Forecasting the impact of the COVID-19 pandemic on South African trade

Dr C Chakamera
Postdoctoral Research Fellow
University of Johannesburg
South Africa
cchakamera@uj.ac.za
*Corresponding author

Dr L Mapamba
Postdoctoral Research Fellow
University of Johannesburg
South Africa
libertym@uj.ac.za

Dr N Pisa
Head of Department: Transport and Supply Chain Management
University of Johannesburg
South Africa
noleenp@uj.ac.za

ABSTRACT

The COVID-19 pandemic has caused significant disruption to global economic activity, global supply chains and international trade. Studies forecasting the impact of the COVID-19 pandemic on South African trade are sparse despite an increase in research on the pandemic. We investigated the effect of COVID-19 on South African export and import values by firstly analysing the effect of other past crises on trade using monthly trade data for South Africa for the period January 2005 to July 2020. Before the forecasts, we validated the forecasting power of ARIMA models in the presence of significant swings in trade. Thereafter forecast values for the period August 2020 to July 2022 were computed. Our findings reveal that the COVID-19 pandemic, like other supply chain disruptions of global proportion, will result in the contraction of South African trade. However, the country is more likely to report a positive trade balance. This will contribute to a positive balance of payments and exchange rates during the forecast period. Weak domestic demand may explain the inferior imports against exports predicted between August 2020 and July 2022. Despite the anticipated positive trade balance, weak domestic demand could also weaken the country‟s economic growth projections. The forecasts in this study may also be used by policymakers to anticipate tariff revenue from the different regions. It is also imperative for policymakers to advance bilateral trade agreements with Asian, European and African countries, the major export destinations. The African Continental Free Trade Area is a welcome strategy that may boost trade between South Africa and other African countries.

Keywords: Trade forecasting, supply chain disruptions, COVID-19, South Africa

INTRODUCTION

Global supply chains have resulted in global interconnectedness among firms and have become a major source of competitiveness both for individual firms and economies at large (Cantwell, 2017; Contractor et al., 2015). Global supply chains or global value chains are characterised by the "international expansion and geographical fragmentation of contemporary supply chains" (Vandenbussche, Connell & Simons, 2019:2; Gereffi & Lee, 2012: 24). Firms at various stages in the global supply chain specialise in specific competences that the entire chain leverages on to be more competitive compared to individual firms or localised supply chains (Vandenbussche, Connell & Simons, 2019:25). Global supply chains have facilitated the transfer of technology and knowledge facilitated through trade (Kalaitzi, 2018:1). In particular, the proliferation of global trade has resulted in easier access to innovative raw materials, production processes, marketing and after sales strategies (Lamy, 2010; Baldwin & Lopez-Gonzalez, 2015). Firms are now more dependent on global suppliers for intermediate inputs. Intermediate inputs account for 20 to 50 percent of final manufacturing output globally (Blanchard, Bown & Johnson, 2016:5). This is because of globalisation and liberalisation of trade, which have opened markets and increased international trade levels to unprecedented levels (Jenkins, 2018; Siddiqui, 2017:514).

Dependency on trade results in vulnerabilities to disruptions (Lee, 2019:12). Supply chain disruptions are external shocks caused by intentional or unintentional human actions and natural disasters (Ambulkar et al., 2015:111). These disruptions partially or completely negatively impact the inventory levels, contracts and incentives, sourcing decisions, and strategic decisions of the various stakeholders in a supply chain (Snyder et al. 2016). Supply chain disruptions result in supply uncertainty (Begen et al., 2016), increased operational and financial risk (Scheibe & Blackhurst, 2018:43) and a reduction in network reliability (Snyder & Daskin, 2005; Kerivin & Mahjoub, 2005). Developing self-sustaining economies is one approach to mitigating the vulnerability to external shocks (Hosseini et al., 2019:286). However, isolation can be limiting because the interconnectedness and interdependencies among economies brought about by global supply chains cannot be replaced by the internal resource endowments or competencies (WTO & IDE-JETRO 2011: 83-85). Although global trade can result in deficits that are undesirable, the global economy cannot do without international trade (Baldwin & Lopez-Gonzalez, 2015:1686). As a result, global trade continues to be important despite efforts to build self-sustaining economies.

South Africa, an emerging market, has been grappling to position itself a key player in the global market. Like many economies, South Africa depends on imports of intermediate and finished goods, which makes the country vulnerable to external shocks. An analysis of the growth of South African supply (exports) relative to international demand for products exported by South Africa, reveals the structural weaknesses in South Africa"s trade competitiveness (TradeMap, 2019). Exports from South Africa are mainly primary sector products that constitute a small proportion of world market share and are in low growth market segments (TradeMap, 2019). In 2018 South Africa recorded a positive trade balance, however, its exports constituted 0.5 percent of world trade in comparison to other emerging markets namely: Brazil 1.2 percent, Russia 2.3 percent; India and China 13 percent (Trade Map, 2019). A considerable proportion of exports in 2018 were classified as losers in growing markets (TradeMap, 2019). This means that despite these markets experiencing high and positive growth rates, South Africa"s share in world exports between 2014 and 2018 declined. It is evident from the above that South Africa is vulnerable to shocks and disruptions such as a global pandemic, because it is dependent on trade.

The global economy is currently faced with the disruptions of the coronavirus SARS-Cov-2, resulting in the disease known as COVID-19. The COVID-19 pandemic originated in China in December 2019 and has rapidly swept across the world and affecting most of the world (Tindale et al., 2020:2). Consequently, several governments imposed travel and trade restrictions to contain the spread of the virus as they recognised that global connectedness was an enabling factor for spread of the disease (Fauver et al., 2020:994). The COVID-19 pandemic has been a significant disruption to global economic activity and to global supply chains. Attempts to contain the virus led to national and worldwide shutdowns with the concomitant disruption of global supply chains. Past pandemics show that at the onset people tend to perceive a higher risk of infection due to insufficient information and this can lead to avoidance of public spaces (Brahmbhatt & Dutta, 2008; McKibbin & Sidorenko, 2006). On the response end, public health protocols guide governments to impose restrictions to public spaces as a containment measure while an appropriate disease management approach is identified (Noy & Shields, 2019:7; Kleinman & Watson, 2006:31). Thus, the perceptions of the public and the reaction of government lead to business disruptions that result in demand and supply shocks (Chou et al., 2004:96).

Similar observations can be seen in non-pandemic crises such as the global financial crisis (GFC) of 2009 (Anderton & Tewolde, 2011). At the onset of the GFC, loss of confidence in banks caused the mortgage market to collapse as the market was perceived to be too risky (Makin, 2019:13). This resulted in a run on deposits and drying up lines of corporate credit and trade finance related products resulting in decline of global trade (Ahn et al., 2011:298). Governments responded by measures that included improved regulation of the financial sector, raising deposit insurance limits, stimulus, and stabilisation packages (Morrison, 2009:5; Khatiwada, 2009:2,10,13; Bhaskar & Gopalan, 2009:13).

Despite the growth in empirical studies about the COVID-19 pandemic, it remains unclear how South Africa"s international trade performance will be in the future as studies concerning this issue are sparse. Having established South Africa"s vulnerable international position and trade dependency, this paper aims to address this gap by assessing the impact of the COVID-19 pandemic on South African trade. This will be done by forecasting imports and exports using the auto regressive integrative moving average (ARIMA) model. This was achieved by pursuing three objectives:

- Compare the effects of the COVID-19 pandemic on South Africa"s international trade performance against the effects of other previous crises.
- Examine the forecasting power of the ARIMA model in the presents of significant shocks in South Africa"s international trade values.
- Forecast South Africa"s future international trade values from August 2020 to July 2022.

The first objective involved trend and descriptive analysis. The second objective involved the assessment of the ARIMA model"s capability to forecast future movements in international trade values in the presence of significant shocks. The third objective involved the use of the model to predict the export and import values for South Africa for the period August 2020 to July 2022.

The contributions of this article in quantifying the impact will assist policymakers and firms, among other stakeholders, who are concerned with supply chains disruptions as they manage the impact of the pandemic on their firms and the national economy at large.

LITERATURE REVIEW

Pandemics fall in the class of low frequency high impact risks (Ivanov, 2020:1). They fall outside the theory on economic costs of disease on an economy (Luh et al., 2018:218). In the normal context, disease introduces additional costs through lost opportunities, reduced productivity, and expenditure incurred in disease treatment (McKibbin & Sidorenko, 2006:7). In pandemic cases, the economy loses out due to demand shocks and supply side disruptions (McKibbin & Fernando, 2020:4; McKibbin & Sidorenko, 2006:39). These shocks result from a combination of risk perception and impact of containment strategies (Mackey & Liang, 2012:122). Despite being considered as one of the worst pandemics, the COVID-19 pandemic is not the first the world has experienced in the recent past. Notable pandemics include the plague originating from Surat, India in 1994 (Guha, 2020; Epstein, 2009), severe acute respiratory syndrome (SARS) in Guangdong, China in 2002 (Yang et al., 2020; Petersen et al., 2020; Kleinman & Watson, 2006), and the H1N1 swine flu in Mexico, 2009 (Maines et al., 2009:1).

