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A comparative time series analysis of crude mortality rate in the BRICS countries

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Abstract
Proper research and analysis of mortality dynamics is essential to provide reliable economic information about any country. This paper deals with the historical comparative time series analysis of the mortality rate dynamics in the BRICS countries to determine their economic performances over the years. This article presents stochastic models based on autoregressive integrated moving average (ARIMA (p, d, q)) models of various orders with a view to identifying the optimal and comparative model for the crude death rate (CDR) in the BRICS countries. The ARIMA (p, d, q) models were formulated for the crude death rates in the BRICS countries and the overall annual crude death rate for the period 1960–2018. The optimal choice of ARIMA models of order p and q was selected for each of the series. The results indicate that the ARIMA (2, 2, 0) model was the optimal model for predicting mortality dynamics in the overall BRICS data. In addition, there was a significant decrease in trends (p-value $< 2.22e-16$) during the study period from 1960 to 2018. In addition, the crude death rate's data for the BRICS countries proved to be mostly non-linear, non-seasonal and without structural breaks. Finally, the findings of this study were discussed and recognized as having relevant policy implications for forecasting, insurance planning, as well as for disaster or risk reduction in the context of unprecedented global happenings in the post-pandemic era.

Keywords: crude death rate, decreasing trend, ARIMA, structural breaks, seasonality, nonlinearity.

JEL: C5, C55, C58.

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Introduction

Apart from other important and crucial economic indicators, the mortality rate of a nation is one of the most important determinants of its relative level of economic and medical well-being. Over the past few decades, the governments of the BRICS countries have worked tirelessly to improve the quality of modern health care facilities and services available to their populations as well as reduce childhood and other forms of mortality (Snow et al., 2001). The crude death rate of a nation is generally perceived as a picture of the general health status of its populace. In 2001, the acronym BRIC was coined to represent the fast-growing economies of Brazil, the Russian Federation, India, and China, and in 2010, the acronym evolved into BRICS with the addition of South Africa. Over the last two decades, all these five BRICS countries have expanded in terms of their economic relevance and influence, as well as their citizens' health thanks to their domestic health programs and foreign assistance. Collectively, these five countries account for over 40% of the world population and a significant part of the global burden of disease (World Health Organization, 2017).

In the light of the growing role of BRICS on the global health arena, we wish to investigate in this article the historical progress in the field of health achieved by each of the five countries between 1960 and 2018, through their crude death rates. In this paper, we focus on changes and trends observed in mortality in these countries over the years. Studies have shown that hypertensive diseases, pregnancy-related causes (health challenges), malnutrition, accidents, and injuries are the main causes of death among adults in these nations. For instance, in 2012, South Africa had more people infected with the human immunodeficiency virus (HIV) – 6.1 million – than any other country in Africa, whereas in many other African countries, measles and malaria are considered the most common causes of child and infant mortality (Gething et al., 2016).

According to the WHO report (WHO, 2020), the top 10 causes of death account for 55% of the 55.4 million deaths worldwide. Causes of death were grouped into three categories: communicable (infectious and parasitic diseases and maternal, perinatal and nutritional conditions), non-communicable (chronic), and injuries. Essentially, the main global causes of death, in order of the total number of lives lost, were further categorized into three broad areas: cardiovascular (ischemic heart disease, stroke), respiratory (chronic obstructive pulmonary disease, lower respiratory infections), and neonatal diseases, which include birth asphyxia, birth trauma, preterm birth complications, and other neonatal infections.

In addition, according to the ILO (2018), although the BRICS countries[1] rose rapidly as fast-growing economies, there has been significant slow growth in the last decade. The average growth rates in China and India ranged from 7 to 8%. In Brazil, Russia and South Africa, this figure averaged from 1 to 2%. Brazil recorded a huge variable performance, with the annual growth rate falling from 7.5% in 2010 to –3.6% in 2015.

[1] They represent about 42% of the world's population, cover 30% of the land area, and account for 23% of world GDP and 18% of global trade.

Specifically, China grew by 6.1% in 2019, followed by India with a 4.2% annual growth rate, Russia with 1.3%, and Brazil and South Africa with growth rates of 1.1% and 0.2%, respectively.

Although many past studies have shown that mortality rates (especially infant and child mortality) have been steadily declining in most of the BRICS countries over the years, there is still an uneven decline in these nations due to various environmental factors (Heft-Neal et al., 2018). Some countries are definitely performing better than others (Gayawan et al., 2021). Hence, there is a need to analyze econometric trends in each country in order to easily identify the change points, so that international organizations and policy makers can take necessary spotlight actions. Moreover, the study of mortality rate dynamics has a wide range of practical applications. For instance, governments rely on forecasts made on the basis of such studies to engineer social security systems and demographic policies, while insurance companies rely on such studies in the pension and life assurance segment of the market to quantify the cost and risk associated with contingent liabilities (Sijbrands et al., 2009; Li et al., 2017; Rabbi & Mazzuco, 2018; Kulinskaya et al., 2021).

