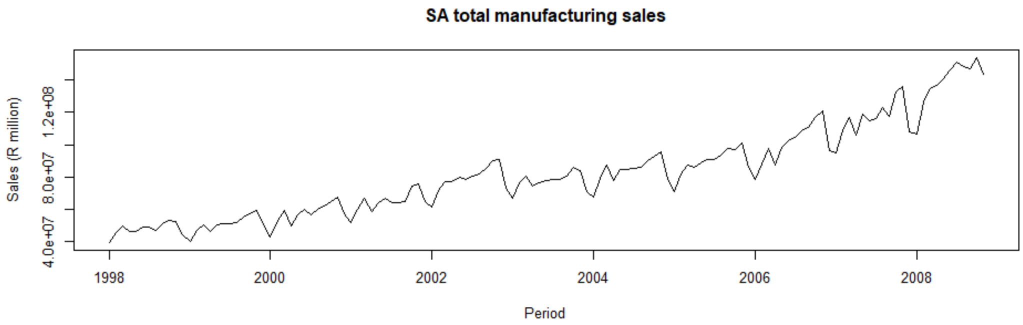

Figure 1. SA total manufacturing sales (Y_t) plot.

The time-series plot in Figure 1 reveals a noticeable upward trend, increasing volatility, and seasonality. The manufacturing series for SA is evidently non-stationary. The plot shows that, despite periodic downturns, the manufacturing sector experienced significant growth between 2004 and 2007, driven by robust export demand for certain manufacturing goods and strong domestic demand, as reported by the Industrial Development Corporation (IDC) (2013). Venter (2009) reported that energy supply disruptions, which affected production in the manufacturing and mining sectors that rely heavily on electricity, contributed to a decline in manufacturing sales in the first quarter of 2008. The optimal and appropriate data transformation to be applied is determined using the Box–Cox technique.

A logarithmic transformation is found to be optimal for reducing variation and smoothen manufacturing sales, as seen in Figure 2, where the maximum log-likelihood of the transformation parameter lambda (λ) is very close to 0. Thus, the total manufacturing sales (Y_t) are logarithmically transformed using the formula $Z_t = \log(Y_t)$. Figure 3 displays a plot of the Z_t.

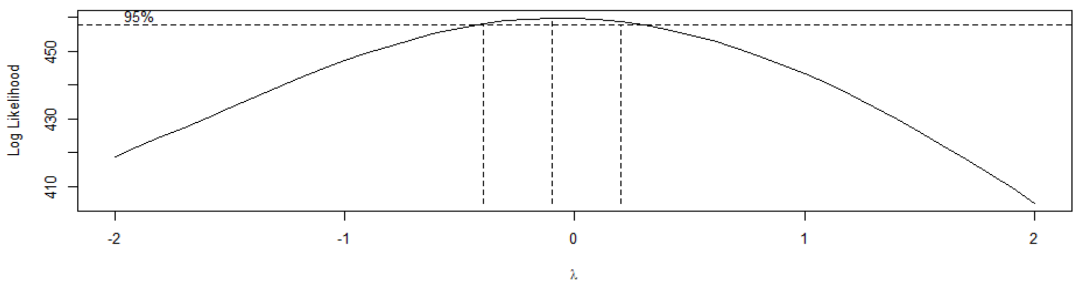

Figure 2. Box–Cox plot of SA total manufacturing sales (Y_t).

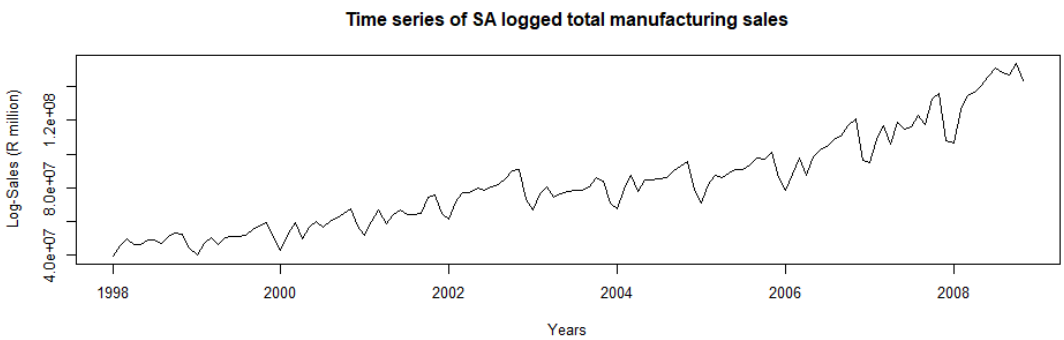

Figure 3. Log-transformed total manufacturing sales (Z_t).