Several important lessons emerge from both pandemic and non-pandemic crises. Five of the key lessons are discussed here. Firstly, transmission of crisis from one nation to another is through interconnections such as global supply chains. Hence, economies that are connected and open to trade tend be more affected (Hale et al., 2016:16; Coelho et al., 2020:5). Secondly, disruptions in the global supply chains also account for a significant decline in trade during crises (Ivanov, 2020:3). Thirdly, economies with high degrees of specialisation in supply chains (Yi, 2009:46; Miroudot & Ragoussis, 2009:6) and making use of distributed production facilities are particularly vulnerable (Amador & Cabral, 2017:4). Fourthly, the sectors most affected include those producing goods that rely on global trade of intermediate goods such as capital goods and automotive sectors (Makin, 2019:17). Finally, information about the degree of risk and the impact of the crisis is usually scarce (Strekalova, 2017:334).

The information scarcity does not only affect supply and demand but also affects institutions responsible for executing the response (Alcantara-Ayala, 2002:119). Inefficient flow of information causes delays in decision making that can compromise response coordination and timing, leading to suboptimal outcomes (Araz et al., 2020:3; Quarantelli, 1988:18). This is critical in an environment where resources are constrained by competing priorities in the pandemic context (Wankmuller, 2020:3). Predicting the impact of the pandemic on outcomes through forecasting can mitigate these challenges by guiding decision making (Calnan et al., 2018:401; Buyuktahtakin et al., 2018:1048).

While there are differences in the nature and severity of pandemics, they have all been observed to contribute to economic decline (Calnan et al., 2018:402). This poses a challenge for leaders to craft an appropriately timed response that balances the need to contain the pandemic and prevent irreparable economic damage (Ivanov, 2020:2).

Since trade will play a significant role in mitigating both disease spread and economic decline, responses to the crisis need to factor the impact of the pandemic on the nation"s trade (Kassa, 2020:5). For the response to be effective it must be fact based, recognising the disruption of trade. Studies predicting the impact of the coronavirus pandemic on South African trade are sparse despite an increase in research on the pandemic.

RESEARCH APPROACH

Data

Monthly data for South African export and import values of products were obtained from the World Trade Organisation‟s Trade Map database, although COVID-19 restricted the movement of products and services. The period for the analysis was determined by the availability of monthly import and export data for South Africa. At the time of extraction, monthly data for exports and imports were available from January 2005 to July 2020. The data was in United States Dollars (USD: Thousands). Consumer Price Index (CPI) data was collected from Statistic South Africa‟s website and was used to adjust the export and import values for inflation. Thus, the data was converted to USD Constant Prices with January 2005 used as a base month. It is important to filter out the effects of changes in inflation, which allows the values to be reasonably compared across the different months.

Estimation methods

The initial step, in line with the first research objective, was to use trend analysis and descriptive statistics to analyse South African monthly international trade data from January 2005 to July 2020. The effects of COVID-19 on trade performance were compared against other previous crises (2008-2009) or notable shocks (2016). To address the second research question, we validated the forecasting power of the ARIMA model using historical data. This step aims to test the predictive power of the model by computing forecast values for the periods January 2008 to December 2009, January 2016 to December 2017, and July 2018 to July 2020; comparing them to actual import and export values during the same periods. After validation of the ARIMA model, research question three was addressed by forecasting the future movements of exports and imports. The ARIMA approach is discussed in detail, which begins with an assessment for autocorrelation and partial autocorrelation to determine suitability for ARIMA forecasting.

Autocorrelation and partial autocorrelation

As indicated in Guha and Bandyopadhyay (2016: 118), the autocorrelation function (ACF) is defined as follows: ACF=corr(X_t,X_(t-k)), where X_t is the current observation and X_(t-k) is an observation k periods ago. The values of the ACF ranges between -1 and +1. The partial autocorrelation function (PACF) measures the correlation between an observation k periods ago and the current observation, after accounting for observations at intermediate lags (lag<k) (Brooks, 2008: 222). For instance, the PACF for lag 4 measures the correlation between X_t and X_(t- 4) after accounting for the effects of X_(t-1) , X_(t-2) and X_(t-3). The ACF and PACF plots are generated and checked for spikes, which occur outside the range -1 to +1. Moreover, the data is checked for seasonality to ensure no critical information is left out in the building of ARIMA models.

ARIMA model

Theoretical foundation

Time series analysis is the backbone of ARIMA models. As explained by Asteriou (2006: 246) in his book, Applied Econometrics: A Modern Approach using Eviews and Microfit, for the time series framework, the initial point is to exploit the information about a variable that is present within the variable itself. The advance of time series analysis brought a view that contradicts that of the traditional econometricians as argued in the book. Traditional econometricians underscored the application of economic theory and the study of contemporaneous relationships to describe associations among explained and explanatory variables . That said, "...times series analysis contradicts the beliefs of economic theory, in that it is not based on any theoretical framework, but it considers it better to let the data „speak for themselves‟ to determine the model" (Asteriou, 2006: 246). Although these different approaches were not interrelated in the past, there seems to be convergence, as some of their basic features can be adopted and applied simultaneously. Since this study applies a single time series (i.e. series for trade), it is a univariate time series analysis. More specifically, it is a univariate ARIMA model.

To better understand time series and ARIMA models, the key concept of stationarity is described. According to Stock & Watson (2015: 577-578), in times series analysis, the notion that historical relationships can be generalised to the future is formalised by the stationarity concept, which suggests that the probability distribution of a time series variable does not change over time. Consequently, a stationary process requires the future to be the same as the past, at least in a probabilistic sense. Three characteristics of a stationary time series are as follows:

E(Y_t)=constant for all t

Var(Y_t)=constant for all t

Cov($Y_t, Y_{(t+k)}$)=constant for all t & all k^0

Characteristic one shows that a series (Y) exhibits mean reversion; the mean fluctuates around a constant long- run mean, it is constant over time. Characteristic two shows that the variance of a series is constant over time. The last characteristic is that the autocovariances remain constant over time and for each given lag.

Brooks (2008: 318) summarises the definition of a stationary series as one with “constant mean, constant variance and constant autocovariances” for each given lag. The key idea that is necessary for our ARIMA models and forecasts is that shocks to a stationary time series are essentially temporary, but as time goes on the effects of the shocks disappear and the series will revert to its long-run mean level (Asteriou, 2006: 247). In this case, the COVID-19 pandemic shocked South African trade values, but the effect will disappear over time. From a policy perspective, it is imperative to know the future movements of trade values, especially after the crisis. This is achieved through ARIMA forecasting.

ARIMA models and application

Given the earlier discussion, the ARIMA model is an approach for forecasting time series by assuming that past value of the series and past error terms contain information for forecasting (Ngan, 2016: 38). ARIMA models were first introduced by Box and Jenkins (1976). An ARIMA model is decomposed into autoregressive (AR) - indicates weighted moving average over past observations, integrated (I) - indicates linear trends or polynomial trend, and moving average (MA) - indicates weighted moving average over past errors (Guha and Bandyopadhyay, 2016: 118).

The AR (1) model is expressed as follows:

n = 0^+

where p_t is a white noise error term and 10 |<1 is a constrain that ensures the mean reverting characteristic of a stationary time series. This AR (1) model suggests that the present value of a variable (Y_t) is largely dependent on its previous value (Y_{t-1}). It also means that what will happen to the future value of the variable (Y_{t+1}) is dependent on the current values of the variable (Y_t).

The MA (1) model is expressed as follows:

Y=P+^-.I

where p_t is a white noise error term and |9|<1 is required to avoid an explosive time series. This MA (1) model suggests that the present value of a variable (Y) is dependent on its immediate previous error terms (u_1).

Both AR and MA models give the rationale for forecasting future values using historical observations. When many lags are considered, the general forms of autoregressive and moving average models become AR(p) and MA(q).

By combining the AR(p) and MA(q) models, an ARMA(p, q) model is built. Adding the integrated (I) component leads an ARIMA model and it shows that the series is transformed into a stationary time series. In most cases, time series often contain seasonal effects, and seasonal differencing is used to eliminate the seasonal effects, leading to SARIMA models (Han et. al., 2010: 1399). Thus, two general expressions exist, which are non-seasonal ARIMA(p, d, q) and multiplicative seasonal ARIMA(p, d, q)(P, D, Q) where (P,D,Q) are the model‟s seasonal components.

The non-seasonal ARIMA model can be written as follows:

= a + 71^-1 + 72^-2 + ------------------------ *■ Yp^t-p + + ^2^-2 + --------------- *■ ^qt^t—q

where Y_t is the observed series (i.e. trade value, in this study), p,q are orders of the model (i.e. chosen lags or previous trade values & errors), a and Y are parameters of the model. The random errors (u_t) are assumed to be independently and identically distributed with a mean of zero and a constant variance of 6^2 . The Box-Jenkins ARIMA model, to estimate and forecast a univariate time series, involves three stages: identification, estimation and diagnostics checking (Asteriou, 2006: 257, Brooks, 2008: 230).

Identification is the stage for choosing appropriate order of the model, that is, p, d, and q. The series needs to be stationarity and hence if it is not, it can be differenced (i.e. including the d component) to make it stationary. This study starts by fitting an auto-ARIMA, which automatically chooses an appropriate model. But whenever the auto-ARIMA shows evidence of autocorrelation or partial autocorrelation, the model is customised to control for the identified lag order. But the stationarity test of the series is also undertaken using the Augmented Dickey-Fuller (ADF) unit root test.

