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The impact of the pandemic on the retail industry sales in South Africa: A Box-Jenkins approach

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Abstract. The objective of this study is to investigate the long-term impact of the COVID-19 pandemic on the South African retail industry sales using the seasonal autoregressive moving average (SARIMA) from the time series analysis tool pack called Box-Jenkins methodology. The model with the best fit to the total monthly retail sales series is the SARIMA$(0,1,1)(0,1,0)_{12}$ model as it has the lowest values of the model selection and adequacy measures such as the Akaike's information criterion, Bayesian information criterion, root mean square error and the mean absolute percentage error. This study concludes that the South African retail industry is remarkably resilient sector because while it was unstable during lockdown, the total retail sales recovered to their pre-intervention levels as soon as less strict lockdown levels were implemented.

1 Introduction and literature review

Unarguably, the COVID-19 pandemic caused severe disruption to the global economy. The South African retail sector is not an exception. In South Africa, the retail sector is classified into seven categories. Although the impact was uneven across various categories of the retail industry, this sector experienced an overall loss of trade sales because of the COVID-19 pandemic. The year-on-year comparison between 2019 and 2020 trade sales indicated that of the seven categories, the worst affected were the retailers in textiles, clothing, footwear, and leather goods with a 92% contraction in sales, whilst the least affected were the general dealers with approximately 14% contradiction in sales [1]. Movement restrictions during lockdown created the dependency on technology for shopping, thus encouraged the move to digitised spending/e-commerce. The pandemic caused a long-term behavioural spending transformation of South African consumers, as more households have shifted a considerable proportion of their spending to essential goods. According to [2], the South African retail sector showed an impressive adoption and use of digital technologies such as mobile applications and the customer click and collect system to facilitate sales. Amongst the most severely affected by the abrupt policy measures by the government were the small and medium sized retailers due to the complete shutdown of the South African informal sector [3]. Next, [4] discovered a three-way mixed effect among retail businesses because, (i) businesses that were classified as essential service providers were the only ones allowed to trade under the lockdown restrictions, (ii) retail business that primarily traded face to face

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were more affected than those which operated virtually, (iii) businesses ran by experienced business owners were mostly likely to survive the impact of the pandemic than others. Large retail firms were not exempted from the devastating effects of the COVID-19 pandemic. The analysis of financial reports of twenty-two Johannesburg Stock Exchange (JSE) listed South African retail firms showed that the COVID-19 pandemic had a statistically significant negative impact on the financial performance of these firms [5].

Ref [6] noted a downward trend in conventional brick and mortar retail businesses in Saudi Arabia, while e-retailing experienced exponential growth during the COVID-19 pandemic. In addition, [7] also noted a similar change in consumer purchasing preferences and behaviour. Moreover, [8] also highlighted a significant drop in consumer satisfaction on retail supply stores in Austria. Ref [9] used numerous forecasting techniques, including the Box-Jenkins class of ARIMA models, to forecast the seasonal South African total retail sales data from 1970 until 2012. The analysis of the study revealed that models with seasonal dummy variables produced better forecasts compared to the full seasonal models. Amongst the performance metrics used were the root mean squared errors (RMSE), the mean squared forecast errors (MSFE) and the modified Diebold-Mariano (MDM) test statistic. The study by [9] found it difficult to single out the best model for forecasting the South African retail sales as some models were more appropriate during economic booms while others were more appropriate during economic recessions.

Ref [10] further emphasised the importance of accurate forecasting intervals to retail companies due to the high volatility of food retail industry sales. In [10], they fitted the Seasonal Autoregressive Integrated Moving Average (SARIMA), hybrid SARIMAX (SARIMA with Exogenous factors) and quantile regression models to forecast daily sales of perishable food in Germany. The results of the study showed that the SARIMA-MLR model (SARIMA using multiple linear regression) and the SARIMA-QR (SARIMA model using the quantile regression) produced better out of sample forecasts compared to the traditional SARIMA model. In the attempt to address food waste, which was perpetuated by inaccurate forecasting of sales, [11] assessed the applicability of the SARIMAX model to forecast daily retail store sales of perishable foods in Germany. The choice of model was advocated by its ability to incorporate the time series components such as level, trend, seasonality, and external variables such as the variation due to environmental conditions, promotions, holidays, store promotions and discounts. The RMSE and the mean absolute percentage error (MAPE) performance measures indicate that the SARIMAX model (i.e., $\mathrm{SARIMA}(0,0,3)(1,0,0)_6$) performed better than the SARIMA model due to better forecasting accuracy improved by adding the exogenous variables.

