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Quantifying the impact and recovery of South Africa's manufacturing sales from the COVID-19 pandemic using a time series intervention analysis

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Abstract The South African manufacturing sector, a cornerstone of the nation's economy, was significantly disrupted by the COVID-19 pandemic. These disruptions severely impacted production networks and supply chains, forcing manufacturing firms to rapidly adjust their operations. Despite increasing interest in evaluating the pandemic's effects, rigorous quantitative analyses that fully capture both impact and recovery phases across economic sectors remain scarce. This study measures the impact of the pandemic on South Africa's manufacturing sector using time series intervention analysis. Employing a SARIMA $(0, 1, 1)(0, 1, 1)_{12}$ model enhanced with intervention functions for the COVID-19 pandemic, the July 2021 civil unrest, and two statistically identified outliers, the model provides a strong fit to monthly manufacturing sales data. The results indicate that South Africa's manufacturing sector saw a sharp decline in sales of 53.67% in April 2020, immediately following the economic lockdown, underlining the pandemic's severe and immediate financial impact. This was followed by a gradual recovery, reaching a complete rebound approximately fourteen months later. The dual-intervention SARIMA model effectively captures both the initial shocks and subsequent lingering effects, highlighting the sector's vulnerability to overlapping crises. The total loss in manufacturing sales over this period is estimated at ZAR 189 million, emphasising the significant economic toll. These findings showcase the value of dynamic intervention modelling for forecasting and policy assessment in emerging markets. Policy-makers and industry stakeholders can utilise such models to anticipate disruptions more effectively and mitigate their impacts, thereby enhancing economic resilience and informing targeted recovery efforts. Forecasts indicate that South Africa's manufacturing sales will increase steadily in the coming months, reflecting a strong recovery from pandemic-related disruptions. This anticipated growth underscores the need for policy-makers and industry leaders to invest in infrastructure, technological innovation, and supply chain resilience to sustain and accelerate the long-term development of the manufacturing sector.

Keywords SARIMA model, South Africa, Intervention Analysis; Manufacturing Sales; COVID-19 Pandemic

AMS 2010 subject classifications 62M10, 91B84, 37M10

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1. Introduction

The manufacturing sector is a cornerstone of South Africa's economy, serving as a critical driver of economic growth and resilience. Its strong linkages with key industries, such as mining, agriculture, and services, amplify its influence, benefiting both upstream and downstream activities. In 2022, the sector contributed 11.4% of the total GDP, totalling approximately R3 trillion, and employed around 1.5 million individuals [1]. By 2024, its GDP contribution rose to 13%, with nominal growth projected to average 5.7% annually over the next decade [2]. This trajectory underscores the sector's importance in driving industrial progress and shaping the broader economic landscape in South Africa (SA). The manufacturing industry experienced a modest 0.2% increase during the fourth quarter of 2023 [3].

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Despite challenges such as the COVID-19 pandemic, the manufacturing sector has demonstrated remarkable resilience, recovering and expanding despite adversity. Its ability to adapt and maintain operations during turbulent times underscores its crucial role in ensuring economic stability. Besides its contributions to GDP, the sector is crucial for job creation and trade, accounting for 12% of formal sector employment and 42% of export value in 2019 [4]. These statistics reinforce the sector's position as a cornerstone of SA's economic framework, with the potential for further development and global competitiveness.

[5] reported that approximately 11,400 VAT-registered businesses are integral to SA's manufacturing sector, which ranks fourth most significant in the national economy. This considerable contribution underscores the sector's role as a primary economic driver and highlights its impact on trade balance and employment. Its performance influences supporting industries and supply chains, cementing its pivotal role within the national economic framework. [6] noted that while manufacturing has previously faced disruptions from natural disasters, trade wars, and diseases, the COVID-19 pandemic is unmatched in its severity, significantly impacting the global economy, as emphasised by [7]. External events, such as financial crises, natural disasters, and policy changes, can significantly influence time series data, and these effects are often viewed as interventions in time series analysis [8].

The COVID-19 pandemic has dramatically changed the global financial and economic landscape. Increasing infection rates, widespread lockdowns, and growing concerns over falling corporate earnings caused significant market volatility, resulting in a loss of over $5 trillion in the SP 500 value in early 2020 [9]. In South Africa, [10] examined the pandemic's effects on manufacturing sales but did not provide a quantitative assessment of its impact. The current study aims to measure the effect of the COVID-19 pandemic on South African manufacturing sales using intervention analysis within a SARIMA framework. A dual-intervention approach is used: a temporary shift captures the immediate effects of the pandemic, while a gradual, long-term adjustment reflects ongoing disruptions to the sector. The model also considers the short-term shock from the July 2021 civil unrest. This method builds on the approaches of [11] and [12], who highlight the importance of dynamic interventions in time series models with structural changes.

The study contributes both methodologically and empirically. Methodologically, it introduces a dual-intervention SARIMA model that captures both short-term shocks and long-term adjustments while accounting for seasonal patterns, representing an improvement on standard intervention models. Empirically, it applies this advanced framework to assess the impact of COVID-19 and civil unrest on South African manufacturing sales, an area that remains under-explored. The novelty of this research lies not only in the model's structure but also in its application to a complex real-world setting, offering insights with direct relevance for researchers, industry stakeholders, and policy-makers.

Incorporating intervention time series analysis is crucial for evaluating the impact of unforeseen events on time series data. [13] emphasise that this method is advantageous for identifying and measuring the effects of sudden disruptions within data patterns. Adopting this approach enables the isolation and quantification of the impact of these unexpected events, leading to a more precise understanding of their effects. [14] further emphasises the importance of incorporating a substantial intervention into time series models. Interventions are vital for capturing the actual impact of disruptions that modify the typical trends and cycles within the data, allowing for greater accuracy.

2. Literature Review

[11] utilise an intervention model to evaluate the effects of the September 11, 2001, terrorist attacks on passenger demand in the US air transport sector. Their findings reveal a significant, short-lived decline in domestic and international air traffic, lasting approximately one to two months, respectively. This suggests that the impact was sudden and fleeting rather than gradual or enduring.