Estimation is, at this stage, the estimated models that are computed using the maximum likelihood method or the least-squares method; this study uses the latter.

Diagnostics checking is done to determine whether the model is adequate. The ACF, PACF or Ljung-Box tests could be used to check for autocorrelation (Brooks, 2008: 231). The LBQ statistic test indicates whether the residuals over time are random and independent. The LBQ"s two hypotheses are the null hypothesis - the residuals are independently distributed, and the alternative hypothesis - the residuals are not independently distributed. Independence of residuals shows no autocorrelation. Once the models pass diagnostic checking, forecasting of international trade values is done.

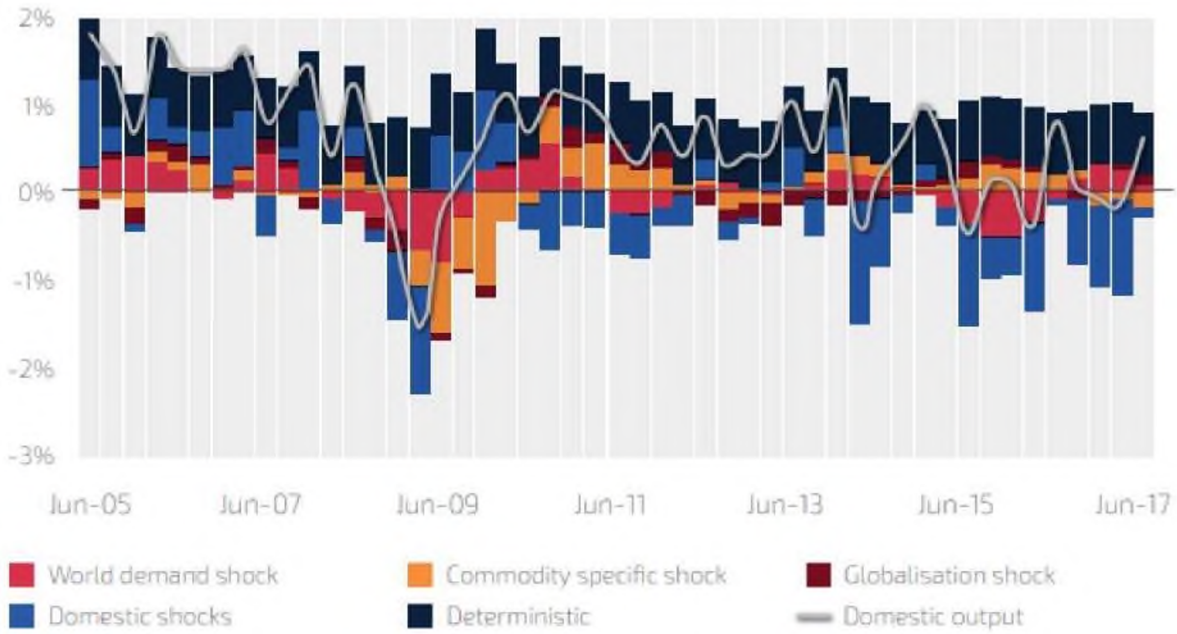
Validating ARIMA models

Having collected trade data from January 2005 to July 2020, the first step is to identify recessions and major swings in trade values that took place since 2005. South African trade values responded to disruptions such as the 2008-2009 recession and the recent COVID-19 pandemic. Another notable shock in economic growth and trade values happened in 2016. Thus, this study chooses three periods: January 2008 to December 2009, January 2016 to December 2017 and July 2018 to July 2020. Data from January 2005 to December 2007 (January 2005 to December 2015) is used to forecast trade between January 2008 to December 2009 (January 2016 to December 2017). Data from January 2005 to June 2017 is used to forecast trade between July 2018 and July 2020. The forecasts are compared against the actual trade values.

Forecasting trade values

After validating the ARIMA models, the next step is to forecast South African trade values from August 2020 to July 2022 using data from January 2005 to July 2020. Thus, the forecasts are starting from a period when nations are still

FIGURE 1: DECOMPOSITION OF SOUTH AFRICAN DOMESTIC OUTPUT (% CHANGE)



Source: World Bank, 2018

battling the COVID-19 pandemic.

RESULTS

Past recessions and international trade value movements

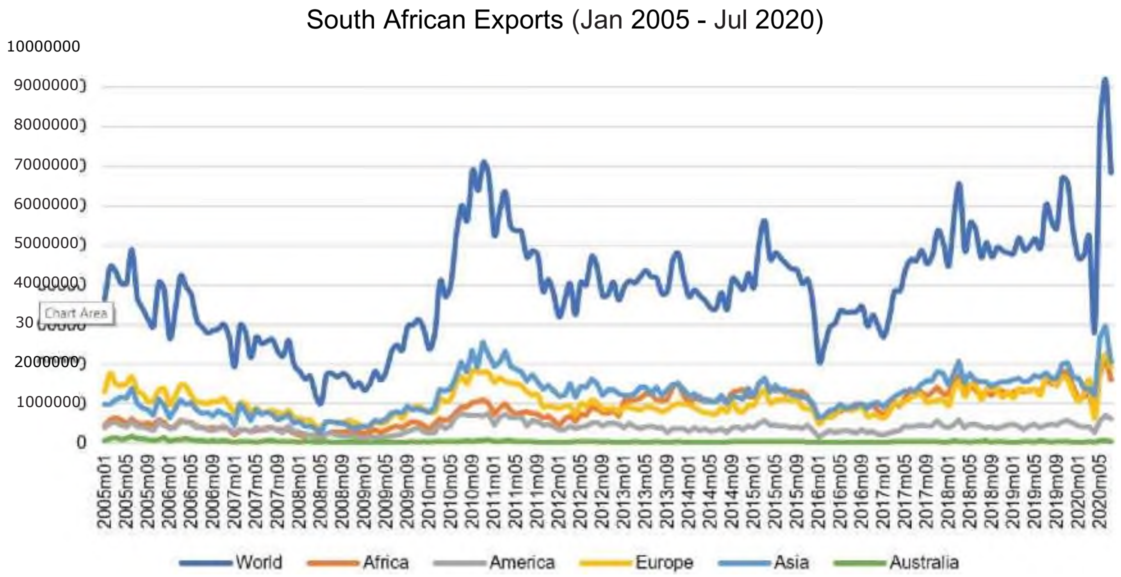
The series of international trade values are expected to respond significantly to recessions or shocks. The major focus was placed on three time periods. Firstly, the 2008-2009 period owing to the global financial crisis (GFC). The second period of interest was 2016, as a significant decline in South African economic growth was observed in that year. Lastly, the recent 2020 decline in growth due to the COVID-19 pandemic was also observed. Owing to the lack of monthly international trade data before 2005, it was not possible to consider other recessions that happened in the past before the 2008-2009 GFC. In South Africa, Figure 1 shows a massive recession that started in 2008, reaching the pick in 2009 and other significant declines in economic growth around 2014, 2015 and 2016. The response of South African trade values to these recessions is discussed.

SA international trade values' response to recessions in the period 2005-2016

During the global financial crisis, both export and import values for South Africa dropped significantly (as presented in Figures 2 and 3). The second notable drop in trade values occurred in 2016. The World Bank (2018:10) reported a drop in South African domestic output in the period 2008 to 2009 resulting from a combination of the global shocks, world demand shock, domestic shocks, and commodity-specific shocks.

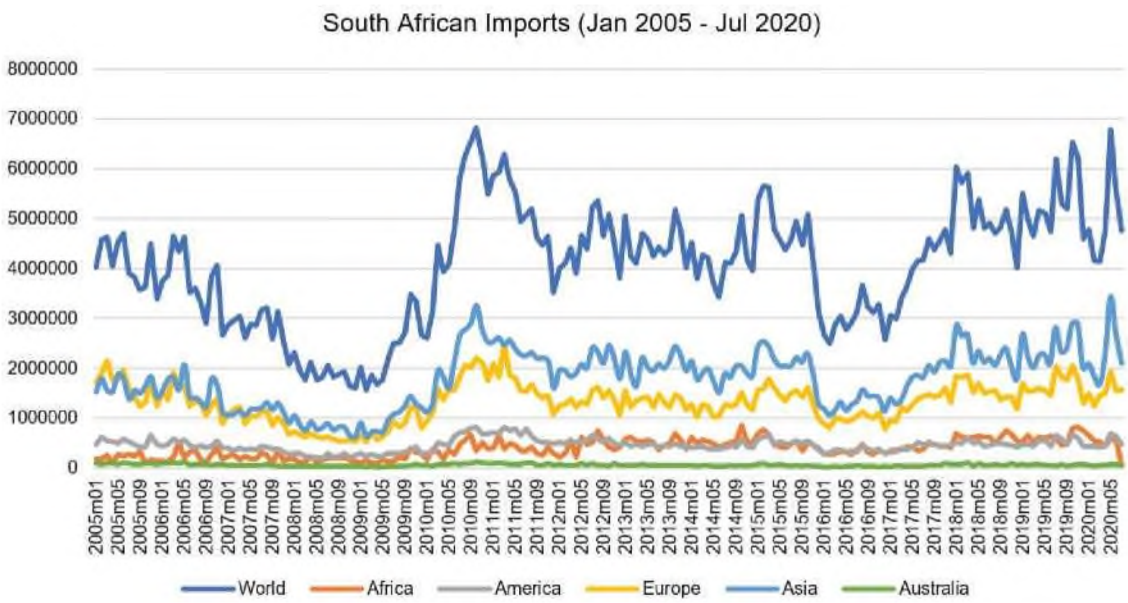
As shown in Figure 1, at the peak of the GFC, the major influence of the recession emerged from domestic shocks, followed by the world demand shock and then the commodity-specific shock. The second major drop in trade values in 2015 and 2016 was also associated with negative growth rates, mostly due to domestic shocks and the influence of the world demand shocks. The trends for the five regions and the rest of the world portray a similar pattern since 2005 as shown in Figures 2 and 3. Generally, the exports to Asia are large, followed by Europe, Africa, America and Australia, in this order. The same order applies for the imports from these continents, except that the imports from America have slightly been higher than imports from Africa. This information is summarised by the descriptive statistics in Table A1, in Appendix A. It is difficult to tell from the trends which of the five regions‟ trade values changed by a larger percentage, possibly due to the effects of recessions or other macroeconomic shocks. The next section