Figure 3 shows a non-stationary and smoother series. To check the stationarity of the data, the Z_t is subjected to an ADF test, and the findings are shown in Table 2.

Table 2. ADF test results of Z_t.

Dickey–Fuller	Lag Order	*p*-Value
−3.1304	5	0.1065

Since the *p*-value of 0.1065 is higher than our chosen significance level of 0.05, the results in Table 2 indicate the acceptance of the null hypothesis that a unit root exists in the smoothed total manufacturing series; hence, the series is non-stationary. In response to the significant seasonality observed in the data, an initial seasonal differencing is conducted. Additionally, a first-order difference is used to eliminate the remaining non-stationarity as seasonally differenced series are getting closer to becoming stationary. Figure 4 visually displays the seasonally and non-seasonally first differenced log-transformed total manufacturing sales.

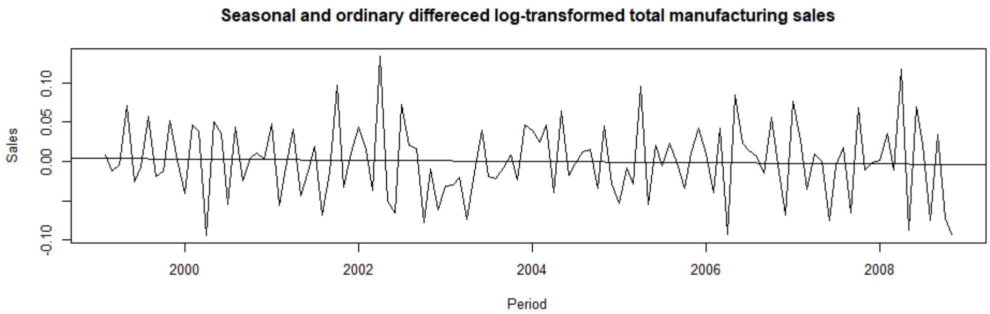

Figure 4. Seasonal and first difference in the log-transformed total manufacturing sales.

Figure 4 shows a stationary series, and the ADF test is used to further verify the series' stationarity. The ADF results of the seasonal and initial difference in the total manufacturing sales after log transformation are summarized in Table 3.

Table 3. Seasonal and initial differenced log-transformed manufacturing sales ADF results.

Dickey–Fuller	Lag Order	*p*-Value
−3.8468	4	0.01911

The results of the ADF test indicate that the series is stationary at the 5% level of significance, as evidenced by the low *p*-value of 0.01911. Figure 5 displays the ACF and PACF charts used to identify potential models.

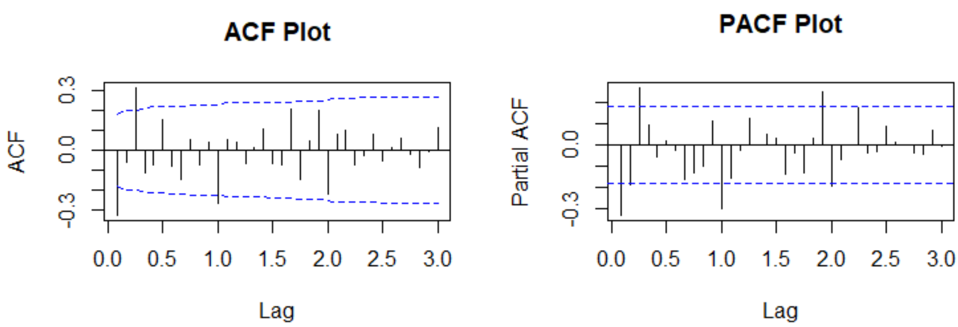

Figure 5. ACF and PACF plots of seasonal and initial differenced log-transformed manufacturing sales.