Time series analysis of trends was used to measure the reasons why suicide rates rose among young men and fell among older men in England and Wales from 1950 to 1998 (Gunnell et al., 2003). Rabbi and Mazzuco (2018) used seven variants of the Lee-Car extrapolation method along with the Bayesian Hierarchical model to produce a coherent probabilistic forecast of mortality in nine Central and Eastern European countries. In the same vein, Kulinskaya et al. (2021) incorporated a landmark analysis of electronic health records of 110,243 subjects in the the United Kingdom who reached the age of 60 between 1990 and 2000 in combination with baseline hazards described by the Gompertz survival distribution. The model was used to dynamically predict the probability of survival and life expectancy. In addition, public health expenditure plays a crucial role in providing better health care to people in the BRICS countries (Arun & Kumar 2016). To analyze the time dependent pattern of stationary and non-stationary time series, (Makinde and Fasoranbaku, 2011) suggested to use Box-Jenkins models (Box & Jenkins, 1976), but in terms of ARIMA model selection, Awe et al. (2020) proposed an alternative algorithm based on the principles of Cartesian products of sets in mathematics that was practically applied to Nigeria's stock price data. As a result of the analysis, the selection of ARIMA model (2, 1, 1) was chosen based on the minimum AIC order.

In this study, we conduct a comparative trend analysis of the recent historical crude death rates in the BRICS countries (Brazil, Russia, India, China, and South Africa). The methods adopted in this study would be useful for comparing economic indicators and activities of governments in the BRICS countries. The results of this study are useful for an international audience, donors, as well as policy makers.

Following this non-exhaustive introductory section, the rest of this paper is structured as follows: Section 2 presents contextual methods for analyzing time series data and methodologies considered in this study; Section 3 presents an empirical analysis and results; Section 4 is devoted to discussing the results; and Section 5 concludes the article.

2. Methodology

2.1. Data

The data used in this study are annual Crude Death Rate per 1000 adults (CDR) data from 1960–2018 obtained from the database of the World Bank's World Development Indicators, 2018. Countries involved in this study are the BRICS countries (Brazil, Russia, India, China, and South Africa).

2.2. ARIMA model

The ARIMA methodology of Box & Jenkins was adopted in this study with a view to identifying an optimal stochastic model for forecasting CDR in the BRICS countries.

The ARIMA (p, d, q) model on the time series Y_t is defined as:

$$\Delta^d Y_t = \varnothing_1 \Delta^d Y_{t-1} + \varnothing_2 \Delta^d Y_{t-2} + \ldots + \varnothing_p \Delta^d Y_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \ldots + \theta_q \epsilon_{t-q}, \quad (1)$$

where p, d and q are the orders of autoregressive, integrated and moving average parts, respectively; ϵ_t is the residual of the estimated Y_t, which is assumed uncorrelated; Δ is the backward shift operator; $\varnothing_1$, $\varnothing_2,\ldots,\varnothing_q$ are the parameters of the autoregressive part of the model; $\theta_1,\theta_2,\ldots,\theta_q$ are the parameters of the moving average part of the model. The choice of optimal values of p and q is based on the ARIMA (p, d, q) model with the least Akaike information criterion and the root mean square of error. The parameters of the ARIMA model are estimated by minimizing the sum of the squares ϵ_t using the maximum likelihood estimation.

2.3. Stationarity tests

It is vital to check whether the CDR data from the BRICS countries are stationary. To check the stationarity of the data, we used Augmented Dickey-Fuller (ADF) test. The ADF test is a statistical test for finding out whether a time series contains a unit root. The null hypothesis for the ADF test is that a time series has a unit root (that is, a time series is not stationary). The choice of the value of d depends on the number of times a non-stationary time series must be differenced to attain stationarity.

2.4. Model adequacy test

The adequacy of the ARIMA model implies that any group of autocorrelations of a time series is different from zero. The test investigates the overall randomness based on a number of lags. The Ljung-Box (Ljung & Box, 1978) test is employed in this paper to test the adequacy of the optimal ARIMA model. The Ljung-Box statistics are defined as:

$$Q(\hat{r}) = n(n+2)\sum_{k=1}^{h} \frac{\hat{h}_k}{n-k}, \quad (2)$$

where $\hat{r}$ is autocorrelation based on a sample at lag k; h is the number of tested lags; and n is the sample size.