FIGURE 2
PLOT FOR SOUTH AFRICAN EXPORTS



Source: Authors' graph

FIGURE 3
PLOT FOR SOUTH AFRICAN IMPORTS



Source: Authors' graph

presents descriptive statistics for the percentage changes in trade values across the five regions and the world at large.

Percentage changes in trade values

Table 1 presents the changes in South African trade values since 2005. Between 2005 and 2020, South Africa recorded the largest decrease in export values to Australia (April 2020), followed by Europe (April 2020), Africa (April 2020), America (April 2020) and Asia (January 2016), in this order.

This illustrates that in general, the major decline in exports to four out of five continents occurred this year. This is reasonable given the lockdowns that happened not only in South Africa but also in several countries over the world. Exporters were not able to produce and demand from other countries dropped due to the COVID-19 pandemic.

TABLE 1
PERCENTAGE CHANGES IN EXPORTS AND IMPORTS VALUES (JAN 2005 - JUL 2020)

	World	Africa	America	Europe	Asia	Australia
	Exports					
Min	-45,286 (Apr 2020)	-48,791 (Apr 2020)	-47,708 (Jan 2016)	-60,477 (Apr 2020)	-36,689 (Jan 2016)	-64,210 (Apr 2020)
Max	181,595 (May 2020)	174,496 (May 2020)	168,257 (Jan 2008)	206,843 (May 2020)	121,478 (May 2020)	239,049 (May 2020)
Avg	1,917	2,374	2,862	1,982	2,154	5,673
	Imports					
Min	-34,367 (Dec 2006)	-90,902 (Jul 2020)	-31,204 (Jan 2016)	-35,196 (Dec 2006)	-32,660 (Dec 2006)	-63,377 (Feb 2009)
Max	43,047 (May 2020)	276,580 (Oct 2007)	58,731 (Mar 2010)	47,050 (Jan 2013)	51,908 (Mar 2010)	167,161 (Mar 2010)
Avg	1,101	7,677	1,281	1,310	1,429	5,321

Note: In parenthesis () are the months when each value was recorded.

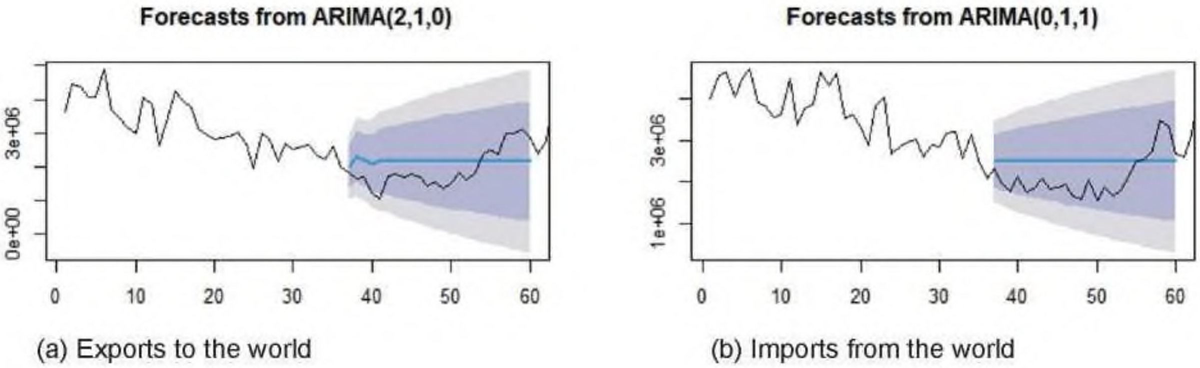
This massive decline in exports exceeded what happened in 2008 to 2009 during the GFC. Another remarkable observation is that the largest percentage increase in exports during the period of study was to Australia (May 2020), followed by exports to America (June 2008), Africa (May 2020) and Asia (May 2020), and then Europe (May 2020). Subsequently, South Africa"s exports to America responded the most to the GFC while exports to the other four regions responded mostly to COVID-19. This is not surprising given the GFC originated in America and was one of the most affected regions. A larger positive percentage change during these recessions shows how export values to a particular region moved from the lower values.

As for imports, the largest percentage drop was for products from Africa (July 2020), followed by Australia (February 2009), Europe (December 2006), Asia (December 2006) and lastly, America (January 2016). In terms of positive changes, the highest percentage increase in imports was from Africa (October 2007) and Australia (March 2010).

It can be concluded from the descriptive analysis that South African trade values have been volatile, with major swings in export and import values reported mostly during recessions (e.g. 2020, 2016, 2008-2009). Figures 2 and 3 reveal the swings in trade values especially in 2008-2009, 2016 and 2020. Moreover, the results show that the COVID-19 crisis caused major swings in exports compared to the previous 2008-2009 GFC and the 2016 economic growth shock. While a major change in imports from the rest of the world was reported in 2020, major changes in regional imports were recorded in different years, as shown in Table 1. This answered the first research question.

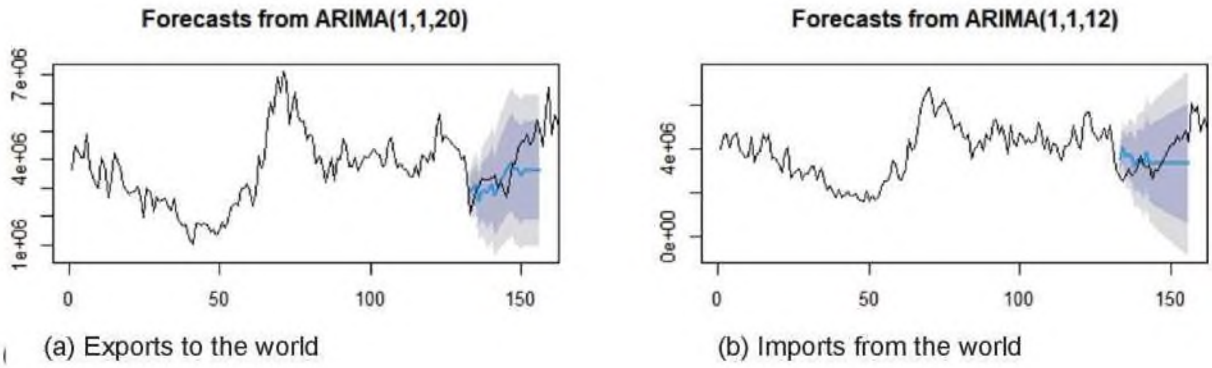
Researchers and policymakers have been using forecasting models such as ARIMA to predict the future movements of trade (e.g. Farooqi, 2014). It is imperative to investigate the predictability power of such forecasting models in the presence of significant shocks. Particularly, in the presence of the recent COVID-19 crisis that forced most economies into national lockdowns, it is of interest to know the potential effect of this on future international trade values. This is because international trade movements play a vital role in other macroeconomic fundamentals such as the balance of trade, exchange rate and economic growth. This study investigates the forecasting power of the ARIMA models in the presence of the major swings in trade values, which then followed by forecasting future values. Checking for autocorrelation and stationarity properties of the data are essential preliminary considerations.

FIGURE 4 FORECASTING 2008-2009 INTERNATIONAL TRADE VALUES



Source: Authors' computation

FIGURE 5
FORECASTING 2016-2017 INTERNATIONAL TRADE VALUES



Source: Authors' computation

Preliminary checks

Stationarity of data

Before evaluating the forecasting power of ARIMA models, stationarity tests were conducted using the ADF unit root test by Dickey and Fuller (1979, 1981). The results showed that except for the exports to Australia, all series were stationary in the first difference and hence the tested ARIMA models should show an integration of order one (i.e. in ARIMA, the „I" part should be 1).

Autocorrelation in original series

The autocorrelations and partial autocorrelations of the export and import values were checked. Across all the ACF plots there were significant spikes that dropped gradually as the number of lags increased. On the other hand, the PACF indicated only a significant initial lag across all the series. Working with the level values of the series could generate poor forecasts due to the presence of autocorrelation. When the Auto-ARIMA detected any autocorrelation, it was eradicated by accounting for the detected lags.

Seasonality check

For instance, Figure A1 in Appendix A reveals seasonality in data. Changes in exports are generally negative in January, April, July, and December while changes in imports are generally negative in February, April, September, November, and December. These seasonal patterns are accounted for in most of the estimated ARIMA models.