Ref [12] highlighted the importance of accurate forecasts in the retail sector more especially where food products with short shelf-life span are involved by comparing ARIMA and Holt-Winters models using the perishable dairy products series in Brazil. Holt-Winters model captured the linear behaviour of the series better, thus performed better than the ARIMA model indicted by lower MAPE and the Theil inequality index (U-Theil) performance measures. Next, [13] conducted a comparative study between the SARIMA and the LSTM (Long Short-Term Memory) model. Both models were found to have good results, although the LSTM model produced better results for products with steady demand and the SARIMA model performed better on products with a strong seasonal behaviour. Incorporating an exogenous component such as promotions in the SARIMAX model produced better results. In a different study, [14] conducted a comparative forecasting performance study between the smoothing methods and ARIMA models using the women footwear data in Portugal. In-depth analysis of both the one-step and multi-step forecasts showed no significance difference in the out of sample forecasting performance between exponential smoothing methods and ARIMA models. However, the forecasts from the multi-step modelling approach were slightly better when compared to the one-step forecasts.

Accurate retail forecasts and well-timed policy interventions based on appropriate forecasting model plays a pivotal role towards the economic growth and stability of both national and global economies. Governments benefit from accurate forecasts when designing and implementing policy interventions for the benefit of both businesses and consumers in the retail sector. Moreover, companies and investors can efficiently strategize and allocate their resources appropriately to maximise profitability. Accurate retail sales forecasting is extremely important to all retail business corporations, small or large, due to the highly volatile demand patterns, as inaccurate forecasts threaten the profitability and long-term survival of businesses or economies [9]. One of the most used techniques to model and forecast retail sales is the Box-Jenkins methodology, which is made up of an iterative three-phase process of model identification, parameter estimation and model diagnostics [15]. In this paper, the main objective is to use the time series Box-Jenkins approach to model and forecast total monthly retail sales in South Africa. The findings of this study will comment on the both resiliency and whether the COVID-19 pandemic had a short- or long-term negative impact on total retail sales in South Africa.

The rest of the paper is structured as follows: In Section 2, the theoretical Box-Jenkins methodology is discussed, and the corresponding empirical analysis is conducted in Section 3. Finally, concluding remarks of the study are provided in Section 4. Note that the SARIMA model is used to lay a good foundation for future research where advanced models can be used comparatively to improve/add on the findings of this study.

2 Methodology

2.1 SARIMA model

A SARIMA model extends the ARIMA model by adding the seasonal component. For more detailed discussion, see [16] wherein the SARIMA $(p,d,q)(P,D,Q)_s$ model where p represents the non-seasonal AR order, d represents the non-seasonal order of differencing and q represents the non-seasonal MA. Moreover, P represents the seasonal AR order, D is the order of seasonal differencing, Q represent the seasonal MA order and s represent the seasonal period. The general expression for the SARIMA model is given as [15],

$$\Phi(B^s)\phi(B)(1-B^s)^D(1-B)^d R_t = \alpha + \Theta(B^s)\theta(B)\varepsilon_t \qquad (1)$$

where $\phi(B)$ is the polynomial of order p and $\theta(B)$ is the polynomial of order q for the non-seasonal components. However, for the seasonal components, $\Phi(B^s)$ and $\Theta(B^s)$ are the polynomials of orders P and Q, respectively. Furthermore, ε_t denotes a white noise process and α is a constant term, B is the backward shift operator such that $B^d R_t = R_{t-d}$, where R_t, in this paper, is the retail trade sales.