A tentative model suitable for the time series is the SARIMA $(2,1,1)(2,1,1)_{12}$ model, as suggested by the ACF and PACF plots. The ACF cuts off after lag 1, and the PACF cuts off after lag 2. Additionally, two significant spikes at lags 12 and 24 and one significant spike at lag 12 on the PACF suggest a seasonal component in the model. The EACF in Table 4 was used to validate the AR and MA parts of the model.

Table 4. The EACF of seasonal and initial differenced log-transformed manufacturing sales.

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

In Table 4, the upper left-hand vertex of the triangle of zeros is marked with the symbol o* and is located in the p = 2 row and q = 2 column, an indication of an ARMA (2,2) model. A triangle of zeroes is depicted at the intersection of the two drawn lines, which are meeting locations according to the suggested parsimonious model. Thus, a SARIMA (2,1,2)(2,1,1)$_{12}$ model is suggested by the EACF since a non-seasonal difference was applied to the data. Thus, a SARIMA (2,1,2)(2,1,1)$_{12}$ model is suggested by the EACF since a non-seasonal difference was applied to the data. However, both the SARIMA (2,1,2)(2,1,1)$_{12}$ and SARIMA (2,1,1)(2,1,1)$_{12}$ models are considered provisional models and are being compared to other models. The AIC, BIC, and RMSE are computed for the fitted models and used to select the best model. The results of AIC, BIC, and RMSE for the fitted models are shown in Table 5.

Table 5. The AIC, BIC and RMSE of fitted models.

Model	**AIC**	**BIC**	**RMSE**
SARIMA (2,1,1)(2,1,1)$_{12}$ model without drift	−447.83	−428.44	0.0311
SARIMA (2,1,2)(2,1,1)$_{12}$ model without drift	**−456.86**	**−434.7**	**0.0297**
SARIMA (2,1,0)(2,1,1)$_{12}$ model without drift	−442.9	−426.28	0.0320
SARIMA (1,1,1)(2,1,1)$_{12}$ model without drift	−438.19	−421.57	0.0327
SARIMA (0,1,1)(2,1,1)$_{12}$ model without drift	−438.82	−424.97	0.0328
SARIMA (1,1,2)(1,0,0)$_{12}$ model with drift	−426.61	−409.41	0.0412
SARIMA (2,1,2)(2,0,0)$_{12}$ model with drift	−446.91	−423.97	0.0369

Note: The final model considered is in bold.

Table 5 shows that the SARIMA (2,1,2)(2,1,1)$_{12}$ model, suggested by the EAFC, has the lowest AIC, BIC and RMSE values and is considered the best model for the data. The SARIMA (2,1,2)(2,1,1)$_{12}$ model is written as follows:

$$(1-\Phi_1 B^{12}-\Phi_2 B^{24})(1-\phi_1 B-\phi_2 B^2)(1-B^{12})(1-B)Z_t=(1+\Theta_1 B^{12})(1+\theta_1 B+\theta_2 B^2)\varepsilon_t, \tag{10}$$

where Z_t are the log-transformed total manufacturing sales; ϕ_1 and ϕ_2 are the non-seasonal AR model parameters; θ_1 and θ_2 are the non-seasonal MA model parameters; Φ_1 and Φ_2 are seasonal AR model parameters, and Θ_1 is the seasonal MA model parameter. Table 6 presents the SARIMA $(2,1,2)(2,1,1)_{12}$ model parameters.

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

Parameter	Coefficient/ Parameter Estimate	Standard Error (SE)	Test Statistic	p-Value
ϕ_1	−0.9425	0.1082	−8.7117	<0.0001
ϕ_2	−0.8197	0.0861	−9.5151	<0.0009
Φ_1	−0.2534	0.1515	−1.6730	0.0943
Φ_2	−0.2884	0.1276	−2.2599	0.0238
θ_1	0.5579	0.1628	3.4266	0.0006
θ_2	0.5015	0.1096	4.5771	<0.0001
Θ_1	−0.6343	0.1513	−4.1917	<0.0001

Table 6 shows that all the model parameters are statistically significant at the 5% significance level, except for the first seasonal AR component, which is significant at the 10% significance level, as suggested by the small p-values. To test the autocorrelation in the SARIMA (2,1,2)(2,1,1)$_{12}$ model residuals, the Portmanteau test is employed, and the results are presented in Figure 6.