Validating ARIMA models in the presence of significant shocks

Our major focus is on how ARIMA models would have been able to make meaningful forecasts during the January 2008 to December 2009 (validation window one), January 2016 to December 2017 (validation window two) and July 2018 to July 2020 (validation window three) periods.

Validation windows one and two

Data for South African exports to and imports from the rest of the world is used to validate ARIMA models during significant swings that occurred in the periods January 2008 to December 2009 and January 2016 to December 2017. Figures 4 and 5 show the results. In both figures, although the point forecasts are supposed to be the best guess of what will happen, they are not realistic as trade values are expected to change or fluctuate due to seasonality and trends (see Figure A1). It is possible in this case that the smaller sample sizes may explain the poor performance of the point forecast. Despite this problem, this does not render ARIMA models unsuccessful since they provide the lower and upper values at both 80 percent and 95 percent forecast intervals (FIs) within which the actual values are expected to fall.

In the plots, the outer interval is the 95 percent forecast interval (FI), and the inner interval is the 80 percent FI. These intervals are essential as policymakers want to get a sense of how far the actual values might be. For both exports and imports, the ARIMA models in Figures 4a, 4b, 5a and 5b correctly predicted that there was an 80 percent chance that the actual future values will fall within the inner forecast intervals.

Validation window three

The results for validating ARIMA models by forecasting trade values between July 2018 and July 2020 are presented in Appendix B. Unlike the previous validation windows, some breaches of the forecast intervals occurred. In June 2020, the 95 percent upper forecast interval was breached in terms of exports to the rest of the World, Africa, America and Asia (see Figures B1a, B1b and B1c, B2a). The lower 95 percent forecast interval was only breached in the case of imports from Africa in July 2020, which shows the lowest import value of 51832 (Figure B2d). Forecasts for imports from Asia were also breached (Figure B3c). For the remaining six forecasts, ARIMA‟s forecast intervals were not breached.

The key conclusions from validating ARIMA models are that:

- The actual values are most likely to lie within the 80 percent FI most of the time.
- When a significant spike in trade values happens, the 95 percent forecast interval might be breached in certain months (in our tests, a breach occurs only in one month).
- The breach of forecasts for exports and imports does not essentially happen across all export and import forecasts (in our tests, it occurs in six out of 16 forecasts), mainly depending on how trade values for a particular region have changed.

Based on these findings, the breach of ARIMA forecast intervals is only experienced when the change in trade values is significantly large. For instance, the breaches in this study were only associated with major changes in trade values due to the COVID-19 effect, but not the other tested periods like the GFC.

South African international trade value forecasts (August 2020 to July 2022)

Forecasts (USD Constant Prices, 2005 base year)

This section presents the forecasts for exports and imports from August 2020 to July 2022. Figure C1a shows the forecasts for total exports and imports from the rest of the world. The forecasts entail that exports for South Africa will be higher than imports during the entire forecasting period. This followed a rise in exports above imports in the last three months (May, June and July) of the sample. Note that the exports and imports are expressed in thousands of USD at constant price (the base month January 2005). In July 2020, the export values were 6850302 while imports were 4757346. The forecasts show that the values will remain generally between 4000000 and 8000000 during the forecasting period while imports will be generally between 3500000 and 5000000. According to OECD (2020: 303), the "COVID-19 outbreak adds to South Africa‟s already severe economic challenges, with depressed growth, large fiscal deficits, increasing debt and high social vulnerabilities." Moreover, strict measures to contain the spread of the coronavirus affected production in major sectors and led to a slump in demand. The domestic demand shock may persist for several months, which may also explain why imports forecast might remain lower than exports.

Holding other factors constant, this prediction shows that the country is likely to experience a positive balance of trade (BOT) position in the coming months. While this may be fascinating from the perspective of BOT, the forecasts indicate that between August 2020 and July 2022 the exports will drop by 34 percent. In the same period, imports will drop by approximately nine percent. The exports from the rest of the world will be fluctuating with notable drops likely to occur in January 2021, December 2021 and July 2022. A fall in export values during these months is evidence for seasonal patterns in exports that are demonstrated in Figure A1 in Appendix A. Major drops in imports are likely to happen in June 2021 and December 2021. Seasonal patterns play a role in these drops. However, fluctuations in exports and imports are likely to emerge from other factors such as the domestic demand shock, world demand shock, commodity-specific shocks and exchange rate volatility. These are future risks exporters and importers should expect.

Figure C1b provides extra information concerning the expected changes in exports and imports compared to the previous periods. The past performance is represented by the yearly averages of exports in the periods August 2018 to July 2019 (5041370 - period 1) and August 2019 to July 2020 (5943896 - period 2). The yearly averages for the export forecasts will be 7502130 and 6355377 in the periods August 2020 to July 2021 (period 3) and August 2021 to July 2022 (period 4), respectively. Thus, exports from the rest of the world increased by 18 percent in period 2 from the preceding period August 2018 to July 2019. The forecasts show that in a year, the yearly average will rise by 26 percent in period 3 but becomes negative (-15%) in period 4. In these four periods, the imports increased by approximately five percent in the second period and predicted to drop by 16 percent in the third period, and another drop (6%) in the fourth period. Subsequently, the yearly average of exports is expected to increase first and then drop, whereas the yearly average of imports continuously decreases.

Figures C1c and C1d decompose the yearly average exports and imports by regional destination and origin (Africa, America, Europe, Asia and Australia) in the four periods: August 2018 to July 2019 (period 1), August 2019 to July 2020 (period 2), August 2020 to July 2021 (period 3), and August 2021 to July 2022 (period 4). Across all periods, most exports have been to Asia, followed by Europe and Africa while America and Australia are the least destinations. China has been the top trading partner of South Africa and it has a major influence on Asia being a major export destination of South Africa. From period 1 to period 2, there was an increase in exports to all regions. ARIMA models forecast that the yearly averages of exports to Africa, Europe and Asia will continue to rise in periods 3 and 4. However, the yearly averages of exports to America and Asia are likely to decline in the fourth period. Figure C1d shows that yearly average imports from America, Europe and Asia increased between period 1 and period 2 while in the same periods the imports from Africa and Asia decreased. In period 3, the forecasts indicate that the yearly average imports from Africa, America, Europe and Asia will be lower than what was reported in period 2. The yearly average of imports from Australia in period 3 will be slightly higher than what was recorded in period 2. Except for Australia, the yearly average imports from the rest of the regions in period 4 will be less than period 2.

The export and import forecasts for the period from August 2020 to July 2022, which are used in Figure C1, are based on ARIMA‟s point forecasts. These values are presented differently in Figure C2 to show the forecasts for each of the 24 months. For the exports, the order of the regions from the one with the highest value is as follows: Asia, Europe, Africa, America and Australia (Figure C2a), which is the same order portrayed in Figure 2 based on past data. In terms of imports, the order of the regions from the one with the highest value is as follows: Asia, Europe, America, Africa and Australia (Figure C2b), which is also the same order illustrated in Figure 3 based on historical data. The forecasts indicate that South Africa will export more to Africa than America but will import more from America than Africa; the highest value of exports and imports are for Asia, which is followed by Europe. The least trade values are between South Africa and Australia, which also has to do with the size of Australia compared to other regions/ continents.

Besides the point forecasts that are discussed above, in practice, the actual future values are likely to be lower or higher than the point forecasts. Accordingly, the ARIMA models also present forecasts intervals (80% FI and 95% FI). The intervals illustrate how high and how low trade values might become. Figures C3 to C5 in Appendix C presents the detailed forecasts that show the high(hi) and low(lo) forecast intervals (lo80 - hi80; lo95 - hi95) within which the actual values might fall. For the 24 forecasted months, each month has two upper limits and two lower limits. The 80 percent

FI that is close to the point forecasts shows that there are is an 80percent chance that the actual values will be within this narrow interval. The 90 percent FI that is far from the point forecast shows that there is a 95 percent chance that the actual values will be within this wider interval.

To reasonably discuss the forecasts across all regions, this study also uses the key results from the validation models. Validation window one and two suggest that the actual trade values are most likely to fall within the 80 percent FI (Figures 4 and 5). At this stage, it could be reasonable to expect South African export and import values (at constant prices) from August 2020 to July 2022 to be found mostly within the lo80 and hi80 interval. As the forecasted period increase, the distance between the point forecast and the intervals becomes wider to accommodate increased potential forecasting error.

The recent global crisis of the COVID-19 pandemic may present different sets of risks with different implications of the forecasting power of ARIMA models. Therefore, the third validation of the ARIMA model, by forecasting the last 25 months (July 2018 to July 2020) of the full sample, provides useful insights. The last months of this forecasting period cover significant changes in international trade values due to the pandemic and the associated lockdowns that occurred. There are significant spikes in actual exports that occurred in April 2020 (drop) and June 2020 (pick), and for imports in March 2020 (drop) and May 2020 (pick) (Figures 2 and 3). The significant drops followed lockdowns initiated in many countries. South Africa"s trade values in March 2020 reveal that COVID-19 containment measures taken by the country"s global partners mainly affected the imports of the country (Viljoen, 2020). Given that the trade values used in this study were adjusted for inflation, a drop in CPI from 3 to 2.2 between March 2020 and June 2020 also shows an improvement in trade values during that period.