3. Empirical analyses and results

A cursory examination of the correlograms, which provides a summary of the CDR correlation in different periods, is shown in Figure 1. It can be seen that all countries experienced a gradual decline in mortality, with the exception of China which declined faster. In earlier years, values close to positive indicate a high CDR or clustering, while a trend towards negative implies a decrease in CDR or dispersion. Figure 1 shows a downward trend, suggesting the presence of autocorrelation. Technically, autocorrelation measures the influence of CDR's past on its future. Persistence of autocorrelation, which is an indication of non-stationarity, can reduce the degrees of freedom in time series modelling. Thus, this is the reason for conducting a stationarity test.

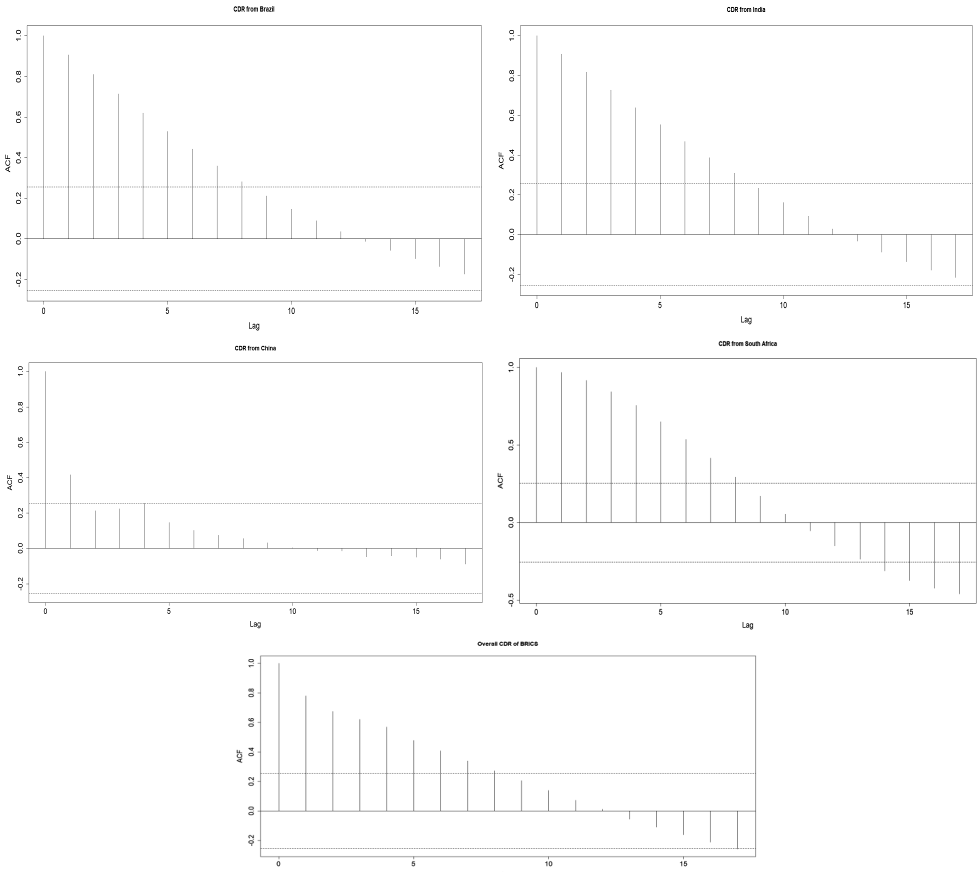

Figure 1. Correlograms of autocorrelation functions at some lags for CDRs from each of the BRICS countries and overall CDR

In Figure 2, we present the crude death rates per 1,000 live births in the BRICS countries between 1960 and 2018. A downward trend was observed in the mortality rate in all the countries. However, the decline in China is happening faster than in other countries. Similarly, there are fluctuations in South Africa, but they are higher in the Russian Federation, where the spikes are larger. The Russian Federation appears to have a lower CDR in earlier years, rising above all other members of BRICS in subsequent years.