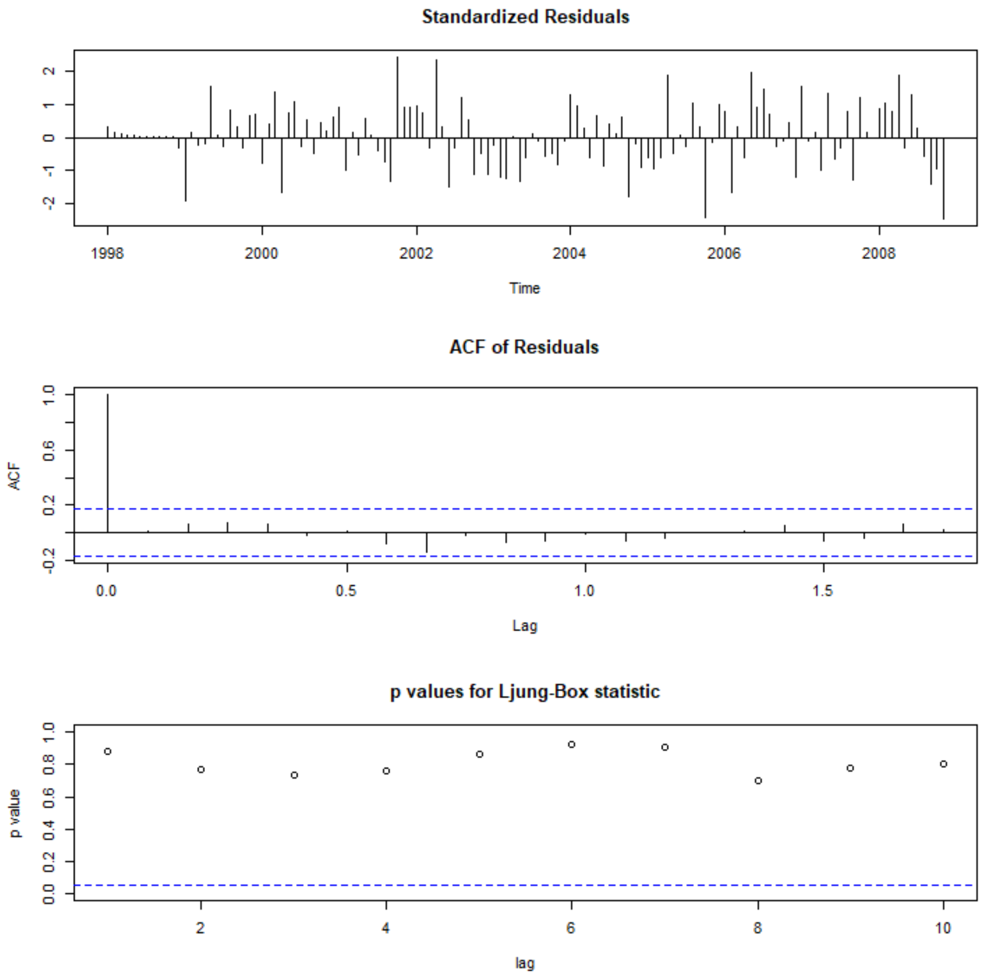

Figure 6. Diagnostic display for the SARIMA (2,1,2)(2,1,1)$_{12}$ model residuals.