Thus, the 95 percent intervals of exports and imports for the various regions in Figures C3 to C5 (Appendix C) might be breached if another massive swing happens in the future trade. If a major global shock occurs, the forecast intervals that are likely to be breached are for exports to the rest of the world, Africa, America and Asia.

Further insight from Figure B1 is that the actual export values to the rest of the world, Africa and America are likely to lie above the point forecast and within the hi80 percent interval. But during a crisis and sharp changes in export values, the 95 percent forecast interval might be breached. This might happen to the forecast intervals in Figure C3a, C3b and C3c but the probability is very low. On the other hand, the actual exports to Europe are more likely to fall below the point forecast and within the lo80 percent interval for much of the forecasting period as revealed in Figure B1d. The actual export values to Asia and Australia are more likely to fluctuate around the point forecast and within the 80 percent interval (Figures E2a and E2b). Based on other ARIMA validation models (Figures E2c, E3a, E3b, and E3c), the actual values of imports from the rest of world, America, Europe and Asia are likely to appear above the point forecast and mostly within the hi80 intervals. In terms of Africa and Australia, the point forecast is more likely to over-value the imports from these two regions; the actual values are most likely to fall within the lo80 percent interval (Figures E2d and E3d).

What is likely to happen to the trends?

While Figures C3 to C5 clearly show the intervals, it is difficult to see from these figures per se whether the trends of trade values for the various regions are likely to decrease or increase in comparison with the last observed values in July 2020. The trends for the international trade values across many regions are presented in Appendix D, Figures D1 to D3. South African total exports to the rest of the world are expected to decrease between July 2020 and July 2022, with a notable decline likely to happen in December 2021 (Figures D1a and C3a). Exports to America are also expected to decrease continuously during the forecasting period (Figure D1c). Exports to Australia may also be declining during the forecasted period, with notable declines likely to occur in April 2021 and April 2022. On the other hand, our forecasts show that exports to Africa, Europe and Asia (Figures D1b, D1d and D2a) are likely to increase in the next 24 months. There has been a general increase in exports to these three regions since another substantial decline recorded in January 2016.

Figures D2c and D3c suggest that the future values of imports from the rest of the world and Asia are likely to decrease in the period between August 2020 and July 2022. Significant drops in imports from the world might materialise in June 2021, December 2021 and April 2022. As for Asia, a major drop is expected in June 2022. No significant changes might be expected in future imports from America, Europe and Australia (Figures D3a, D3b and D3d). Constrained domestic demand in South Africa could be one of the explanations for the expected drop or an insignificant change in import values. The months of national lockdowns depleted household savings and raised debts. As a result, it may take time for households and firms to become financially stable and increase demand for foreign products. However, imports from within the African continent might rise from August 2020 to July 2022, but at the level below the records of the previous calendar. As discussed earlier, it is important to bear in mind that the actual trends may lie above or below the point forecast trend but within the forecast intervals.

Diagnostics and accuracy of the models

This section presents the diagnostics of the estimated models. Table 2 shows the specification statistics for models used to forecast trade values from August 2020 to July 2022. Table 3 presents the diagnostics statistics for the validation models.

TABLE 2
ACCURACY OF THE FORECASTING MODELS AND DIAGNOSTICS

	World	Africa	America	Europe	Asia	Australia
Export models						
Model	ARIMA(1,1,26)	ARIMA(0,1,2)	ARIMA(1,1,24)	ARIMA(2,1,2)	ARIMA(2,1,0)	ARIMA(1,0,13)
MAPE	9,673	11,375	13,457	12,458	12,041	23,490
Accuracy	90%	89%	87%	88%	88%	77%
MAE	365409,700	93252,960	48474,570	117764,900	135873,700	10044,670
LBQ	5.977	18,228	7,003	19,599	13,149	9,870
(P-value)	(0.113)	(0,572)	(0,072)	(0,419)	(0,903)	(0,361)
Import models						
Model	ARIMA(1,1,36)	ARIMA(1,1,24)	ARIMA(2,1,0)	ARIMA(0,1,1)	ARIMA(1,1,25)	ARIMA(1,1,24)
MAPE	8,801	27,841	10,675	10,185	10,393	20,733
Accuracy	91%	72%	89%	90%	90%	79%
MAE	335633.200	77751,830	47481,720	123718,800	178122,300	10652,150
LBQ	7.598	4,488	16,284	18,000	5,347	5,269
(P-value)	(0.055)	(0,213)	(0,638)	(0,522)	(0,148)	(0,153)

Note: LBQ stands for Ljung-Box Q statistic.

This study starts by fitting the Auto-ARIMA model, which automatically select an appropriate model. Residuals of the selected models are checked for autocorrelation and normality. The Ljung-Box Q (LBQ) tests are used to check for autocorrelation. The LBQ statistics in Table 2 are not significant at the five percent level and hence the null hypothesis cannot be rejected, implying the absence of autocorrelation.

TABLE 3
FIT AND ACCURACY OF THE MODELS

Testing period	Jan 2008 to Dec 2009		Jan 2016 to Dec 2017	
	Exports	Imports	Exports	Imports
Model	ARIMA(2,1,0)	ARIMA(0,1,1)	ARIMA(1,1,20)	ARIMA(1,1,12)
MAPE	12,218	12,149	8,766	10,100
Accuracy	88%	88%	91%	90%
MAE	369504,400	408968,300	298110,600	383622,100
LBQ	6,813	3,602	7,677	6,503
(P-value)	(0,235)	(0,730)	(0,053)	(0,090)

Besides the LBQ statistics, during estimations, residuals of the Auto-ARIMA forecasting models were checked for significant spikes across lags. Spikes outside the horizontal dotted lines or 95 percent confidence intervals in ACF imply evidence of autocorrelation and hence an ARIMA model would be customised to account for the observed lags. This is the reason why other models have higher lags. Additionally, the distribution of the residuals was also checked for normality. Across all models, the residuals appeared to be normally distributed .

To assess the accuracy of the forecasts, this study reported the mean absolute percentage error (MAPE) and the mean absolute error (MAE) values of the estimated models. MAE is the average measure of how, in absolute terms, the forecast is from the actual value. MAPE is a measure of how far away in absolute percentage the forecast value is from the actual value. These two measures determine the prediction accuracy of a forecasting model or method. It is not clear to decide whether the size of MAE is reasonable since it depends on what is being measured, but MAPE can provide a better view. The accuracy of the forecasts is calculated by subtracting the MAPE value from 100. Our key forecasting models in Table 2 shows that the accuracy levels of the export and import forecasts are above 77 percent. The validation models in Table 3 show the accuracy levels above 88 percent. While the statistics for the other twelve models for validation window three are not displayed in Table 3 (for the sake of space) there was no autocorrelation; residuals show normality and the forecasts accuracy levels were above 88 percent, except for two models with 74 percent and 77 percent accuracy.

DISCUSSION

This is the first study to our knowledge to test the predictive power of ARIMA models to predict the impact of global crises on South Africa‟s trade, and to subsequently apply the model to predict the impact of COVID-19 on South Africa‟s trade. The results of the descriptive statistics showed South Africa‟s trade responsiveness to the GFC in the period 2008 to 2009, the economic growth shock in 2015-2016 period, and to the COVID-19 pandemic in 2020. In general, South Africa‟s trade contracted significantly in response to the COVID-19 pandemic compared to the GFC. The World Bank (2018:10) reported a drop in South African domestic output in the period 2008 to 2009 resulting from a combination of the global shocks, world demand shock, domestic shocks, and commodity-specific shocks. We believe that these factors apply to the country‟s trade following the effects of the COVID-19 pandemic.

An analysis of South Africa‟s trade with the five regions revealed similar patterns in the proportions of values of trade with Asia; accounting for the largest proportion of import and export, followed by Europe and Africa. The lowest value of trade was observed between South Africa and Australia. In terms of percentage changes in trade values between South Africa and the five regions, South Africa recorded the largest decrease in export values, and the respective periods of significant decline were as follows: Australia (April 2020), Europe (April 2020), Africa (April 2020), America (April 2020) and Asia (January 2016), in this order. This indicates that the major decline in exports to four out of five continents occurred in 2020 and are associated with the COVID-19 pandemic. This is reasonable given the lockdowns that happened not only in South Africa but also in several countries over the world. Exporters were not able to produce, and demand from other countries dropped as a result of the COVID-19 pandemic. This massive decline in exports exceeded what happened in 2008 to 2009 during the GFC. Another remarkable observation is that the largest percentage increase in exports during the period of study was to Australia (May 2020), followed by exports to America (June 2008), Africa (May 2020), Asia (May 2020) and then Europe (May 2020). Subsequently, South Africa‟s exports to America responded the most to the GFC, while exports to the other four regions responded mostly to the COVID-19 pandemic. This is not surprising given the GFC originated in America and was one of the most affected regions. A larger positive percentage change during these recessions shows how export values to a particular region moved from the lower values. As for imports, the largest percentage drop was for products from Africa (July 2020), followed by Australia (February 2009), Europe (December 2006), Asia (December 2006) and then America (January 2016). In terms of positive changes, the highest percentage increase in imports was from Africa (October 2007) and Australia (March 2010).