[8] examine the impact of the COVID-19 pandemic on passenger traffic at Soekarno-Hatta International Airport (also known as Soetta) and compare forecasting models to predict domestic passenger numbers during this period. They assess the effectiveness of the SARIMA intervention and the Prophet models, concluding that the SARIMA

intervention offers superior forecasting accuracy. The study highlights that the SARIMA intervention is better at incorporating the pandemic's impact into predictions, demonstrating its enhanced capability for addressing the disruptions caused by the pandemic.

[15] analyse the impact of the 2008 US financial crisis on SA's real exchange rate. Their study employs a seasonal ARIMA intervention model and finds that the crisis caused an abrupt disruption in the exchange rate starting in March 2008. The SARIMA intervention model outperforms the standard SARIMA model in forecasting accuracy, providing valuable insights into South African monetary policy and demonstrating the effectiveness of intervention models for analysing interrupted time series.

[16] utilised time series intervention analysis to evaluate the effects of the financial crisis on China's manufacturing sector. Their study found that the global financial crisis had a substantial impact on the industry, resulting in a significant decline in gross industrial output value. They also noted that the effects were immediate and severe, although temporary. The current study applies to the SARIMA intervention model to assess the impact of the COVID-19 pandemic on SA's manufacturing sector, quantifying the effect and determining the precise percentage decrease in manufacturing sales.

[17] utilised various time series models, including additive and multiplicative decomposition and Holt-Winters methods, to analyse air passenger demand. They emphasise that air travel is integral to economic activity, catalysing business development and enhancing regional competitiveness. While their study highlighted the effectiveness of the Holt-Winters additive model in capturing trends and seasonality, it did not incorporate an intervention component to account for and quantify disruptions such as the COVID-19 pandemic. Despite this limitation, the findings underscore the importance of robust forecasting in adapting to fluctuating demand and supporting the growth of the air transportation industry.

[18] illustrate the significant negative impact of the COVID-19 pandemic on SA's wholesale and retail sales through an interrupted time series analysis. The study highlights that wholesale trade sales experienced a severe downturn for 15 months, while retail sales were affected for 8 months, with a lag of one month. Notably, the wholesale sector faced more substantial losses, particularly in April 2020, when both sectors were hardest hit due to the implementation of a strict national lockdown. The study emphasises the importance of employing robust interrupted time series methodologies to capture the actual economic impact of unprecedented events.

Unlike [18], who applied a constant intervention effect of 1 across the intervention period in the wholesale sector, this study incorporates a dynamic intervention component to capture the varying impact of external shocks, such as the COVID-19 pandemic, more accurately. While both studies assess sectoral disruptions, it is important to distinguish between wholesale and manufacturing dynamics. Wholesale sales often exhibit rapid declines and swift rebounds, whereas manufacturing is more vulnerable to extended supply chain disruptions and slower recoveries. Therefore, a constant intervention effect may be suitable for wholesale but inadequate for manufacturing, where a dynamic approach provides a more realistic representation of the sector's recovery trajectory.

The current study adds an extra step by validating the SARIMA-intervention model through out-of-sample forecasting. Model forecasts are compared with actual manufacturing sales data, and predictive accuracy is evaluated using RMSE and MAPE. To further test the model's robustness, sensitivity analyses is conducted across different specifications and intervention dates. This validation enhances confidence in the results by examining both the forecasting performance and the model's ability to identify the effects of COVID-19 on manufacturing sales accurately.

3. Methodology

The intervention SARIMA modelling approach, as outlined by [11], [12], and [19], provides a framework for quantifying the influence of significant events on the level or trend of a time series. This study applies these principles to evaluate the impact of external shocks, specifically the COVID-19 pandemic, on South African manufacturing sales. Building on the [20] methodology used by [10], this research enhances the model by incorporating intervention components to provide a more detailed and quantitative analysis of the pandemic's effects.

3.1. SARIMA model

A SARIMA$(p, d, q)(P, D, Q)_s$ model includes a seasonal period s. The non-seasonal parameters p, d, and q denote autoregressive, differencing, and moving average components, respectively, while P, D, and Q represent the seasonal components. The model is specified as:

$$\Phi_P(B^s)\,\phi(B)\,\nabla_s^D\nabla^d Y_t = \Theta_Q(B^s)\,\theta(B)\,\varepsilon_t, \tag{1}$$

where the seasonal components are represented by $\Phi_P(B^s)$ and $\Theta_Q(B^s)$, while the non-seasonal components are denoted by $\phi(B)$ and $\theta(B)$. The backward shift operator is B, the seasonal difference operator is ∇_s^D, and the non-seasonal difference operator is ∇^d.

3.2. Model building

The Box-Cox transformation, proposed by [21], is employed to determine the optimal transformation for the manufacturing sales data. The stationarity of the data is evaluated using the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test under the null hypothesis that manufacturing sales are stationary, as noted by [22] and [23]. Model selection relies on the Bayesian Information Criterion (BIC), favouring simpler models with fewer parameters, while parameter estimation is performed using maximum likelihood estimation (MLE). Additionally, the Ljung-Box test examines autocorrelation in the model residuals, and the Jarque-Bera test evaluates their normality.

3.3. SARIMA model with intervention Analysis

Intervention analysis, first introduced by [24], assesses the impact of events, such as COVID-19, on time series data. Letting X_t, Y_t and n_t represent the observed manufacturing sales, the SARIMA model, and the transfer function describing the effects of COVID-19 pandemic, respectively. The relationship can be expressed as:

$$X_t = n_t + Y_t \quad \text{and} \quad n_t = \sum_{i=1}^{n} W_i(G)\,\gamma_i\,H_t^{(T_i)}, \tag{2}$$

where G denotes a forward shift operator such that $GP_{t+1}^T = P_{t+2}^T$. The term $W_i(G)$ represents the dynamic impact of an intervention i at time T. The coefficient γ_i measures the effect of the intervention. T_i marks the timing of an intervention, while $H_t^{(T_i)}$ represents the intervention variable, which could either be a pulse intervention P_t^T or a step intervention S_t^T.

$$P_t^T = \begin{cases} 1, & \text{if } t = T \\ 0, & \text{if } t \neq T \end{cases} \qquad \text{and} \qquad S_t^T = \begin{cases} 1, & \text{if } t \geq T \\ 0, & \text{if } t < T \end{cases} \tag{3}$$

Figure 1 shows example intervention plots created using pulse, step, and gradual decay functions to illustrate typical time series responses to shocks. These examples provide readers with a basic understanding of how different types of interventions affect series behaviour.