2.2 Tests of stationarity and data transformation

Prior to fitting a SARIMA model, the Augmented Dickey Fuller (ADF) test of stationarity needs to be conducted. The null hypothesis of the ADF test is that the series is not stationary or rather, that it has a unit root [15]. The ADF regression is fitted using ordinary least squares (OLS) regression as follows,

$$\Delta R_t = \alpha + \beta t + \delta R_{t-1} + \sum_{i=1}^{n} R_i \Delta R_{t-i} + \varepsilon_t \qquad (2)$$

where Δ is the first difference operator, α is a constant, β is the coefficient of a simple time trend, δ is the coefficient of the lagged R_{t-1}, and ε_t denotes the white noise error term [17]. The test statistic for the hypothesis test

$$H_0: \delta = 0 \text{ (The series is not stationary)}$$
$$H_1: \delta < 0 \text{ (The series is stationary)}$$

is given as,

$$t_\delta = \frac{\hat{\delta}}{s.e.(\hat{\delta})} \tag{3}$$

where $\hat{\delta}$ denotes the estimated coefficient of the lagged level term in (2) and $s.e.(\hat{\delta})$ is the standard error of the estimated coefficient $\hat{\delta}$ [18]. The Box-Cox will be used to select the appropriate transformation to the retail sales data, for more information, see [19-20].

2.3 Box-jenkins methodology

The Box and Jenkins methodology consists of: (i) Model identification, (ii) Parameter estimation and (iii) Model diagnostics – these are sequentially discussed below.

2.3.1 Model identification

This step involves selecting a set of appropriate time series model using the Autocorrelation Function (ACF) and Partial Autocorrelation function (PACF) to select orders of the SARIMA $(p,d,q)(P,D,Q)_s$ model. A model with the lowest values for both the Akaike's Information Criterion (AIC) and the Bayesian Information Criterion (BIC) is chosen, calculated using the following equations,

$$\begin{aligned} AIC &= -2\log(\text{maximum likelihood}) + 2k, \text{and} \\ BIC &= -2\log(\text{maximum likelihood}) + k\log(n) \end{aligned} \tag{4}$$

where $k = p + q + 1$ if the model has a constant term or $k = p + q$ otherwise, n is the total number of observations, while p and q represent the orders of the AR and MA [15].

2.3.2 Parameter estimation

The best possible estimates of the unknown parameters for the chosen SARIMA model of the retail sales data are calculated using maximum likelihood estimation, given by the following log-likelihood function,

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

where R_t represents the retail sales data and $\hat{\psi}$, denotes the n^{th} estimated parameter.

2.3.3 Model diagnostics

Model diagnostics sometimes referred to as "model verification" is concerned with assessing the quality of the model that has been specified and estimated. This study conducted the root mean square error (RMSE) and mean absolute percentage error (MAPE) computed as follows,

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(R_t - \hat{R}_t\right)^2} \; and \; MAPE = \left(\frac{1}{n}\sum_{t=1}^{n}\frac{\left|R_t - \hat{R}_t\right|}{|R_t|} \times 100\right) \quad (6)$$

where n denotes number of observations in the estimation period, R_t and $\hat{R}_t$ are the observed and estimated retail trade sales, respectively [17].

2.4 Tests for autocorrelation of residuals

The Portmanteau Ljung-Box and Box-Pierce tests are used to assess the presence of autocorrelation in the residuals of the fitted SARIMA model. Both tests examine the null hypothesis that the residuals from the fitted SARIMA model are not autocorrelated (white noise). The test statistic (Q) of Box-Pierce and Ljung-Box (LB) are given as,

$$Q = n\sum_{k=1}^{m}\hat{\rho}_k^2 \sim\chi^2(m)$$
and
$$LB = n(n+2)\sum_{k=1}^{m}\left(\frac{\hat{\rho}_k^2}{n-k}\right)\sim\chi^2(m), \quad (7)$$

respectively, where n is the number of observations and m is the lag length [21].

2.5 R packages

The analysis of this study was conducted using R programming version 4.3.1 software [22]. The TSA, tseries, forecast and MASS R packages by were used in the analysis of this study, see [15, 23-25].

3 Results and discussion

This study will use the South African total monthly retail trade sales dataset for the period starting from January 2009 ending in April 2023, which is available on the Statistics South Africa website (https://www.statssa.gov.za/). The pre-intervention period/training data starts from January 2009 ending in February 2020 and the data from March 2020 until April 2023 is the post-intervention data.