Despite one notable spike in the ACF of residuals, all the graphs in Figure 6, including the plot of standardised residuals, the ACF plot of the residuals, and the Ljung–Box test, indicate that the residuals are sufficient. The residuals (ε_t) from a tentative model are examined to find out if they are a white noise process. If they are, the tentative model is probably a good approximation to the underlying stochastic process. If they are not, the process is started all over again. Therefore, the Box–Jenkins method is an iterative procedure. A plot of autocorrelations, or the correlograms associated with the ACF and PACF are often good visual diagnostic tools for the presence of any autocorrelation. Serial correlation was checked on the SARIMA (2,1,2)(2,1,1)$_{12}$ model residuals because the SARIMA models assume that the residuals (ε_t) are a white noise process. The fitted SARIMA (2,1,2)(2,1,1)$_{12}$ model performs well in capturing the data behaviour of total manufacturing sales. Figure 7 shows the ACF plot of the squared residuals used to examine the presence of homoskedasticity.

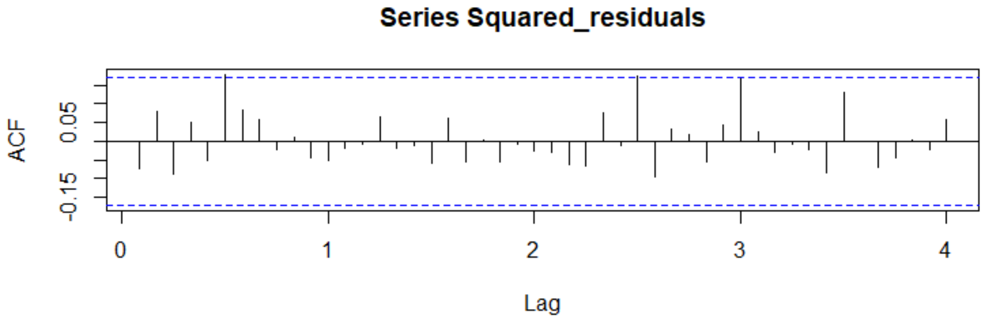

Figure 7. ACF plot of the squared residuals.

Figure 7 confirms the absence of any significant heteroscedasticity and hence, the presence of homoscedasticity in the SARIMA (2,1,2)(2,1,1)$_{12}$ model as confirmed by the behaviour of the squared residuals. The ACF of the squared residuals is within the bounds of no significant autocorrelation hence no evidence of heteroscedasticity is suggested. Figure 8 shows the Q-Q and histogram plots of the model residuals that are used to test for normality.

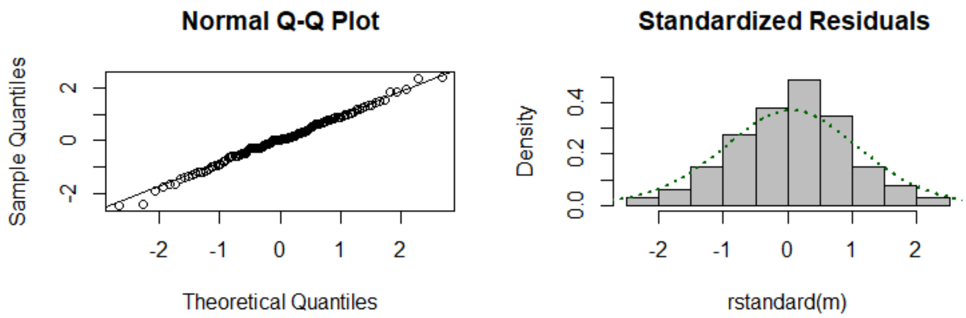

Figure 8. SARIMA (2,1,2)(2,1,1)$_{12}$ model residuals Q-Q and histogram plots.

Since both graphs in Figure 8 closely resemble a normal distribution, the null hypothesis of the residual being normally distributed can be accepted. The fitted SARIMA (2,1,2)(2,1,1)$_{12}$ model can be used to forecast future total manufacturing sales, and the forecasted values can be compared to actual values to assess the model's accuracy.

Figure 9 demonstrates that the fitted model appears to be good and suggests that there is essentially a good fit to the actual values.