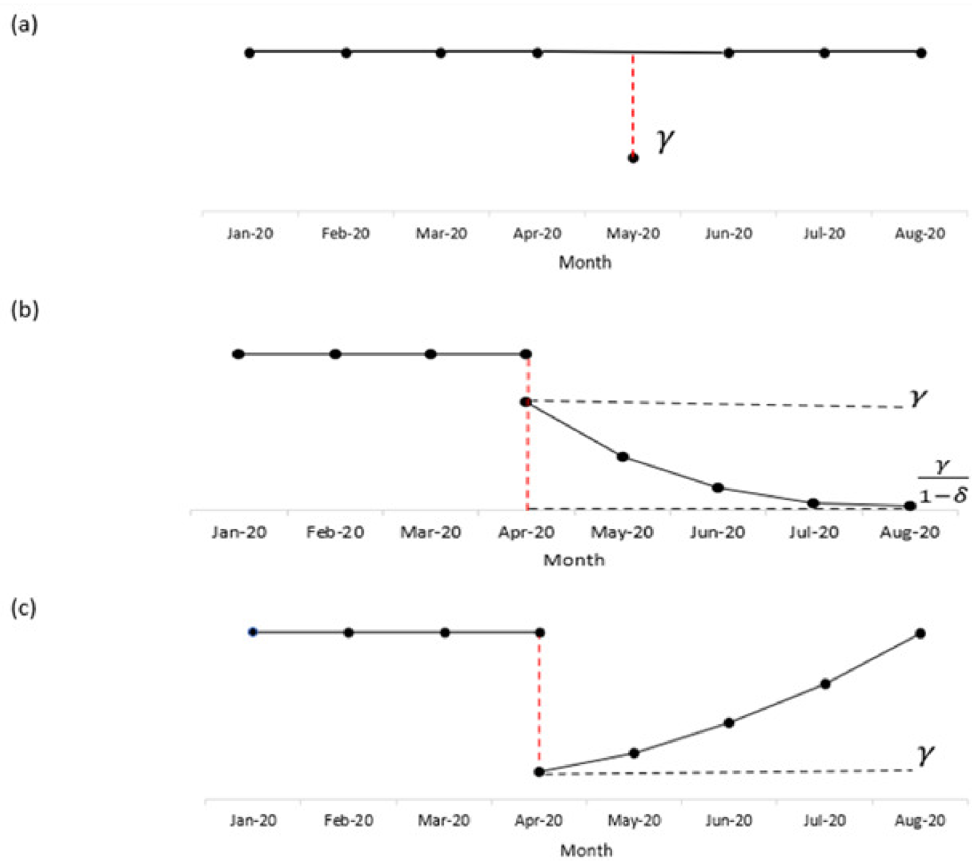

Figure 1. Intervention plots: (a) $\gamma G P_t^T$, (b) $\frac{\gamma G}{1-\delta G} S_t^T$, and (c) $\frac{\gamma G}{1-\delta G} P_t^T$.

The intervention in Figure 1(a) causes a temporary shift in the mean function at $t = T + 1$, where γ represents the magnitude of the shift. Figure 1(b) shows a gradually decreasing change that approaches $\gamma/(1-\delta)$ as t increases, with $0 < \delta < 1$. If $\delta = 1$, the change continues to decline at a constant rate indefinitely. Figure 1(c) illustrates a gradual increase over time.

For South African manufacturing sales, the pulse function is preferred over step or decaying alternatives because it best captures the short-lived, discrete shocks caused by the lockdown, characterised by abrupt disruption and rapid recovery. To model the South African case, a combination of functions (a) and (c) is employed, following the approach of [19], with April 2020 considered as the intervention point. This approach captures both the immediate impact and the gradually diminishing effects of the COVID-19 pandemic and the July 2021 civil unrest over time.

Drawing on [12] framework for expanding or simplifying intervention functions, such interventions in the underlying process can be formally expressed as:

$$n_t = \gamma_0 P_t^T + \gamma_1 (1-\gamma_2 G)^{-1} P_t^T = (\gamma_0 + \gamma_1) P_t^T + \gamma_1 \gamma_2 P_{t+1}^T + \gamma_1 \gamma_2^2 P_{t+2}^T + \gamma_1 \gamma_2^3 P_{t+3}^T + \cdots \quad (4)$$

The immediate intervention effect is given by $(\gamma_0 + \gamma_1)$, while the n^{th} effect is $\gamma_1 \gamma_2^n$ for $n \geq 1$.

4. Data Analysis and Results

4.1. Data overview and outlier detection

The total manufacturing sales data for South Africa, covering the period from January 2009 to May 2025, was obtained from Statistics South Africa's Manufacturing: Production and Sales reports (https://www.statssa.gov.za, accessed 18 July 2025). This study builds upon the SARIMA model developed by [10], which serves as the baseline model. Their work utilised data from January 2009 to November 2022, with the period from January 2009 to March 2020 serving as the training period. In the current paper, the dataset has been updated to include recent observations up to May 2025, and intervention analysis techniques are applied to capture the effects of key disruptions. Data from January 2009 to December 2023 are used to identify intervention effects, while data from January 2024 to May 2025 support out-of-sample model validation. The complete time series and its behaviour are illustrated in Figure 2c to promote transparency and aid interpretation.