3.1 Descriptive statistics and model selection

The mean of monthly retail sales in South Africa amount to R76 919 million. Minimum and maximum retail sales amount to R43 614 million and R142 864 million, respectively. The time series plot of total monthly retail sales is given in Figure 1. The series in Figure 1 has an upward trend and exhibits a highly seasonal behaviour. Time series decomposition model is used to determine key characteristics of the data, see Figure 2. On Figure 2, the original total retail trade sales series is represented by the top series named data, while the seasonality component of the series is shown on the second plot (seasonal), the third plot (trend) distinctly isolates the increasing trend of the underlying series, and the remainder component of the time series is shown on the final plot.

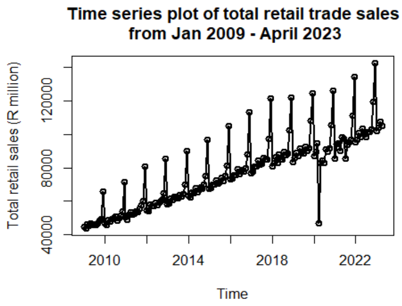

Fig.1. Time series plot of total retail trade sales (R_t) from January 2009 to April 2023.

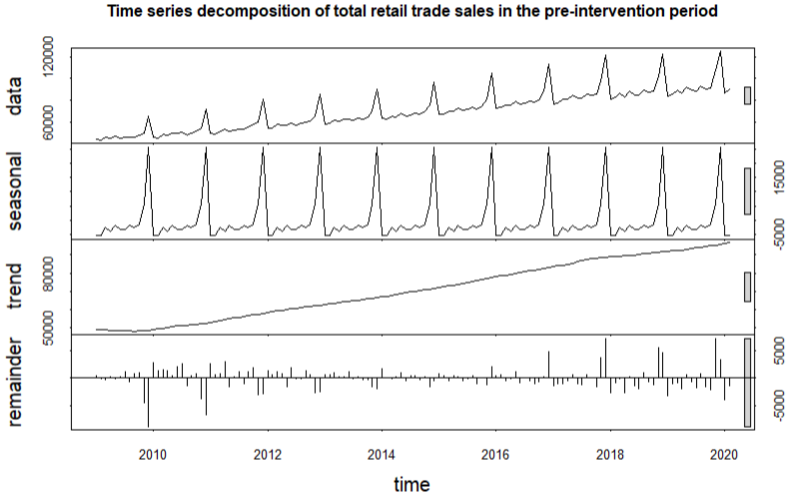

Fig.2. Time series decomposition plot of total retail trade sales (R_t) for pre-intervention.

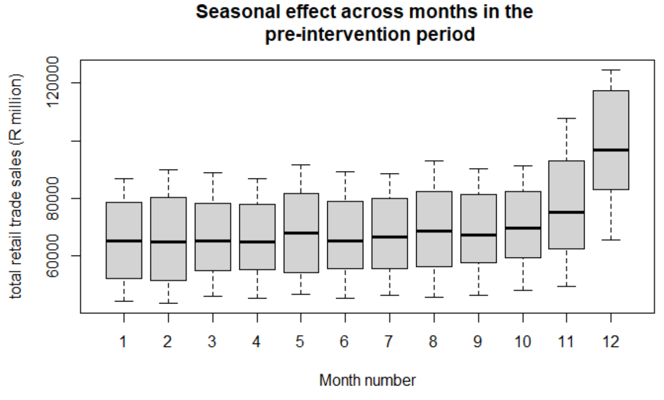

Fig.3. Year on year trend across months for pre-intervention.

Seasonal means of monthly retail trade sales (R_t) in million Rands from January 2009 to February 2020 are provided on Figure 3 (Month number 1 - 12 represents calendar months, i.e. January to December). The results on Figure 3 indicate that November and December have significantly higher average retail trade sales compared to other months. Further indicating the seasonality present in the data. Thus, showing that the South African retail sector attain higher sales in summer (as South Africa is in the southern hemisphere).

The three step Box-Jenkins methodology refer to the three iterative steps involved in the Box-Jenkins methodology model building procedure. These are (1) model identification, (2) parameter estimation and (3) model diagnostic/model verification steps which are discussed in Sections 3.2, 3.3 and 3.4, respectively.