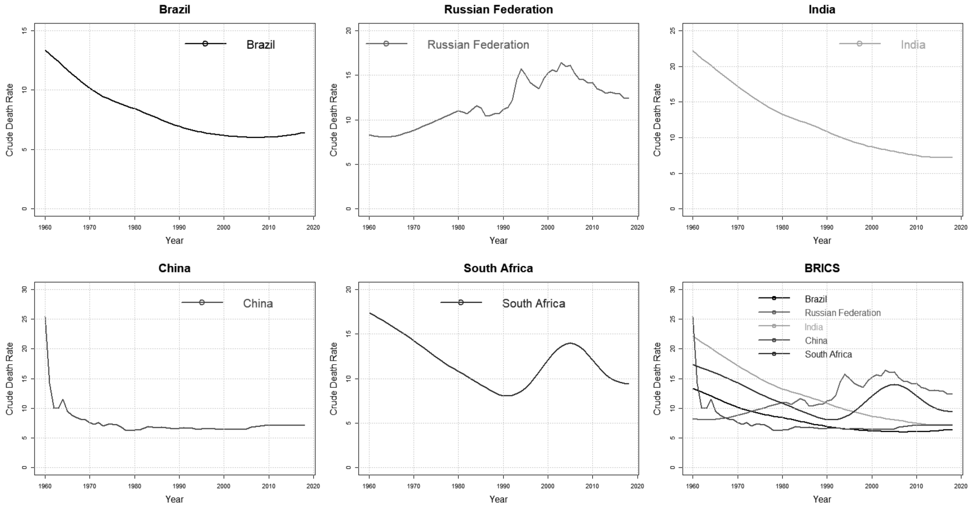

Figure 2. Trends of crude death rates per 1,000 live births in the BRICS countries (1960–2018)

In Table 1, we present a stationarity test using the Augmented Dickey-Fuller test. The CDR data were non-stationary in levels, thus suggesting the trending nature of the dataset for all countries except China, with a *p-value* that is significant at 5%. Since only China remains stationary at levels I (0), we proceeded with the first difference of the dataset.

Table 1. Augmented Dickey-Fuller test of non-stationarity for the CDR of the BRICS countries

	Brazil	**Russia**	**India**	**China**	**South Africa**	***Overall***
ADF statistic	–1.3313	–0.8086	–2.8288	–8.0286	–2.7965	–2.6097
p-value	0.8449	0.9557	0.2399	0.0100	0.2530	0.3285

Source: authors' calculations.

The result of the ADF test after differencing is presented in Table 2. Individual countries and overall results show that the variables are equal to I (1). In other words, the variables were stationary after differencing which suggests that the variables can be used for long-term prediction.

Table 2. Augmented Dickey-Fuller test of stationarity for the CDR of the BRICS countries, including the overall estimates after differencing

	Brazil	Russia	India	China	South Africa	*Overall*
ADF Statistic	–4.7298	–3.8324	–5.3531	–8.0286	–4.2687	–7.6609
p-value	0.0100	0.02316	0.0100	0.0100	0.0100	0.0100

Source: authors' calculations.

The probability density functions of the crude mortality rate for the period under investigation are represented in Figure 3. It indicates a visualization of the distribution of data over a continuous period. The peaks on the density plot show where the concentration of mortality was during a time interval. They show that the series are mostly asymmetric, sloping to the right (except for Russia and South Africa) which are bi-modal in nature for the observed period. The positive skewness of the plots shows a reduction in death rate over time. China indicates a sharp and drastic fall in mortality rate after the initial spark in the early 1960s. There was a rapid decrease in the death rate in the countries of inquiry, though in Russia and South Africa this figure is lower.

By country, this peak is 10 for Russia, India, and South Africa. However, mortality peaked earlier for Brazil and China. The total mortality rate in BRICS averages 50 with a bandwidth of 2.5. This suggests an earlier formulation and implementation of policies that have curtailed the crude death rate in BRICS, especially in China.