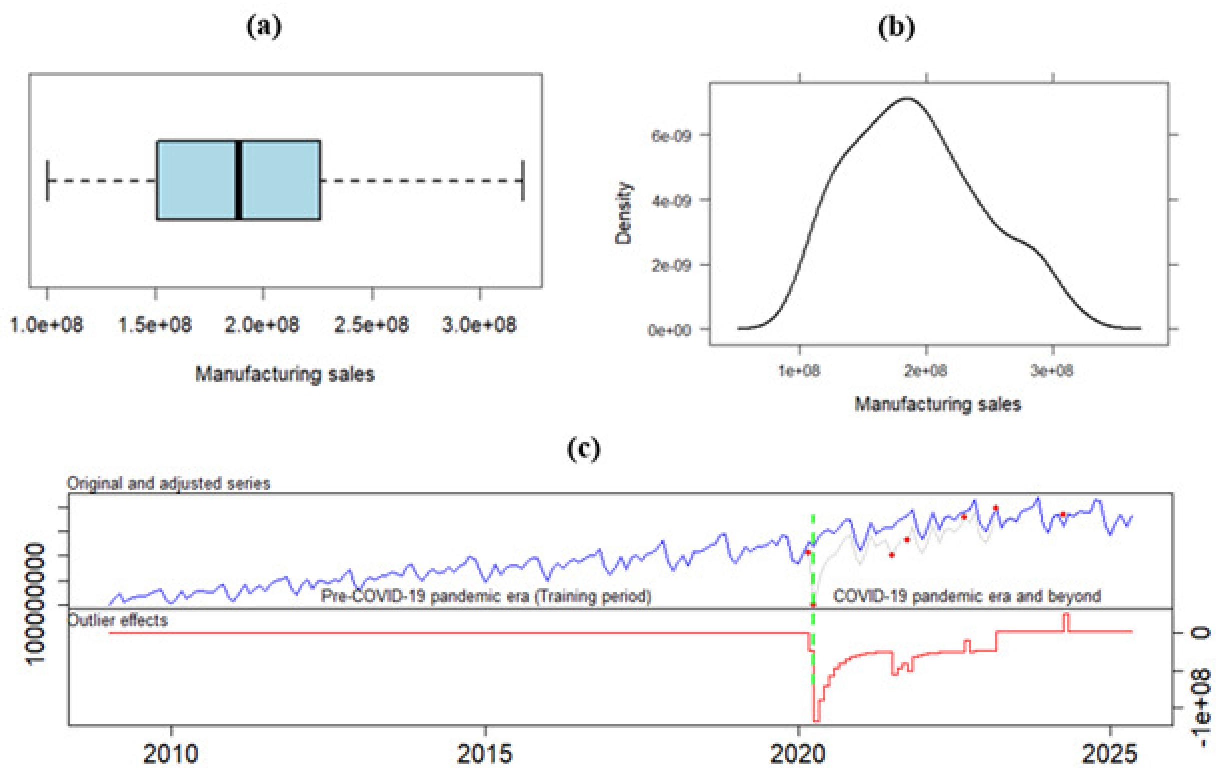

Figure 2. Exploratory and time series outlier analysis of total manufacturing sales in SA

Figures 2(a) and 2(b) illustrate that the data exhibit a nearly symmetric distribution with a slight right skew. In Figure 2(c), an upward trend and seasonality are evident, alongside a significant dip in manufacturing sales (blue line) caused by the COVID-19 pandemic, particularly in April 2020. This intervention occurred shortly after President Cyril Ramaphosa of South Africa announced the first economic lockdown on 26 March 2020. A crucial observation from the graph is the upward linear trend and seasonality in total manufacturing sales, suggesting that the series is not stationary.

Figure 2(c) illustrates that the transfer function can be effectively modelled as a pulse function, with red dots indicating detected additive outliers (AOs). The first two outliers, which occurred in April 2020 (the Intervention point), align with the start of the COVID-19 lockdown, capturing a temporary disruption in manufacturing sales followed by a swift recovery. A third outlier in July 2021 aligns with the widespread socio-political unrest that occurred in KwaZulu-Natal and Gauteng between 9-17 July 2021, which significantly disrupted supply chains and economic activity, particularly in the manufacturing and retail sectors [25]. Additional red dots observed after July 2021 indicate minor, irregular fluctuations in sales. These may stem from intermittent supply chain disruptions, inflationary pressures, or other sector-specific shocks, suggesting that the manufacturing sector continued to face short-term volatility even as the broader economy stabilised. Outliers were identified using the Time Series Outlier (tso) function from the tsoutliers package in R, which implements [26] iterative procedure for the automatic detection and adjustment of outliers in time series data. These outliers represent isolated, temporary shocks that influence manufacturing sales only during specific months, without impacting the underlying process in subsequent periods.

The pulse function was chosen because the lockdown's effect was brief and sharply limited in time, causing sudden but short-lived disruptions in manufacturing sales. A step function suggests a permanent change, which conflicts with the observed quick recovery ([12]). A decaying function typically indicates a gradual return to normal; however, the data show an abrupt rebound, which is inconsistent with a slow decay. Since the phased lockdown relaxations caused discrete, temporary shocks rather than long-lasting effects, the pulse function best reflects the immediate, isolated nature of these outliers. This method is also supported by the short-term economic disturbance caused by the July 2021 civil unrest [25], which created a visible but temporary shock in the manufacturing sector without affecting the long-term trend.

4.2. Pre-intervention Model Confirmation

The Box-Cox transformation suggests that a logarithmic transformation is appropriate for manufacturing sales, as the estimated λ was close to zero. Unlike a fixed log transformation, Box-Cox offers greater flexibility by optimising λ to improve normality and stabilise variance. However, it requires the response variable to be strictly positive [27], which is satisfied in the case of South Africa's manufacturing sales.

The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test revealed that log-transformed manufacturing sales become stationary after applying regular first and seasonal differences (KPSS = 0.1263, p = 0.1000). The ACF and PACF plots, along with the EACF, suggest a SARIMA(0,1,1)(0,1,1)$_{12}$ model as a potential pre-intervention candidate, confirming the model presented by [10]. The model is selected as the best by the AIC criteria. The pre-intervention model shows good fit, with no significant autocorrelation ($\chi^2 = 0.2999$, p = 0.8608) and residuals that are approximately normally distributed (Jarque-Bera $\chi^2 = 1.8118$, p = 0.4042). The model parameters estimated through MLE are presented in Table 1.