3.2 Model selection

The appropriate data transformation or modification is investigated using the Box-Cox transformation diagram in Figure 4.

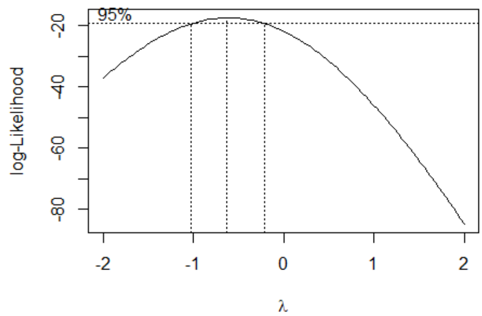

Fig.4. Box-Cox plot of total retail trade sales (R_t) for pre-intervention.

The lambda value from the Box-Cox plot in Figure 4 is equal to $-0.6262 \approx -1$, suggesting that inverse transformation is necessary to transform the data towards stationarity or normality. The time series plot of the inverse transformed $(1/x)$ retail trade sales is given on Figure 5 and it is shown to depict a decreasing trend and a strong seasonal behaviour.

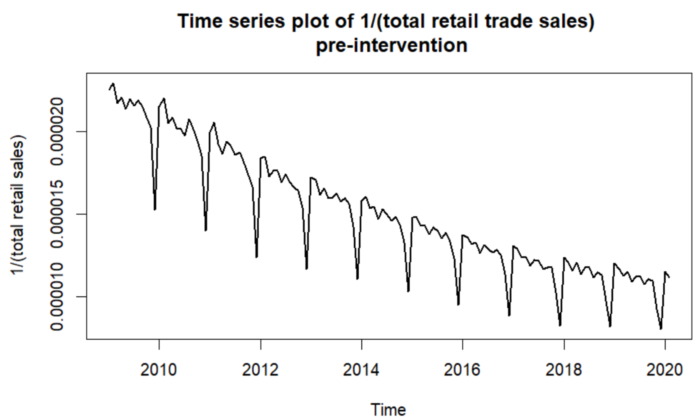

Fig.5. Time series plot of inverse transformed retail trade sales $(\frac{1}{R_t})$ for pre-intervention.

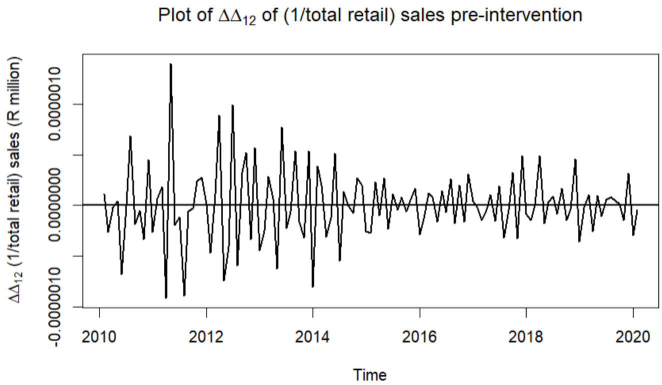

Fig.6. First and seasonally differenced data for pre-intervention.

The ADF test of stationarity was conducted at 5% significance level. The ADF test has a highly significant p-value (0.01), which suggest that the series is stationary. However, close graphical inspection of Figure 5 suggests first, and seasonal differences are necessary to de-trend and accurately capture the seasonality in the series. First and seasonally differenced retail series (R_t) on Figure 6 appears to be stationary, with no apparent trend. Similar to the inverse transformed retail data ($\frac{1}{R_t}$), the ADF test of stationarity was conducted. The p-value (0.01) from the ADF test is statistically significant at 5% significance level, therefore, the first and seasonally differenced ($\Delta\Delta_{12}\frac{1}{\mathrm{R_t}}$) series is stationary.

The ACF and PACF of $\Delta\Delta_{12}\frac{1}{\mathrm{R_t}}$ series are provided on Figure 7(a) and (b). On Figure 7(a), lag 1 is highly significant from zero, while lags 3, 6, 7, 9, 11 and 12 of the ACF are slightly significant. The PACF on Figure 7(b) cuts-off after lag 2.