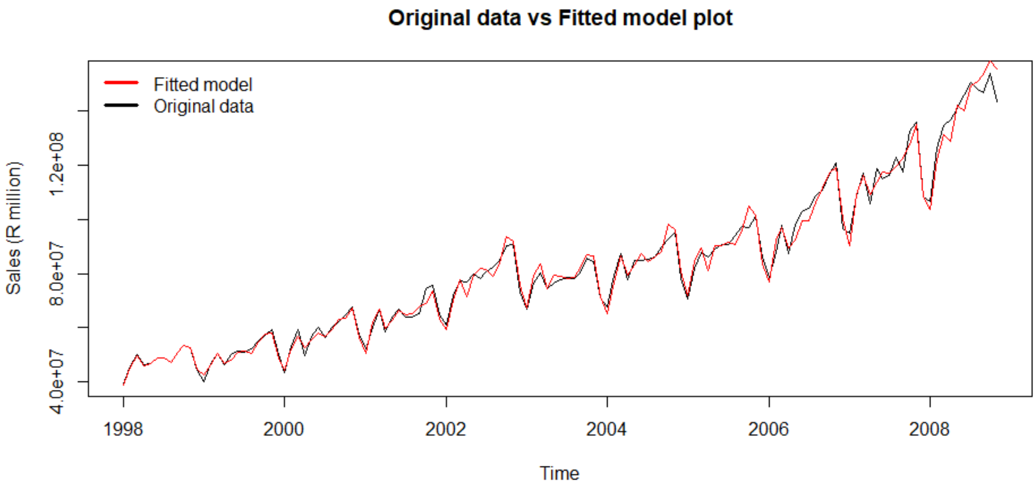

Figure 9. Actual versus fitted total manufacturing sales.

4.2. In- and Out-of-Sample Forecasting

The SARIMA (2,1,2)(2,1,1)$_{12}$ model is used to produce in-sample predictions and out-of-sample projections/forecasts for the upcoming 181 months (December 2008 to December 2022). Actual and predicted total manufacturing sales are shown in Figure 10, together with both the 80% and 95% forecast intervals that account for uncertainty in the forecasts.

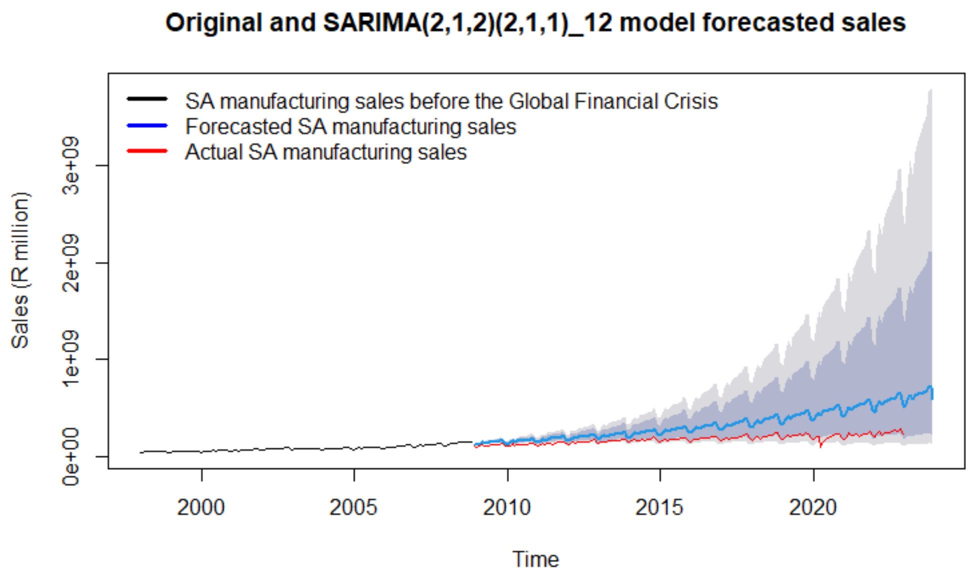

Figure 10. Actual and forecasted total manufacturing sales.