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

Parameter	Parameter Estimate	Standard Error (SE)	Test Statistic	P-value
θ_1	-0.6677	0.0743	-8.9861	< 0.0001
Θ_1	-0.7368	0.0934	-7.8921	< 0.0001

All the SARIMA(0,1,1)(0,1,1)$_{12}$ pre-intervention model parameters exhibited in Table 1 are significant at the 5% significance level. The pre-intervention SARIMA(0,1,1)(0,1,1)$_{12}$ model is expressed as:

$$Z_t = (1-B)^{-1}(1-B^{12})^{-1}(1+0.6677B)(1+0.7368B^{12})\epsilon_t. \quad (5)$$

4.3. SARIMA-intervention model

A SARIMA-intervention model was developed using data from January 2009 to December 2023, extending the pre-intervention dataset to identify structural shocks. Data from January 2024 to May 2025 were reserved for out-of-sample validation. Interventions were initially introduced based on known events, including a pulse intervention in April 2020 to capture the immediate impact of the COVID-19 lockdown, and another significant outlier in July 2021 reflecting the civil unrest in South Africa, as documented by [25]. The model was then iteratively refined using the tso() and detectIO() functions in R to detect and incorporate additive and innovational outliers. This process continued until no further significant outliers were identified and model diagnostics confirmed a stable and well-specified fit.

Table 2 summarises the parameter estimates, statistical significance, AIC, and performance metrics (RMSE, MAE) for all competing models, starting from the baseline SARIMA, through models with interventions only, and finally those incorporating both interventions and outliers. This comparative analysis enables a clear assessment of model performance and robustness under varying structural assumptions.

Table 2. Model Comparison and Sensitivity Analysis Results for South African Manufacturing Sales

Model	Parameter	Estimate	SE	Z value	P-value	RMSE	MAE	AIC
SARIMA$(0,1,1)(0,1,1)_{12}$ (No intervention)	$\hat{\theta}_1$	-0.3656	0.1022	-3.5794	< 0.0001	0.0598	0.0308	-416.76
	$\hat{\Theta}_1$	-0.9999	0.1024	-9.7658	< 0.0001			
SARIMA$(0,1,1)(0,1,1)_{12}$ + COVID-19 Pandemic Intervention	$\hat{\theta}_1$	-0.3353	0.0943	-3.5556	0.0004	0.0392	0.0275	-559.71
	$\hat{\Theta}_1$	-0.9999	0.1007	-9.9323	< 0.0001			
	$\hat{\omega}_0$	-0.5134	0.0379	-13.5305	< 0.0001			
SARIMA$(0,1,1)(0,1,1)_{12}$ + COVID-19 Pandemic Intervention + Unrest	$\hat{\theta}_1$	-0.3485	0.0963	-3.6179	0.0003	0.0378	0.0265	-568.12
	$\hat{\Theta}_1$	-0.9999	0.1373	-7.2806	< 0.0001			
	$\hat{\omega}_0$	-0.5151	0.0371	-13.8907	< 0.0001			
	$\hat{\omega}_1$	-0.1348	0.0375	-3.5908	0.0003			
	$\hat{\omega}_2$	0.7315	0.2070	3.5337	0.0004			
$(0,1,1)(0,1,1)_{12}$ + COVID-19 Pandemic Intervention + Unrest + 1 IO	$\hat{\theta}_1$	-0.5033	0.0736	-6.8398	< 0.0001	0.0310	0.0237	-634.64
	$\hat{\Theta}_1$	-0.9942	0.2905	-3.4229	0.0006			
	$\hat{\omega}_0$	-0.6132	0.0303	-20.2113	< 0.0001			
	$\hat{\omega}_1$	-0.1295	0.0298	-4.3534	< 0.0001			
	$\hat{\omega}_2$	0.7358	0.1406	5.2320	< 0.0001			
	IO_1 (May 2020)	-0.2768	0.0313	-8.8456	< 0.0001			
SARIMA$(0,1,1)(0,1,1)_{12}$ + COVID-19 Pandemic Intervention + Unrest + 2 IOs	$\hat{\theta}_1$	-0.5717	0.0678	-8.4265	< 0.0001	0.0292	0.0227	-652.61
	$\hat{\Theta}_1$	-0.9980	0.1539	-6.4838	< 0.0001			
	$\hat{\omega}_0$	-0.6446	0.0292	-22.0909	< 0.0001			
	$\hat{\omega}_1$	-0.1247	0.0277	-4.5086	< 0.0001			
	$\hat{\omega}_2$	0.7261	0.1285	5.6501	< 0.0001			
	IO_1 (May 2020)	-0.3215	0.0298	-10.7918	< 0.0001			
	IO_2 (June 2020)	-0.1343	0.0295	-4.5487	< 0.0001			

The model comparison results in Table 2 demonstrate progressive improvement in model performance with the inclusion of structural interventions and innovational outliers (IOs). The baseline SARIMA(0,1,1)(0,1,1)$_{12}$ model, without any interventions, yields the poorest fit, as indicated by the highest RMSE (0.0598), MAE (0.0308), and the least favourable AIC value (-416.76). Introducing a COVID-19 intervention in April 2020 substantially enhances model performance, reducing RMSE and MAE, and improving the AIC to -559.71.

Adding a second intervention for the July 2021 civil unrest further improves the fit, with a lower RMSE (0.0378), MAE (0.0265), and a more favourable AIC (-568.12), while all intervention parameters remain highly significant ($p < 0.0001$). The incorporation of one IO (May 2020) results in a sharp performance gain, reducing RMSE to 0.0310, MAE to 0.0237, and lowering the AIC to -634.64. The best-performing model includes both interventions and two IOs (May and June 2020), achieving the lowest RMSE (0.0292), MAE (0.0227), and the most negative AIC (-652.61), indicating the best overall model fit.

All estimated parameters in the final model are statistically significant at the 5% level ($p < 0.0001$), confirming the model's robustness in capturing both persistent structural changes and short-term shocks. These findings highlight that the SARIMA(0,1,1)(0,1,1)$_{12}$ model with COVID-19 interventions, civil unrest, and two IOs (SARIMA-COVID-19-Unrest-2IOs) offers the most accurate and parsimonious representation of South African manufacturing sales data.

4.4. SARIMA-COVID-19-Unrest-2IOs Model Diagnostics

Figure 3 illustrates the in-sample forecast of the SARIMA-COVID-19-Unrest-2IOs model. The plot compares the actual logged manufacturing sales with the model's fitted values, demonstrating the model's capacity to capture both structural breaks and seasonal patterns.