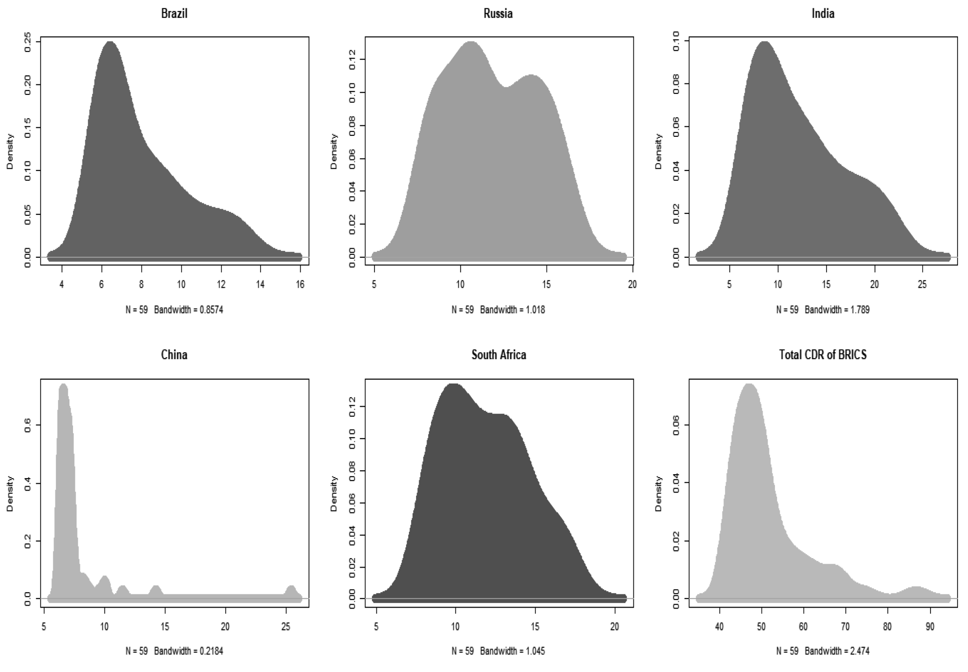

Figure 3. Density plots of the CDR in the BRICS countries (1960–2018)

In Figure 4, boxplots further support the density plots discussed previously. While the Russian Federation, India and South Africa have the same middle quartiles, Brazil and China have the same median, but different distribution. China's boxplot is comparatively short. This suggests that the overall crude death rate is lower in China than in other BRICS countries. The 25% CDR in China falls below the lower quartile. A corollary is India's boxplot that is relatively taller, which suggests a higher CDR in the country. Furthermore, a similar CDR is observed both in Russia and South Africa, which indicates similar patterns of mortality in both countries.

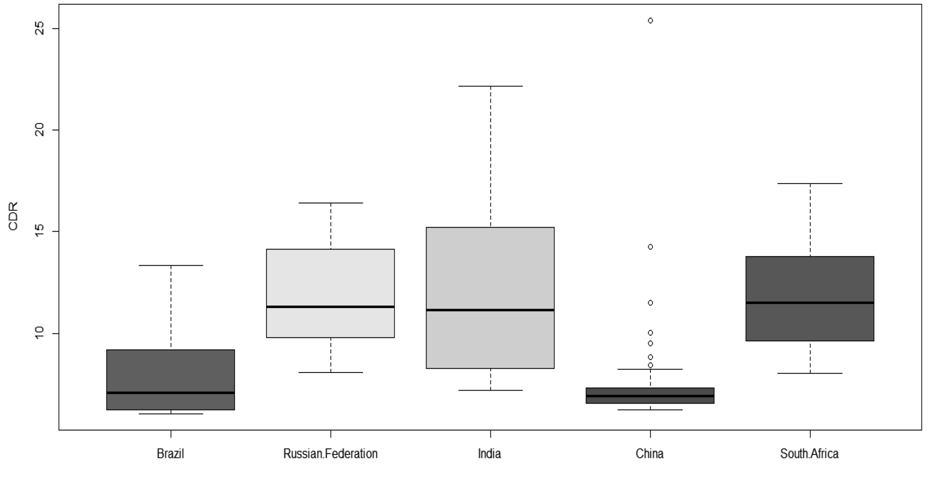

Figure 4. Boxplots of the CDR in the BRICS countries (1960–2018)

In addition, a number of tests were conducted to ascertain the nature, trend pattern and linearity of the CDR data for the BRICS countries. These include Keenan's one-degree test for nonlinearity, Ljung-Box test of adequacy for optimality and Mann-Kendall trend test.

In Table 3, we present the Keenan one-degree test for nonlinearity. The null hypothesis holds that the series are not linear, while the alternative hypothesis states that the series are linear. The result shows that at a 5% level of significance we reject the null hypothesis for Brazil, the Russian Federation, India and China since their *p-values* were less than 0.05. We conclude that the series is linear. However, South Africa and the overall CDR data have *p-values* which are more than 0.05, thus, we reject the null hypothesis and conclude that the series is non-linear. Therefore, in the light of the foregoing mixed results, this means that the mortality data for the BRICS countries is non-linear.

Table 3. Keenan one-degree test for nonlinearity for the CDR of the BRICS countries

	Brazil	**Russia**	**India**	**China**	**South Africa**	***Overall***
Keenan statistic	12.52450	4.22930	4.69610	11.43990	2.49830	3.1030
p-value	0.00085	0.04487	0.03512	0.00146	0.12097	0.0853

Source: authors' calculations.

The reports on the Ljung-Box test for robustness of ARIMA model are presented in Table 4. The Ljung-Box test results for the selected ARIMA models show that the Ljung-Box Q-statistic values correspond to *p-values* which are greater than alpha equals to 0.05 for each of the countries and overall. This indicates that the test is not significant and the residuals appear to be uncorrelated. This implies that for this model the CDR residual exhibits random white noise. Therefore, ARIMA models can be used to forecast CDR data, while applying a parsimonious ARIMA model for each country.