Figure 10 clearly shows that the forecasted manufacturing sales (blue solid line) exhibit a persistent upward trend, consistent with actual data before the crisis. The dark grey colour shows the 80% confidence limit, while the grey colour represents the stricter 95% confidence limit. After the GFC period, the upward trend in manufacturing sales is not as upward-slopping as before. The seasonality is still evident, as shown in Figure 10. The discrepancy between the red solid line (actual total manufacturing sales after the crisis) and the blue solid line (forecasted total manufacturing sales if the GFC had not occurred) indicates how the GFC had such a negative impact on the manufacturing sector. Although the rate of growth in overall manufacturing sales has stabilised, it has not yet reached the level that would have been anticipated in the absence of the GFC. It will take some time for overall manufacturing sales to ever reach the pre-GFC projected sales levels. A strict interpretation of the 95% confidence limit suggests statistically significant differences between forecasted manufacturing sales and actual sales. The less strict 80% confidence limit would suggest mostly no significant differences.

4.3. Discussion of Results

This study's results are consistent with the findings of Rena and Msoni (2014), who reached similar conclusions concerning the adverse impact of the GFC on the economy of SA. Verick (2010) and Mohamed (2009) also observed a severe negative impact of the GFC on the South African economy. The authors concluded that in 2009 alone, the GFC caused the real unemployment rate to rise to 32%. Verick (2010) and Mohamed (2009) further concluded a significant decline in the demand for SA products as a result of the GFC. Similarly, Ratko and Ulgen (2009) found that Sweden's small and medium-sized enterprises' production was severely affected by the GFC. The International Labour Office (ILO) (2011) had similar findings on the negative impact of the GFC on manufacturing production in many Asian countries, which were mainly export-driven. Additionally, Moore and Mirzaei (2014) concluded that the GFC had an adverse effect on both developed and developing industries, supporting the aforementioned findings.

The World Bank (2020) has reported that the South African rand has undergone substantial instability and devaluation in relation to major currencies, such as the US dollar. This has been attributed to various economic and political factors. A weaker rand and higher inflation can limit disposable income for local consumers, which may make it more difficult for them to afford manufactured goods produced in SA. This can have a negative impact on the domestic manufacturing industry, as decreased demand for their products may lead to reduced sales and revenue.

The manufacturing industry in SA has been impacted by electricity load shedding as it utilises over 46% of the electricity produced by the power utility company Eskom (Department of Energy (DoE) (2013)). Fluctuations in global demand, particularly in developed markets, and changes in trade policies and agreements have the potential to negatively impact SA's manufacturing sector and, ultimately, its GDP (Deloitte 2019).

Furthermore, the South African manufacturing industry faces fierce competition from global players, particularly China, which has emerged as a major manufacturing powerhouse in recent years (Edwards and Jenkins 2014). This competition can be difficult to face up to, as manufacturers in China have access to cheaper labour and materials, as well as government subsidies. This competition can negatively impact South Africa's manufacturing sales and is likely to have a ripple effect on the whole economy in general. A number of industries, most notably textiles and apparel, rubber, paper, and metal products, have called for more protection from Chinese imports, which had a detrimental and direct competitive effect on SA's industrial production and employment (Morris and Einhorn 2008). Additionally, Chinese exports have indirectly and badly impacted South African exports of manufactured goods to its neighbours (Burke et al. 2008). There is, therefore, a variety of reasons why there is a significant discrepancy between anticipated/projected/forecasted and actual manufacturing sales, as depicted in Figure 10.

Money laundering and political events can have a detrimental effect on financial institutions that are crucial for economic growth and can reduce productivity in the real economy, including the manufacturing sector. As a result, the variance between actual sales and projected sales could also, in part, be attributed to money laundering and political and corruption issues in South Africa. Recently, SA was placed on the FATF Grey List in February 2023 due to its inability to fulfil specific international standards for preventing money laundering and other serious financial crimes (South African Government 2023). This, in turn, could diminish investment opportunities and negatively impact SA's reputation in global trade. The increased risk associated with investing in SA could lead to higher interest rates and capital costs. Production costs could increase as a result of increased investment expenditures that businesses face when investing or manufacturing within SA's borders. This, in turn, could lead to higher manufacturing expenses and reduced sales, particularly for high-end or luxury products. As foreign investment is necessary to encourage economic expansion and job creation, the recent corruption and other incidents and subsequent bad publicity have certainly deterred foreign investors and may also have contributed to the decreased manufacturing sales.