The predictive power of the ARIMA models was initially validated by assessing whether the model could make meaningful forecasts during the 2008-2009 GFC and during 2016. For both exports and imports, the ARIMA models correctly predicted that there was an 80 percent chance that the actual future values in the periods January 2008 to December 2009, and January 2016 to December 2017 may fall within the forecasting interval. Further validation of the ARIMA model was made to forecast trade between July 2018 and July 2020 (last 25 months of the dataset), the period associated with a massive swing in trade due to COVID-19. This validation shows that it is possible that the 95 percent FI could be breached, but the chances are thin. Overall, the results revealed that the predictive power of ARIMA models is good even in the presence of significant swings in the South African export and import values. However, policymakers should not rely on the point forecast, especially when the forecasts are based on a small sample size of historical data. Forecast intervals are very crucial due to the high probability of success.

Having tested the forecasting power of ARIMA models, the next step in the analysis was to forecast the future international trade values from August 2020 to July 2022. The forecasts show that exports for South Africa will be higher than imports during the entire forecasting period, following a rise in exports above imports in the last three months (May, June and July) of the sample. According to OECD (2020: 303), the "COVID-19 outbreak adds to South Africa‟s already severe economic challenges, with depressed growth, large fiscal deficits, increasing debt and high social vulnerabilities." Moreover, strict measures to contain the spread of the coronavirus affected production in major sectors and led to a slump in demand. The domestic demand shock may persist for several months, which may also explain why imports forecast might remain lower than exports. Additionally, the results show that seasonal patterns play a role in these drops. However, fluctuations in exports and imports are likely to emerge from other factors such as the domestic demand shock, world demand shock, commodity-specific shocks and exchange rate volatility. These are future risks exporters and importers should expect. The regional analysis of the destination of South African exports shows the major destinations Asia, Europe and Africa respectively while America and Australia are the least destinations. China has been the top trading partner of South Africa and it has a major influence on Asia being a major export destination of South Africa.

The ARIMA model forecasts show that the yearly averages of exports to Africa, Europe and Asia will continue to rise in periods August 2020 to July 2021 (period 3) and August 2021 to July 2022 (period 4). However, the yearly averages of exports to America and Asia are likely to decline in the fourth period. In contrast, except for Australia, the yearly average imports from Africa, America, Europe and Asia are expected to be lower than in August 2019 to July 2020 (period 2).

The main contribution of this study is that it provides forecasts on South Africa‟s trade post the COVID-19 pandemic. The primary role of forecasting is to provide support for future decisions (Elliott & Timmermann, 2016:82). In a pandemic context where there are information and resource constraints, data lean and agile forecasting approaches are preferable (Prideaux et al., 2003:477). Besides, among the strengths of this study is the use of time series data. Time series data captures the variation of macroeconomic situations with time. They are useful when relating temporal macroeconomic trends to the occurrence of significant events. The autoregressive integrative moving average (ARIMA) models are a powerful tool for analysing empirically observable patterns (Hochrainer, 2009:12). ARIMA models have been applied in diverse contexts for analysing the impact of macroeconomic disruptions such as natural disasters (Zhu et al., 2018), pandemics (Song et al., 2016) and market failures (Cui, 2011;Wang et al., 2018), yielding reasonably accurate results. Hence, assessing the applicability and performance of ARIMA models to forecasting COVID-19 macroeconomic impacts is of academic interest.

Derived from this analysis, among the key insights for policymaking, South Africa is high likely to report a positive trade balance (exports > imports). This will contribute to a favourable balance of payment (BOP) position and exchange rate during the forecasted period. However, the ultimate outlook of the South African trade values (at constant prices) will also depend on other factors such as the exports and imports of services and inflation. We believe that the poor domestic demand may explain the inferior imports against exports predicted between August 2020 and July 2022. While this may be good for the trade balance, poor domestic demand could also weaken the country‟s economic growth projections. The forecasts in this study may also be used by policymakers to anticipate tariff revenue from the different regions. It is also important for policymakers to advance bilateral trade agreements with Asian, European and African countries; the major export destinations. The African Continental Free Trade Area (AfCFTA) is a welcome strategy that may boost trade between South Africa and other African countries.

CONCLUSION

While there are differences in the nature and severity of pandemics, they have all been observed to contribute to economic decline. Information about the unfolding of the impact is usually scarce in the early phases of a pandemic. This poses a challenge for leaders to craft an appropriately timed response that balances the need to contain the pandemic and prevent irreparable economic damage. Since trade will play a significant role in mitigating both disease spread and economic decline, responses to the crisis need to factor the impact of the pandemic on the nation‟s trade. This study demonstrates that the COVID-19 pandemic, like other supply chain disruptions of global proportion, will result in the contraction of South African trade. This calls for firms and the government to reinforce competencies in the domestic supply chains, and to strengthen trade agreements with trade partnerships in Africa, Asia and Europe to strengthen the adaptive power of firms and the economy in response to the pandemic. The results show that the impact worsens with time, which implies that the sooner the competency reinforcements are done, the better the economic outcomes. The study provides policymakers and business management a basis for the development of fact-based responses to the pandemic.

REFERENCES

Ahn, J., Amiti, M. & Weinstein, D. E. 2011. Trade finance and the great trade collapse. American Economic Review, 101, 298-302.

Alcantara-Ayala, I. 2002. Geomorphology, natural hazards, vulnerability and prevention of natural disasters in developing countries. Geomorphology, 47, 107-124.

Amador, J. & Cabral, S. 2017. Networks of value-added trade. The World Economy, 40, 1291-1313.

Ambulkar, S., Blackhurst, J. & Grawe, S. 2015. Firm's resilience to supply chain disruptions: Scale development and empirical examination. Journal of operations management, 33, 111-122.

Anderton, R. & Tewolde, T. 2011. The global financial crisis: Understanding the global trade downturn and recovery 1. The World Economy, 34, 741-763.

Araz, O. M., Choi, T.-M., Olson, D. & Salman, F. S. 2020. Data analytics for operational risk management. Decision Sciences. https://doi.org/10.1111/deci.12443.

Asteriou, D. 2006. Applied Econometrics: A Modern Approach using Eviews and Microfit. United States of America, New York: Palgrave Macmillan.

Baldwin, R. & Lopez-Gonzalez, J. 2015. Supply chain Trade: A Portrait of Global Patterns and Several Testable Hypotheses (Working Paper No. 18957). National Bureau of Economic Research (NBER). doi, 10, w18957.

Begen, M. A., Pun, H. & Yan, X. 2016. Supply and demand uncertainty reduction efforts and cost comparison. International Journal of Production Economics, 180, 125-134.

Bhaskar, R. R. & Gopalan, Y. K. 2009. The financial crisis in S, M and L: three very different countries respond similarly. The Regional Economist, 2.

Blanchard, E. J., Bown, C. P. & Johnson, R. C. 2016. Global supply chains and trade policy, The World Bank.

Box, G, E, P. & Jenkins, G, M. 1976. Time Series Analysis: Forecasting and Control. Revised edition. San Francisco: Holden-Day.

Brahmbhatt, M. & Dutta, A. 2008. Economic Effects during Outbreaks of Infectious Disease. World Bank Research Digest, 2, 7.

Brooks, C. 2008. Introductory Econometrics for Finance. Second Edition. United States of America, New York: Cambridge University Press.

Buyuktahtakin, i. E., Des-Bordes, E. & Kibi§, E. Y 2018. A new epidemic-logistics model: Insights into controlling the Ebola virus disease in West Africa. European Journal of Operational Research, 265, 1046-1063.

Calnan, M., Gadsby, E. W., Konde, M. K., Diallo, A. & Rossman, J. S. 2018. The response to and impact of the Ebola epidemic: towards an agenda for interdisciplinary research. International journal of health policy and management, 7, 402.

Cantwell, J. 2017. Innovation and international business. Industry and Innovation, 24, 41-60.

Chou, J., Kuo, N.-F. & Peng, S.-L. 2004. Potential impacts of the SARS outbreak on Taiwan's economy. Asian Economic Papers, 3, 84-99.

Coelho, M. T. P., Rodrigues, J. F. M., Medina, A. M., Scalco, P., Terribile, L. C., Vilela, B., Diniz-Filho, J. a. F. & Dobrovolski, R. 2020. Global expansion of COVID-19pandemic is driven by population size and airport connections. PeerJ, 8, e9708.

Contractor, F. J., Kumar, V. & Dhanaraj, C. 2015. Leveraging India: Global interconnectedness and locational competitive advantage. Management International Review, 55, 159-179.

Cui, F. 2011. ARIMA models for bank failures: Prediction and comparison.

Dickey, D. A. & Fuller, W. A. 1979. 'Distribution of the estimators for autoregressive time series with a unit root', Journal of the American statistical association, 74(366a): 427-431.

Dickey, D. A., & Fuller, W. A. 1981. 'Likelihood ratio statistics for autoregressive time series with a unit root', Econometrica: Journal of the Econometric Society, 49(4): 1057-1072.

Elliott, G. & Timmermann, A. 2016. Forecasting in economics and finance. Annual Review of Economics, 8, 81-110.

Epstein, J. M. 2009. Modelling to contain pandemics. Nature, 460, 687-687.

Farooqi, A. 2014. 'ARIMA model building and forecasting on Imports and Exports of Pakistan', Pakistan Journal of Statistics and Operation Research,10(2): 157-168.