Table 4. Ljung-Box test for adequacy of optimal ARIMA models for the CDR of the BRICS countries

Component	Brazil	Russia	India	China	South Africa	*Overall*
Ljung-Box test	0.7924	0.1132	0.6199	0.5236	0.0301	0.1138
p-value	0.3734	0.7365	0.4311	0.4693	0.8603	0.7358

Source: authors' calculations.

The Mann-Kendall (MK) test of trend pattern is subjected to statistically vary if there is a significant upward or downward trend in the long term. The null hypothesis holds that there is no monotonic trend versus an uptrend or downtrend alternative over a period of time. The result presented in Table 5 shows that on the bases of the 5% significance level, the alternative hypothesis was not rejected. This indicates the presence of a trend in the data for individual countries and the bloc as a whole.

Table 5. Mann-Kendall test of trend pattern for the CDR of the BRICS countries, including the overall

Country	*p-values*
Brazil	*p-value* < 2.22e-16
Russia	*p-value* < 2.22e-16
India	*p-value* < 2.22e-16
China	*p-value* = 0.00046631
South Africa	*p-value* = 1.3277e-05
Overall	*p-value* = 4.7358e-13

Source: authors' calculations.

The distribution of the future values of country-specific crude mortality rates was predicted for ten years (2019–2028) using the *auto.arima* package in the R software (Awe et al., 2020). This package conducts an automatic ARIMA search for each data after differencing and selects the optimal model. The results[2] of the CDR forecast for the BRICS countries presented in Tables 6 to 10 indicate a marginal, but varied trend for the individual BRICS countries. The forecasts for Brazil with the parsimonious ARIMA model (3, 2, 2) suggest a continuation of the upward trend, although marginal. The crude mortality per 1,000 live births is expected to increase minimally for several years until 2028. This may be a result of a possible improvement in life expectancy at birth. These forecasts suggest slight changes in Brazil's future crude mortality rate (see Table 6).

[2] Both points and interval estimates from 2021 through to 2028.

Table 6. 10-year point and interval CDR forecasts for BRAZIL (ARIMA (3, 2, 2))

Year	Point forecast	LCL	UCL
2019	6.53	6.53	6.54
2020	6.62	6.59	6.64
2021	6.71	6.66	6.76
2022	6.81	6.72	6.89
2023	6.91	6.75	7.06
2024	7.01	6.77	7.25
2025	7.12	6.76	7.48
2026	7.22	6.72	7.72
2027	7.33	6.66	8.00
2028	7.44	6.57	8.31

Note: the interval forecast is given by the range between LCL and UCL, which represents the lower class limit and the upper class limit, respectively.

Source: authors' calculations.

The suitable ARIMA model for the Russia Federation is ARIMA (1, 1, 0). Interestingly, the forecast of the crude death rate for Russia, presented in Table 7, suggests a constant point forecast of 12.4 overtime until 2028, although with confidence intervals (LCL and UCL). The Russian Federation's policy on reducing mortality rate is likely to be effective if the current trend continues.

Table 7. 10-year point and interval CDR forecasts for RUSSIA (ARIMA (1, 1, 0))

Year	Point forecast	LCL	UCL
2019	12.4	11.44	13.36
2020	12.4	10.75	14.05
2021	12.4	10.19	14.61
2022	12.4	9.71	15.09
2023	12.4	9.29	15.51
2024	12.4	8.92	15.88
2025	12.4	8.59	15.88
2026	12.4	8.28	16.21
2027	12.4	7.99	16.81
2028	12.4	7.72	17.08

Note: the interval forecast is given by the range between LCL and UCL, which represents the lower-class limit and the upper-class limit, respectively.

Source: authors' calculations.

Furthermore, for India, ARIMA (3, 2, 0) provides the appropriate model for prediction purposes. The model predicts a steady, but slow fluctuation in the crude death rate averaging about 7.26. While the predicted values of the crude death rate will continue to move up and down during this period, the increase will not be substantial. All other things being equal, this may equate the rate of natural death (Table 8).

Table 8. 10-year point and interval CDR forecasts for INDIA (ARIMA (3, 2, 0))

Year	Point forecast	LCL	UCL
2019	7.26	7.25	7.27
2020	7.29	7.25	7.32
2021	7.31	7.22	7.39
2022	7.32	7.17	7.48
2023	7.33	7.10	7.59
2024	7.32	6.91	7.72
2025	7.29	6.71	7.88
2026	7.26	6.46	8.06
2027	7.21	6.15	8.27
2028	7.10	5.81	8.49

Note: the interval forecast is given by the range between LCL and UCL, which represents the lower class limit and the upper class limit, respectively.