The manufacturing industry in SA is impacted by oil prices, as product transportation and some manufacturing facilities in the country use diesel. SA's manufacturing industry primarily relies on energy and oil imported from Middle Eastern and West African countries. Hence, a sharp increase in oil prices can adversely affect manufacturing production in SA. Elder and Serletis (2010) have shown that oil price uncertainty can significantly and negatively impact manufacturing output, which could explain, in part, the significant variance between the projected and actual manufacturing sales in SA.

5. Conclusions

This study examined the impact of the GFC on overall manufacturing sales in SA. Sales forecasting is crucial for manufacturing organisations to make informed operational decisions, and the Box–Jenkins time-series approach was used in modelling the time series. The total manufacturing sales data exhibited a persistent upward trend and strong seasonality. After data transformations, and based on the ACF, PACF, and EACF plots, as well as the AIC, BIC, RMSE, and MAE, the SARIMA$(2,1,2)(2,1,1)_{12}$ model was recommended as the best model. The results of the autocorrelation and normality tests conducted on the residuals indicated that the SARIMA$(2,1,2)(2,1,1)_{12}$ model was valid.

The findings indicate that the 2008/2009 GFC had a significant negative impact on the South African manufacturing sector. Despite some recovery, the volume of manufacturing production has not been restored to its pre-crisis projection levels. The SA manufacturing sector is influenced by various factors, such as input and output prices, monetary and fiscal policy, infrastructure, power availability, and exchange rate fluctuations of the rand. Other factors, such as productivity, industrial relations, investment, competitiveness, and business confidence, also play a crucial role in determining manufacturing sales.

To restore manufacturing sales to pre-GFC projection levels, it is necessary to manage all these factors effectively. However, it is not unreasonable to expect that it may take some time for the manufacturing sector to ever reach its expected or projected sales levels, hindering GDP growth and employment. This study's findings emphasise the importance of using statistical techniques, such as the Box–Jenkins time-series approach, to assess the impact of economic shocks on sales and to forecast future sales accurately. The long-term effects of such shocks become evident from such an analysis.

The findings of this study could assist SA manufacturing companies in better understanding their industry, preparing for future negative shocks, and formulating potential policies for stocking inventories, marketing, and production levels. Effective management of factors, such as innovation, research and development, and technology adoption, enhances the capabilities of South African manufacturing firms to produce competitive high-quality and value-added products. Furthermore, strengthening connections between South African manufacturers and multinational companies allows local firms to access international markets, technology, and knowledge and benefit from global value chains. By investing in training, education, and affordable finance, the manufacturing industry of SA will upskill the workforce, and this will increase manufacturing sales and drive growth, create jobs, and lead to economic recovery. All these policy/decision makers need reliable information, as provided herein, to understand and increase the trajectory of manufacturing sales in SA.

6. Recommendations

Indeed, focusing on value addition is a crucial strategy for improving the competitiveness and growth of the manufacturing sector in SA. By adding value to their products or services, firms can differentiate themselves from competitors and offer unique features that meet consumers' changing preferences and needs. To achieve this, policies and initiatives that support innovation, research and development, and technology adoption can enhance the capabilities of SA manufacturing firms to design, develop, and produce high-quality and value-added products. In addition, strengthening the connections between SA manufacturers and multinational companies can provide opportunities for local firms to access international markets, technology, and knowledge and benefit from global value chains.

Access to finance and human capital and skills are also vital components of building a stronger manufacturing industry in SA. Investing in training and education programs to upskill and reskill the workforce can increase labour productivity and innovation capabilities. Access to affordable finance can enable firms to make capital investments, expand their operations, and improve their competitiveness. In summary, a comprehensive approach that addresses the challenges and opportunities facing the manufacturing sector in SA, such as value-addition, technology adoption, market access, finance, and human capital development, can increase manufacturing sales to drive growth, job creation, and economic recovery.

Author Contributions: T.M.—writing original draft of the manuscript, D.C.—review, editing, and supervision. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The dataset is available at the following link: https://www.statssa.gov.za/, accessed on 5 February 2023.

Conflicts of Interest: The authors declare no conflict of interest.

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