Fauver, J. R., Petrone, M. E., Hodcroft, E. B., Shioda, K., Ehrlich, H. Y., Watts, A. G., Vogels, C. B., Brito, A. F., Alpert, T. & Muyombwe, A. 2020. Coast-to-coast spread of SARS-CoV-2 during the early epidemic in the United States. Cell.

Gereffi, G. & Lee, J. 2012. Why the world suddenly cares about global supply chains. Journal of supply chain management, 48, 24-32.

Grosfeld-Nir, A. & Gerchak, Y. 2004. Multiple lotsizing in production to order with random yields: Review of recent advances. Annals of Operations Research, 126, 43-69.

Guha, B. & Bandyopadhyay, G. 2016. 'Gold Price Forecasting Using ARIMA Model', Journal of Advanced Management Science, 4(2), 117-121.

Guha, S. 2020. India in the pandemic age. Indian Economic Review, 1-18.

Hale, G., Kapan, T. & Minoiu, C. 2016.Crisis transmission through the global banking network. Federal Reserve Bank of San Francisco.

Han, P., Wang, P. X., Zhang, S, Y. & Zhu, D, H. 2010. 'Drought forecasting based on the remote sensing data using ARIMA models', Mathematical and Computer Modelling, 51: 1398-1403.

Hochrainer, S. 2009. Assessing the macroeconomic impacts of natural disasters: are there any?, The World Bank.

Hosseini, S., Ivanov, D. & Dolgui, A. 2019. Review of quantitative methods for supply chain resilience analysis. Transportation Research Part E: Logistics and Transportation Review, 125, 285-307.

IDE-JETRO & WTO 2011. Trade patterns and global value chains in East Asia: from trade in goods to trade in tasks. World Trade Organisation, Geneva, Switzerland-2011.

Ivanov, D. 2020. Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. Transportation Research Part E: Logistics and Transportation Review, 136, 101922.

Jenkins, R. 2018. Globalisation, trade liberalisation and industrial pollution in Latin America. Industry and Environment in Latin America. Routledge.

Kalaitzi, A. S. 2018. The causal effects of trade and technology transfer on human capital and economic growth in the United Arab Emirates. Sustainability, 10, 1535.

Kassa, W. 2020. COVID-19and Trade in SSA: Impacts and Policy Response. World Bank.

Kerivin, H. & Mahjoub, A. R. 2005. Design of survivable networks: A survey. Networks: An International Journal, 46, 1-21.

Khatiwada, S. 2009. Stimulus packages to counter global economic crisis: a review.

Kleinman, A. & Watson, J. L. 2006. SARS in China: prelude to pandemic?, Stanford University Press.

Lamy, P. 2010.Facts and fictions in international trade economics. Speech made at the Conference of trade and inclusive globalization, Paris School of Economics. Paris. April, 2010.

Lavenbach, H. 2017. Why Use ARIMA Models for Demand Forecasting? Delphus, Inc. United States.

Lee, D. 2019. Transmission of domestic and external shocks through input-output network: Evidence from Korean industries, International Monetary Fund.

Luh, D.-L., Liu, C.-C., Luo, Y.-R. & Chen, S.-C. 2018. Economic cost and burden of dengue during epidemics and nonepidemic years in Taiwan. Journal of Infection and Public Health, 11, 215-223.

Mackey, T. K. & Liang, B. A. 2012. Lessons from SARS and H1N1/A: employing a WHO-WTO forum to promote optimal economic-public health pandemic response. Journal of public health policy, 33, 119-130.

Maines, T. R., Jayaraman, A., Belser, J. A., Wadford, D. A., Pappas, C., Zeng, H., Gustin, K. M., Pearce, M. B., Viswanathan, K. & Shriver, Z. H. 2009. Transmission and pathogenesis of swine-origin 2009 A (H1N1) influenza viruses in ferrets and mice. Science, 325, 484-487.

Makin, A. J. 2019. Lessons for macroeconomic policy from the Global Financial Crisis. Economic Analysis and Policy, 64, 13-25.

Mckibbin, W. & Fernando, R. 2020. The economic impact of COVID-19. Economics in the Time of COVID-19, 45.

Mckibbin, W. J. & Sidorenko, A. 2006. Global macroeconomic consequences of pandemic influenza, Lowy Institute for International Policy Sydney, Australia.

Miroudot, S. & Ragoussis, A. 2009. Vertical trade, trade costs and FDI.

Morrison, W. M. 2009. China and the global financial crisis: Implications for the United States.. Library of Congress Washington DC Congressional Research Service.

Ngan, T. M. U. 2016. Forecasting Foreign Exchange Rate by using ARIMA Model: A Case of VND/USD Exchange Rate. Research Journal of Finance and Accounting, 7(12), 38-44.

Noy, I. & Shields, S. 2019. The 2003 Severe Acute Respiratory Syndrome Epidemic: A Retroactive Examination of Economic Costs. Asian Development Bank Economics Working Paper Series.

OECD. 2020. OECD Economic Outlook Volume 2020 issue 1. https://www.oecd-ilibrary.org/sites/87f64769en/index.html?itemId=/content/component/87f64769-en Date of access: 14 Sep 2020.

Petersen, E., Koopmans, M., Go, U., Hamer, D. H., Petrosillo, N., Castelli, F., Storgaard, M., Al Khalili, S. & Simonsen, L. 2020. Comparing SARS-CoV-2 with SARS-CoV and influenza pandemics. The Lancet infectious diseases.

Prideaux, B., Laws, E. & Faulkner, B. 2003. Events in Indonesia: exploring the limits to formal tourism trends forecasting methods in complex crisis situations. Tourism management, 24, 475-487.

Quarantelli, E. L. 1988. Disaster crisis management: A summary of research findings. Journal of management studies, 25, 373-385.

Scheibe, K. P. & Blackhurst, J. 2018. Supply chain disruption propagation: a systemic risk and normal accident theory perspective. International Journal of Production Research, 56, 43-59.

Siddiqui, K. 2017. Globalisation, trade liberalisation and economic development in the developing countries: An overview. Journal of Economics Library, 4, 514-529.

Snyder, L. V. & Daskin, M. S. 2005. Reliability models for facility location: the expected failure cost case. Transportation Science, 39, 400-416.

Snyder, L. V., Atan, Z., Peng, P., Rong, Y., Schmitt, A. J. & Sinsoysal, B. 2016. OR/MS models for supply chain disruptions: A review. Iie Transactions, 48, 89-109.

Song, X., Xiao, J., Deng, J., Kang, Q., Zhang, Y. & Xu, J. 2016. Time series analysis of influenza incidence in Chinese provinces from 2004 to 2011. Medicine, 95.

Stock, J, H. & Watson, M, W. 2015. Introduction to Econometrics. Third edition. United States, Pearson.

Strekalova, Y. A. 2017. Health risk information engagement and amplification on social media: News about an emerging pandemic on Facebook. Health Education & Behavior, 44, 332-339.

Tang, C. S. 2006. Perspectives in supply chain risk management. International journal of production economics, 103, 451-488.

Tindale, L., Coombe, M., Stockdale, J. E., Garlock, E., Lau, W. Y. V., Saraswat, M., Lee, Y.-H. B., Zhang, L., Chen, D. & Wallinga, J. 2020. Transmission interval estimates suggest pre-symptomatic spread of COVID-19. MedRxiv.

Trademap 2019. International Trade Statistics. https://www.trademap.org/Index.aspx? Date of access 5 Sep 2020.

Vandenbussche, H., Connell Garcia, W. & Simons, W. 2019. Global value chains, trade shocks and jobs: an application to Brexit.

Viljoen, W. 2020. South Africa's April 2020 trade statistics - reduced exports lead to a significant trade deficit. https://www.tralac.org/blog/article/14662-south-africa-s-april-2020-trade-statistics-reduced-exports-lead-to-a-significant- trade-deficit.html Date of access 5 Sep 2020.

Wang, D., Wang, Y., Song, X. & Liu, Y. 2018. Coal overcapacity in China: Multiscale analysis and prediction. Energy Economics, 70, 244-257.

Wankmuller, C. 2020. European disaster management in response to the COVID-19pandemic. Mind & Society.

World Bank. 2018. South Africa Economic Update: Jobs and Inequality, Edition 11, http://pubdocs.worldbank.org/en/798731523331698204/South-Africa-Economic-Update-April-2018.pdf Date of access: 15 Sep 2020.

Yang, Y., Peng, F., Wang, R., Guan, K., Jiang, T., Xu, G., Sun, J. & Chang, C. 2020. The deadly coronaviruses: The 2003 SARS pandemic and the 2020 novel coronavirus epidemic in China. Journal of autoimmunity, 102434.

Yi, K. 2009. The collapse of global trade: the role of vertical specialisation in http://www. voxeu. org/reports. Murky_ Protectionism. pdf.

Zhu, Y., Wang, Y., Liu, T. & Sui, Q. 2018. Assessing macroeconomic recovery after a natural hazard based on ARIMA—a case study of the 2008 Wenchuan earthquake in China. Natural Hazards, 91, 1025-1038.

Zipkin, H. 2000. Foundations of Inventory Systems. Mc Graw Hill, New York.

APPENDIX

Due to many figures in the Appendix, these figures are not included in this journal article but can be requested from any of the authors at any time.