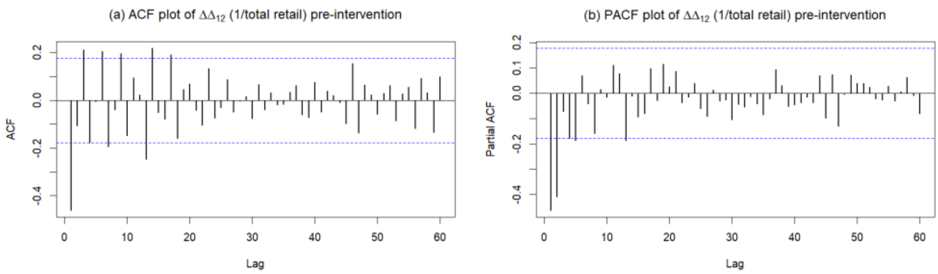

Fig.7. (a) and (b) ACF and PACF of the first and seasonally differenced data for pre-intervention.

Table 1 summarises the AIC, BIC, RMSE and MAPE of possible SARIMA models using the ordinary and seasonally differenced inverse transformed retail trade sales data. The $\mathrm{SARIMA}(0,1,1)(0,1,0)_{12}$ from Table 1 provides the best fit to the South Africa's total retail trade sales series since it has relatively lowest AIC, BIC, RMSE and MAPE values according to the model selection and adequacy measures. Note that using (6), we obtained small values for RMSE and MAPE values which means that the SARIMA model is a relatively good fit for the data.

Table 1. AIC, BIC, RMSE and MAPE from the fitted SARIMA models for pre-intervention.

Model	AIC	BIC	RMSE	MAPE
$SARIMA(0,1,0)(0,1,0)_{12}$	-3248.12	-3245.35	3.38033×10^{-7}	1.622799

$SARIMA(1,1,0)(1,1,0)_{12}$	-3273.17	-3264.99	2.99248×10^{-7}	1.452538
$SARIMA(0,1,1)(0,1,0)_{12}$	-3299.62	-3294.13	2.70062×10^{-7}	1.310853
$SARIMA(1,1,0)(0,1,0)_{12}$	-3274.96	-3269.47	2.99683×10^{-7}	1.438800

3.3 Parameter Estimation

The model parameter provided in Table 2 is estimated using the MLE method. The model parameter of the SARIMA$(0,1,1)(0,1,0)_{12}$ is statistically significant at 5% significance level, indicated by low p-value. The SARIMA$(0,1,1)(0,1,0)_{12}$ model is written using the backshift operator as,

$$(1-\phi_1\beta)(1-\Theta_1\beta^{12})(1-\beta)(1-\beta^{12})W_t = \varepsilon_t \qquad (8)$$

where $W_t = \Delta\Delta_{12}\frac{1}{\mathrm{R_t}}$.

Table 2. SARIMA $(0,1,1)(0,1,0)_{12}$ model parameters for pre-intervention.

Parameter	Estimate	Standard Error (SE)	Test statistic	p-value
$\boldsymbol{\theta_1}$	-0.868733	0.144873	-5.9965	2.02×10^{-9}

3.4 Residual Analysis

The time series plot, the ACF and histogram of standardised residuals from the fitted SARIMA$(0,1,1)(0,1,0)_{12}$ model are provided in Figure 8. The standardised residuals in Figure 8(a) are random with no apparent trend. The ACF plot on Figure 8(b) suggests no autocorrelation on residuals except for 1 significant lag. The pattern of the histogram of the residuals on Figure 8(c) almost resembles that of normal distribution.

The Portmanteau Ljung-Box and Box-Pierce tests are used to test for serial autocorrelation in the residuals of the chosen SARIMA$(0,1,1)(0,1,0)_{12}$ model. The p-values from both the Ljung-Box (0.208) and Box-Pierce (0.264) tests are not statistically significant at 5% significance level. Therefore, as per the null hypothesis, there is no autocorrelation in the residuals from the fitted SARIMA$(0,1,1)(0,1,0)_{12}$ model. Therefore, the SARIMA$(0,1,1)(0,1,0)_{12}$ model may be used for forecasting future retail trade sales.