Source: authors' calculations.

Finally, Tables 9 and 10 present the ARIMA (1, 2, 0) and ARIMA (2, 2, 0) of the CDR forecast for China and South Africa, respectively. For both countries, the crude mortality rate forecast is likely to decrease until 2028. The drop in CDR is higher in South Africa compared to China. While for the former country, CDR is expected to fall by 54.2% between 2019 and 2028, the CDR for the latter is expected to fall by 8.2% over the same period. In general, according to forecasts, China and South Africa will experience a larger fall in mortality rate compared to other BRICS members countries.

Table 9. 10-year point and interval CDR forecasts for CHINA (ARIMA (1, 2, 0))

Year	Point forecast	LCL	UCL
2019	7.10	4.90	9.24
2020	7.03	0.90	13.20
2021	6.98	4.89	18.86
2022	6.93	12.35	26.20
2023	6.87	21.29	35.04
2024	6.81	31.61	45.24
2025	6.75	43.17	56.67
2026	6.69	55.87	69.25
2027	6.63	69.62	82.87
2028	6.56	84.35	97.48

Note: the interval forecast is given by the range between LCL and UCL, which represents the lower class limit and the upper class limit, respectively.

Source: authors' calculations.

Table 10. 10-year point and interval CDR forecasts for South Africa (ARIMA (2, 2, 0))

Year	Point forecast	LCL	UCL
2019	9.38	9.36	9.39
2020	9.29	9.23	9.36
2021	9.16	9.00	9.33
2022	8.96	8.64	9.28
2023	8.67	8.11	9.24
2024	8.29	7.41	9.19
2025	7.84	6.54	9.14
2026	7.30	5.50	9.11
2027	6.71	4.32	9.09
2028	6.08	3.04	9.11

Note: the interval forecast is given by the range between LCL and UCL, which represents the lower class limit and the upper class limit, respectively.

Source: authors' calculations.

4. Discussion of results

Figure 1 presents the correlograms of autocorrelation functions at some lags for CDRs from each of Brazil, Russia, India, China and South Africa (BRICS) and overall CDR. It is shown, that all the mortality series are not stationary. A formal test based on the ADF test is employed to investigate if any of the series is stationary. The null hypothesis for this test states that the data series are not stationary, while the alternative hypothesis states that the series are stationary. A 5% level of significance was used for the test. Table 1 presents the results of the ADF test carried out for each of the CDR of Brazil, the Russian Federation, India, China, South Africa (BRICS), including the overall CDR. The result indicates that there was no sufficient reason to reject the null hypothesis, as the *p-value* seems to exceed the level of significance. This implies that the series are not stationary.

In addition, each correlogram shows that each series does not demonstrate long-range dependence. As a result, fractional integration of the data series to achieve stationarity may not produce an optimal model, as the autocorrelation functions experience a fast decay. The outcome of this is that recent methods, such as autoregressive fractionally integrated moving average (ARFIMA) and its seasonal version (SARFIMA), can produce sporadic results when applied to analyze the crude death rate on BRICS data. This is due to the fact that the use of ARFIMA and SARFIMA requires a long-range dependence series of data (Awe & Gil-Alana, 2019; Makinde et al., 2020).

These non–stationary time series data were differenced d times until the differenced series became stationary, where d is an integer. Table 2 shows the result obtained after the data for each of the CDR of the BRICS countries, including the overall, were differenced. The data for Brazil and the Russian Federation were differenced once (i.e., $d = 1$). The data for India and South Africa were differenced twice to attain stationarity (i.e., $d = 2$), China does not require any differencing to be stationary (i.e., $d = 0$), while the overall CDR data was differenced thrice (i.e., $d = 3$). The optimal model for each of the componential CDR data is obtained based on the choice of parameters p and q of the stationary data series that minimizes the Akaike information criteria (AIC) and Root mean square of error (RMSE).

Figure 2 presents the CDR trends for the BRICS countries from 1960 to 2018. There exists a downward CDR trend in Brazil, India and China. The Russian Federation experienced an upward trend in CDR from 1960 to 1998, but there was a sharp downward trend between 1998 and 1999, before it turned into an upward trend from 1999 to 2005, and after that — a downward trend from 2006 to 2018. South Africa has a sinusoidal trend over these years. There was a downward trend from 1960 to 1990, while from 1991 to 2005 there was an upward trend that changed into a downward trend from 2006 to 2018. The sixth chart in Figure 2 shows a combination of trends for all the BRICS countries that resulted in a downward trend by 2018.