Figure 3 illustrates the strong fit of the SARIMA-COVID-19-Unrest-2IOs model to the logged manufacturing sales data. The close alignment between the actual values (black line) and the fitted in-sample forecasts (red line) demonstrates that the model effectively captures the underlying trends, seasonal patterns, and intervention effects, including the COVID-19 lockdown and subsequent shocks. The model also reflects the sharp decline around early

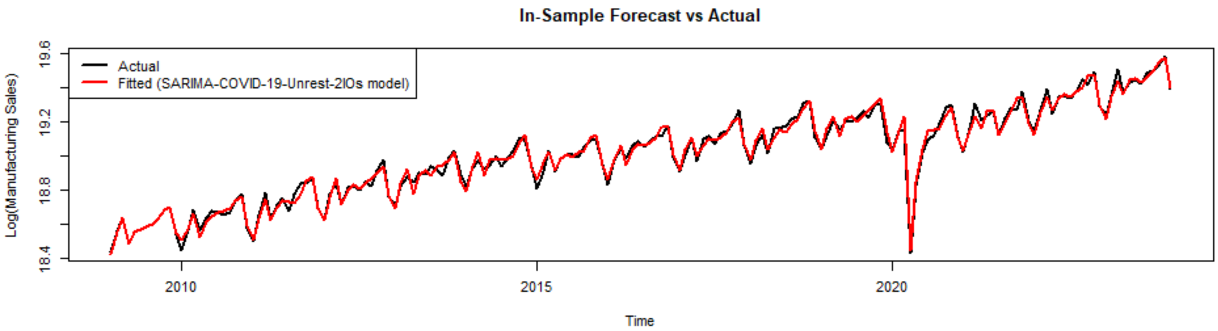

Figure 3. SARIMA-COVID-19-Unrest-2IOs model in-sample validation

2020 and the subsequent recovery, indicating the impact of the interventions and innovative outliers incorporated in the model.

Figure 4 presents the ACF plot and histogram of the standardised residuals from the final model.

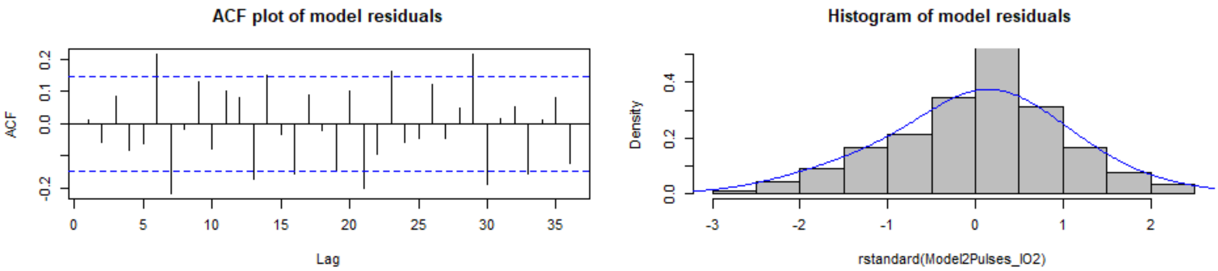

Figure 4. SARIMA-COVID-19-Unrest-2IOs model residuals

The ACF plot suggests the absence of autocorrelation, as most spikes lie within the confidence bounds and only a few exceed them. The Ljung-Box test ($\chi^2 = 0.6800$, $p = 0.7118$) confirms that the residuals are free of autocorrelation, indicating that the model adequately captures time dependence in the data. Additionally, the Jarque-Bera test ($\chi^2 = 1.6076$, $p = 0.4476$) supports the normality of residuals, suggesting no significant skewness or excess kurtosis. The histogram of residuals further validates this, displaying an approximately normal distribution. Despite the presence of a few visually prominent lags in the ACF plot, these do not translate into statistically significant auto-correlations, affirming the model's adequacy.

The final intervention model (SARIMA-COVID-19-Unrest-2IOs) can be expressed as:

$$X_t = Z_t - 0.6446P_t^T - 0.1247(1 - 0.7261G)^{-1}P_t^T - 0.3215\text{IO}_{\text{May 2020}} - 0.1343\text{IO}_{\text{June 2020}} \quad (6)$$

where

$$Z_t = (1 - B)^{-1}(1 - B^{12})^{-1}(1 + 0.5717B)(1 + 0.9980B^{12})\varepsilon_t \quad (7)$$

and G denotes the forward shift operator such that $GP_t^T = P_{t+1}^T$. The terms $\text{IO}_{\text{May 2020}}$ and $\text{IO}_{\text{June 2020}}$ represent innovative outliers, each affecting only a single time period.

Equation (6) indicates that the log of mean manufacturing sales experienced an immediate decrease of -0.7693 in April 2020 due to the COVID-19 pandemic. This is calculated as the combined effect of the level shift and the short-term decaying adjustment: $(-0.6446 - 0.1247)$. In terms of percentage, this corresponds to an approximate 53.67%

reduction in manufacturing sales in April 2020, computed as: $\left[1 - e^{(-0.7693)}\right] \times 100 = 53.67\%$. The month-on-month change in manufacturing sales after June 2020 is given by: $\left[1 - e^{(-0.1247)\times(0.7261)^k}\right] \times 100\%, \quad \text{for } k \geq 3$. For example, in December 2020, manufacturing sales were approximately 1% lower than in the same month of the previous year.

The estimated cumulative financial loss in manufacturing sales between April 2020 and April 2022 is approximately ZAR 188.99 million, reflecting the substantial economic impact of the pandemic and civil unrest on South Africa's manufacturing sector.

Figure 5 presents effect bars illustrating the estimated impact of the COVID-19 pandemic and related shocks on South African manufacturing sales.