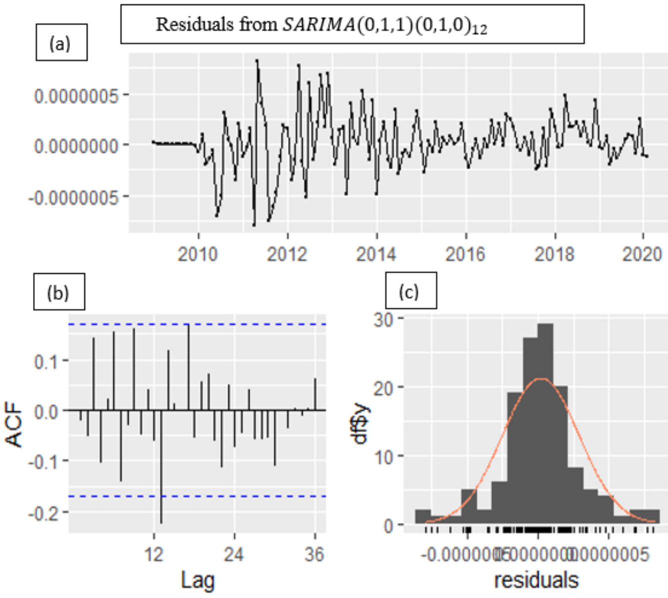

Fig.8. (a) Time series plot, (b) ACF and (c) histogram of standardised residuals.

3.4 In-sample forecasting

The inverse transformed retail trade sales ($\frac{1}{R_t}$) versus in-sample fitted values from the $\text{SARIMA}(0,1,1)(0,1,0)_{12}$ model, as well as the original retail sales versus the in-sample values from the fitted SARIMA model are shown in Figures 9(a) and (b), respectively. The plot on Figure 9(a) suggests that $\text{SARIMA}(0,1,1)(0,1,0)_{12}$ model has a good fit on the inverse transformed pre-intervention retail trade sales $\frac{1}{R_t}$, showing that the chosen SARIMA model is appropriate. The same results when using the original retail trade sales (R_t) data as shown in Figure 9(b). Figure 10 provides the 38 months retail trade sales forecasts. The light grey area shows the 80% confidence limits, and the dark grey area demonstrates the 95% confidence limits. The forecasted values on both Figures 10(a) and (b) follow the same trend/pattern as the pre-intervention series. Therefore, they can be used as the counterfactual series to show the expected retail trade sales if the COVID-19 pandemic did not occur using both the inverse transformed and original retail sale data, respectively.

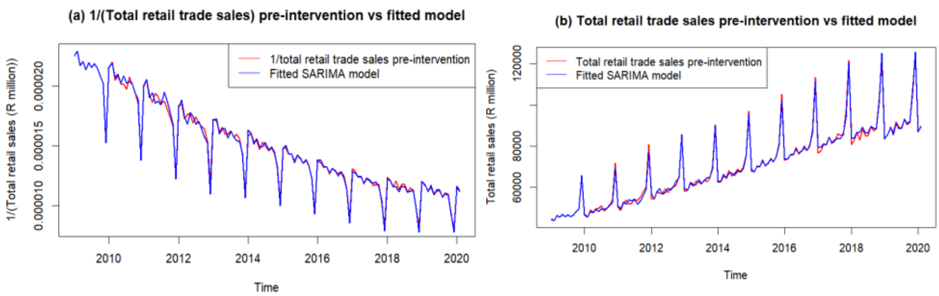

Fig.9. (a) Inverse-transformed $\frac{1}{R_t}$ versus fitted $\frac{1}{\hat{R}_t}$ inverse transformed retail sales, (b) Retail trade sales R_t versus retail sales from the fitted $\text{SARIMA}(0,1,1)(0,1,0)_{12}$ model for pre-intervention.