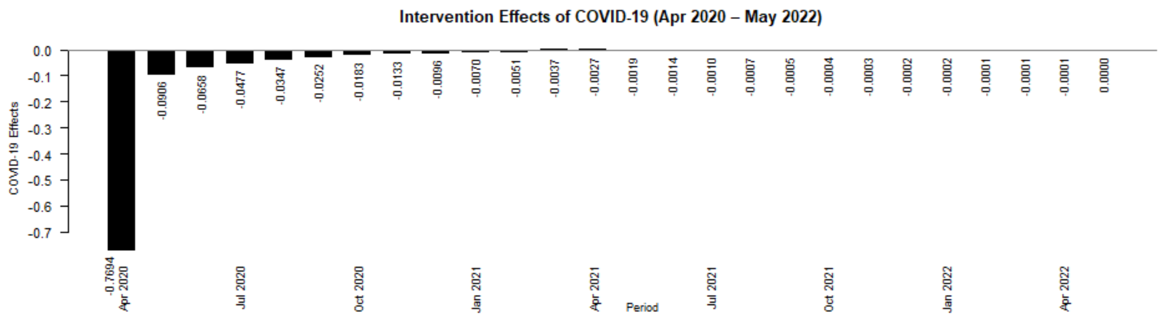

Figure 5. Estimated Effects of COVID-19 and Related Shocks on Manufacturing Sales

Figure 5 shows the substantial negative effect of the COVID-19 pandemic on South African manufacturing sales, with the steepest decline happening in April 2020 during the initial lockdown. The effects gradually lessened over time, indicating a slow but steady recovery. Although the civil unrest in July 2021 caused a brief additional disruption to the sector, its impact appears less significant in the chart. Manufacturing sales are demonstrated to have fully recovered by May 2022, as the effects of interventions return to nearly zero.

Out-of-sample validation was conducted using manufacturing sales data from January 2024 to May 2025 to assess the forecasting accuracy of the SARIMA-COVID-19-Unrest-2IOs model compared to the pre-intervention model developed by [10]. Figure 6 illustrates this comparison by plotting the forecasted values from both models alongside the observed sales data, highlighting the improved alignment of the intervention model with actual trends.

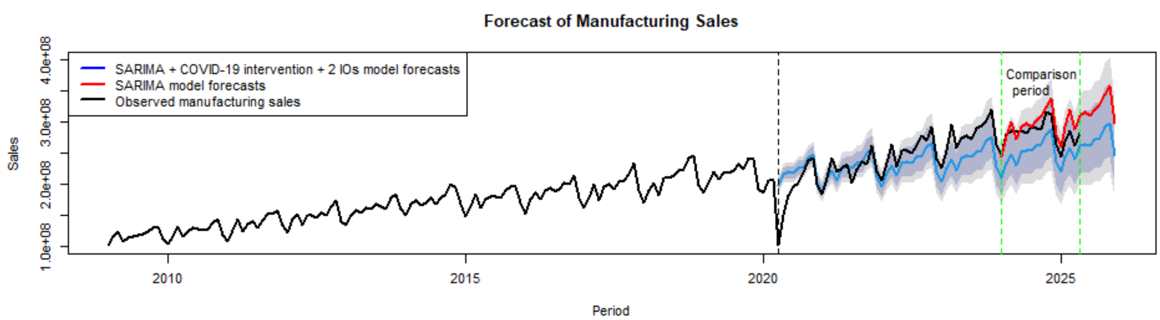

Figure 6. SARIMA-COVID-19-Unrest-2IOs model out-of-sample validation and forecasting

The comparison period from January 2024 to May 2025, highlighted by the dashed green lines in Figure 6, illustrates the forecasting performance of the models. The SARIMA-COVID-19-Unrest-2IOs model forecasts show a marked improvement over the baseline SARIMA model, aligning closely with the actual sales data. The grey shaded areas represent confidence intervals that account for forecast uncertainty, further demonstrating the model's reliability. This indicates that incorporating the intervention function effectively captures the COVID-19 pandemic's impact on manufacturing sales, especially during crisis periods, thereby enhancing predictive accuracy. Quantitatively, the intervention model achieved a root mean squared error (RMSE) of ZAR 18.45 million and a mean absolute error (MAE) of ZAR 16.11 million, substantially outperforming the baseline model, which recorded an RMSE of ZAR 32.65 million and an MAE of ZAR 31.46 million. Considering the average monthly manufacturing sales of approximately ZAR 194 million during the study period, the intervention model's errors represent less than 10% of the mean, indicating strong forecast reliability. In contrast, the baseline model's errors exceed 16% of the mean, underscoring its limited capacity to account for structural shocks. These results reinforce the value of incorporating interventions, such as those related to the COVID-19 pandemic, and identifying outliers in time series models for improved forecasting in dynamic environments.

The forecast in Figure 6 suggests that South Africa's manufacturing sales are projected to increase steadily over the coming months. This projected recovery implies that manufacturing firms and policy-makers should capitalise on the positive momentum by investing in infrastructure, innovation, and supply chain resilience to sustain long-term growth. Strengthening these areas can help the sector absorb future shocks and maintain competitiveness in a recovering global market

5. Discussion of findings

The COVID-19 pandemic had a severe impact on South Africa's manufacturing sector, as indicated by the study results. This aligns with [18], who reported similar challenges in the country's wholesale trade sales, although those sales have since fully recovered. These findings highlight the significant impact of the pandemic on key sectors of the South African economy. The extent of these disruptions reflects the broader economic difficulties experienced during this period and emphasises the vulnerability of essential industries to global crises. Consistent with this study, the current results indicate substantial adverse effects from both COVID-19 and the July 2021 civil unrest on manufacturing sales, confirming the notable and lasting disruptions that were endured.

[28] found that the COVID-19 pandemic had a significant impact on manufacturing companies, prompting them to adapt their operations to recover. The disruptions caused by lockdowns and shutdowns resulted in fluctuations in supply and demand, as well as shifts in consumer behaviour, negatively affecting the manufacturing sector. Similarly, research by [29], [30], [31], and [32] underscored the severe effects of pandemics and epidemics on global manufacturing and industrial operations. The model extends these findings by quantifying the lingering monthly impacts and identifying the temporal patterns of recovery, which is essential for informing more precise policy interventions.

[33] found that the COVID-19 pandemic caused significant disruptions to production networks and severely impacted the supply and demand chains critical to manufacturing. The current study's results corroborate these findings by quantifying both the immediate and prolonged declines in South African manufacturing sales, illustrating how supply chain interruptions and demand shocks translated into tangible output losses. Our dual-intervention SARIMA model effectively captures the sharp initial impact alongside the extended recovery period, highlighting the sector's vulnerability and reinforcing the urgent need for robust, adaptable production strategies as emphasised by [33].

[34] observed similar effects during the global financial crisis, noting sudden and temporary disruptions in container throughput in Belgium and China's manufacturing sectors, respectively. These findings highlight that, much like the COVID-19 pandemic, the global financial crisis had a significant and immediate impact on key manufacturing operations. In the current study, while South African manufacturing sales experienced a sharp decline due to COVID-19 and the July 2021 civil unrest, lingering effects persisted, with gradual recovery observed only by April 2022. This underscores the prolonged disruptions faced by the sector and the critical importance of strategies to enhance resilience against such extended shocks.

Building on these insights, this study advances the understanding of COVID-19's impact by employing a SARIMA-intervention model validated through both in-sample and out-of-sample forecasting, complemented by sensitivity analyses to ensure robustness. This dynamic intervention approach captures not only the immediate adverse shocks but also the lingering monthly effects of COVID-19 and the later noted July 2021 civil unrest on manufacturing sales. By quantifying monthly percentage losses and modelling gradual recovery trajectories, the model provides a detailed and dynamic assessment that surpasses static approaches.

The inclusion of sensitivity analyses further confirms the stability and reliability of the model results across varying assumptions, addressing potential concerns regarding model specification and increasing confidence in the findings. The study provides a comprehensive understanding of the manufacturing sector's disruption and recovery patterns, enabling policymakers to design more effective and targeted interventions in response to complex and overlapping shocks.

6. Conclusion

The COVID-19 pandemic has significantly disrupted the global economy, affecting manufacturing industries worldwide, including those in South Africa, which face considerable challenges. This study builds on the foundational work of [10] by incorporating the impacts of the COVID-19 pandemic, the July 2021 civil unrest, and two additional statistically identified outliers, thereby extending the analysis of disruptions and recovery in South Africa's manufacturing sector. While [10] laid the necessary groundwork in modelling structural breaks within South African manufacturing data, this study uses a dual-intervention SARIMA model to capture both immediate shocks and persistent monthly effects dynamically. This improved modelling framework not only quantifies the extent of disruptions but also tracks the recovery process with greater accuracy, addressing complex overlapping crises. Building on the frameworks of [11] and [12], this research integrates the impacts of the COVID-19 pandemic, the July 2021 civil unrest, and two additional statistically identified outliers. These results emphasise the distinct and severe disruptions experienced by South Africa's manufacturing sector, disruptions that are markedly different from the more gradual effects usually seen in developed economies. By capturing these specific shocks, the study showcases the flexibility and relevance of intervention models in emerging markets with complex structural dynamics. A novel dual-intervention SARIMA model was used to identify both the immediate and lingering impacts of external shocks on manufacturing sales. While the model effectively captures major measurable disruptions such as COVID-19 and civil unrest, it does not explicitly consider other concurrent influences like energy shortages and policy changes, which may also have affected manufacturing performance. The findings show that South Africa's manufacturing sector experienced a sharp decline in sales of 53.67% in April 2020, immediately after the economic lockdown, highlighting the pandemic's severe and immediate economic impact. Partial recovery started around May 2021, with full recovery observed by May 2022. The total estimated cumulative loss in manufacturing sales from April 2020 to April 2022 is approximately ZAR 188.99 million, reflecting the significant financial toll of the crisis.

These findings underscore the need for manufacturing firms to develop resilient supply chains and adaptable strategies to withstand future global disruptions better. Policymakers and industry leaders should prioritise robust contingency planning, technological innovation, and infrastructure development to enhance sector resilience. Practical recommendations include diversifying supply sources to reduce reliance on single suppliers, investing in digital technologies to enhance operational flexibility, improving transportation and logistics infrastructure to mitigate bottlenecks, and providing targeted financial support to small and medium-sized enterprises to help them withstand shocks.

Forecast results indicate a growth trajectory in manufacturing sales, reflecting the sector's sustained recovery following the COVID-19 disruptions. This outlook underscores the necessity for sustained strategic investment in innovation, infrastructure, and risk mitigation to ensure long-term stability and resilience.

Furthermore, South Africa's existing structural challenges, such as infrastructure deficiencies, labour market informality, and uneven regional industrial development, likely amplified the pandemic's disruptive effects. Based on the observed recovery patterns, targeted policy measures should focus on diversifying local supply chains, improving digital and transport infrastructure, and providing tailored support for small and medium-sized manufacturers. These context-specific strategies can enhance resilience locally and offer valuable lessons for other developing economies facing similar structural constraints.

This study's dynamic intervention approach effectively measures the scale and duration of manufacturing disruptions, providing policymakers with vital evidence to guide strategic responses that reduce losses and speed up recovery during crises.

7. Limitations of the study

This study is limited to the South African context and other developing countries with similar structural settings; therefore, its findings may not be directly generalizable to economies with different industrial compositions, policy responses, or levels of economic development. Furthermore, the model used does not account for other simultaneous factors that may have influenced manufacturing sales. Events such as ongoing load shedding, trade policy changes, and global commodity price fluctuations were omitted due to data limitations and the study's univariate focus. These unaccounted influences may have contributed to additional variability in the observed trends.

8. Future research

Future research should investigate the long-term effects of the COVID-19 pandemic on the resilience of the manufacturing sector, with a focus on technological adoption and workforce adaptation. Interdisciplinary approaches that combine economic, technological, and social perspectives are essential for creating comprehensive strategies that support sustainable recovery and growth. Building on the current univariate framework, future studies should incorporate exogenous variables and utilise multivariate time series models to gain a deeper understanding of external influences, such as energy crises and policy changes. Alternative forecasting methods, such as Prophet, could provide additional insights into dynamic intervention effects. Comparative analyses between developed and developing economies are also advisable to identify different recovery paths and resilience mechanisms. These diverse and interdisciplinary approaches will enhance understanding and facilitate more targeted policy development and intervention.

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