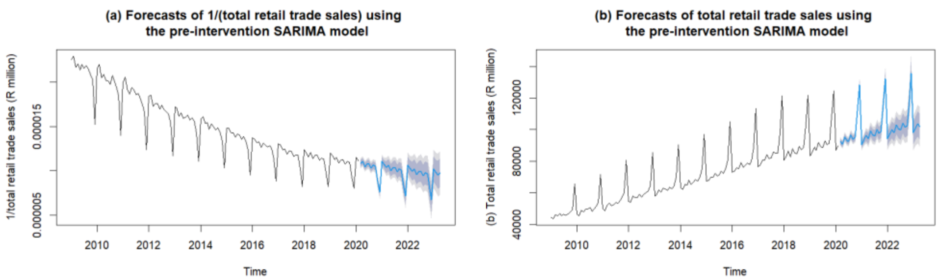

Fig.10. (a) Forecasted $\frac{1}{\hat{R}_t}$ retail trade sales, (b) Forecasted $\hat{R}_t$ retail trade sales for pre- and post-intervention.

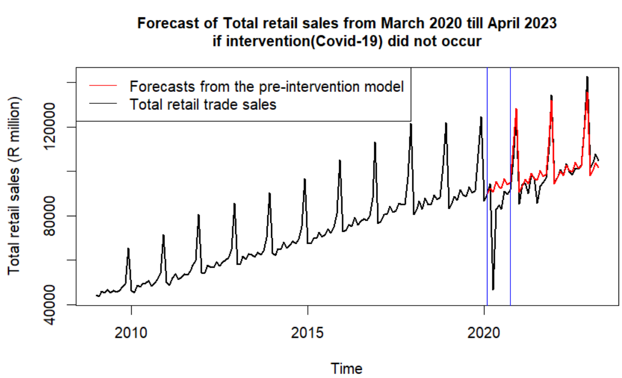

Fig.11. Impact of COVID-19 on retail trade sales post February 2020 for pre- and post-intervention.

Figure 11 partitions the total monthly retail trade sales into the pre-intervention, intervention, and post intervention periods aimed at showing the impact of the COVID-19 post February 2020 graphically. The COVID-19 pandemic had a severe detrimental impact on South Africa's total monthly retail trade sales. This is shown by the abrupt/immediate drop in sales shortly after February 2020 following the announcement of national lockdown level 5 which started towards the end of March 2020 in South Africa. It is important to note that the lowest sales since the onset of the pandemic were recorded in April 2020, valued at R46 864 million. This translates to 50,43% percentage decrease in total retail sales from the preceding month (March 2020) which had sales amounting to R94 541 million. The gap/area on Figure 11 between the observed retail trade sales (black line) and forecasted sales (red line) post the intervention point (February 2020) narrowed narrowing over time as the retail sector recover from the abrupt drop in sales. October 2020 indicated by the second vertical blue line on Figure 11 is a good cut-off point of the intervention period as the observed and forecasted sales have similar levels from this point onwards. The South African retail sectors is evidently a resilient sector as the observed retail sales returned to their pre-intervention levels from October 2020, which was merely 8-9 months after the onset of the COVID-19 pandemic.

4 Conclusion

In this study, the three step Box-Jenkins time series methodology was used to assess the long-term impact of the COVID-19 pandemic on SA's retail industry using the total monthly retail sales data. Several models were fitted and evaluated, but $\text{SARIMA}(0,1,1)(0,1,0)_{12}$ model provided the best fit to the data due to its relatively lower values for the model selection and adequacy measures (AIC, BIC RMSE and MAPE). The COVID-19 pandemic had a negative immediate, temporary level change on the monthly total retail sales. However, the forecasted values in the post intervention period indicate that the South Africa's monthly retail sales recovered to their pre-intervention levels 8-9 months from the onset of the intervention in February 2020. It can be concluded that the South African retail industry is a remarkably resilient sector. The forecasts from the $\text{SARIMA}(0,1,1)(0,1,0)_{12}$ model can be relied on because the recovery point corresponds with the time frames when lower and less strict lockdown levels were implemented.

The findings of this study provide additional justification for the use of Box-Jenkins time series seasonal autoregressive integrated moving average (SARIMA) in modelling intervention effects in the retail industry. Additionally, the findings of this study shed light on the resilience of the South Africa's retail sector in the eventuality of large scale/global interventions such as the COVID-19 pandemic. The study serves as an addition to the limited literature on the use of statistical time series models to assessing the long-term impact of interventions such as COVID-19 using highly seasonal data such as the retail industry sales.

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