It is apposite to test the non-linearity of the CDR series of all the BRICS countries. In lieu of this, Keenan's one-degree test for nonlinearity (Keenan, 1985) is employed to test the nonlinearity of the crude death rate data in BRICS. The null hypothesis for this test states that the CDR series are not linear, while the alternative hypothesis states that the series are linear. A 5% level of significance was used for the test. Table 3 shows the outcome which rejects the null hypothesis for Brazil, the Russian Federation, India and China (i.e., their *p-values* are less than 0.05 which is the level of significance). This indicates that the data is linear. For South Africa and the overall, CDR data fails to reject the null hypothesis because their *p-values* are greater than 0.05, which is the level of significance. This means the mortality is nonlinear. This may be related to the situation that occurred in South Africa when the country's political and economic space was opened after the end of the apartheid era (Adam & Moodley, 1993). This also affected the overall CDR data.

The Kruskall-Wallis test of seasonality (Kruskal & Wallis, 1952; Hyndman & Khandakar, 2008) was employed to test the seasonality of the crude death rate data for BRICS. The null hypothesis for this test states that the series is not seasonal, while the alternative hypothesis states that the CDR series is seasonal. A 5% level of significance was adopted for the test. The result of the test rejects the null hypothesis, which indicates that the data is seasonal at a 5% level of significance ($p\text{-}value < 2.2\mathrm{e}-16$). In addition, structural break tests help to determine whether there are significant changes in the CDR in BRICS and at what time the changes occur. The Chow test was employed to test if there are structural breaks in the overall CDR time series data. The null hypothesis for this test states that there are no structural breaks in the data, while the alternative hypothesis states that the series have structural breaks. A 5% level of significance was used for the test. The test result ($p\text{-}value = 0.500597$) does not have sufficient reasons to reject the null hypothesis that there are no structural breaks in the provided data and thereby concludes that there are structural breaks in the CDR of BRICS, including the overall CDR data.

To show whether the residuals of the optimal ARIMA model are correlated or not, the Ljung- Box test is employed. The null hypothesis for this test states that the residuals of the optimal ARIMA model are not correlated, while the alternative hypothesis states that the residuals of the optimal ARIMA model are correlated. A 5% level of significance was adopted for the test. Table 4 presents the result of the Ljung-Box test in terms of the test statistic and the *p-value* for each of the CDR of BRICS, including the overall CDR. Statistically, the result does not provide enough reason to reject the null hypothesis, since the *p-values* exceed the level of significance, which confirms that the residuals of the optimal ARIMA models for CDR from Brazil, Russian Federation, India, China, South Africa and the overall CDR do not correlate. Consequentially, the optimal time series models for the BRICS CDR data are ARIMA (3, 2, 2) model for Brazil, ARIMA (1, 1, 0) for Russia, ARIMA (3, 2, 0) for India, ARIMA (1, 2, 0) for China, and ARIMA (2, 2, 0) for South Africa. The optimal ARIMA model for the overall data is ARIMA (2, 2, 0).

The Mann-Kendall test was employed to determine whether the CDR of the BRICS countries and the overall CDR has a monotonic upward or downward trend. The null hypothesis for this test states that there is no trend, while the alternative hypothesis states that there is either an upward or downward trend. A 5% level of significance was adopted for the test. Table 5 presents the result of the test, and we reject the null hypothesis, since the *p-values* were less than the level of significance, which indicates that there is a downward trend of CDR for all the BRICS countries and overall for all the years under consideration.

Concluding remarks and policy implications

This paper presents ARIMA processes with different orders for the comparative econometric analysis of the CDR of the BRICS countries from 1960 to 2018 with the aim of discovering an optimal model from a class of models available. It was found that the CDR data for the BRICS countries were mostly linear, with the exception of South Africa and the overall CDR data, which is due to the incidence that occurred in South Africa at the opening of the "Apartheid mind: Options for the new South Africa" (Adam & Moodley, 1993) which affected the overall CDR data. After applying the Kruskal-Wallis test, the data also turned out to be non-seasonal and had structural breaks according to the result of the Chow test used. The Mann-Kendall test was used to check the trend pattern, and the result indicates that the data follows a downward trend.

Barring any unforeseen contingencies, such as the pandemic, our findings provide a basis for policy implications in three major areas. First, in the future, decelerated mortality rate will enhance economic growth of the BRICS countries by increasing labor supply, provided that infant mortality does not increase. Second, assessment by insurance companies of the risk associated with life insurance and contingencies is important for stability of financial institutions, functioning of a sound money market, as well as predictability of monetary instruments. This result will help in insurance, annuity and pension liabilities management by reducing unforeseen mortality losses by the actuaries and government pension agencies, as is also opined by Sijbrands et al. (2009), Li et al. (2017), Rabbi and Mazzuco (2018), Kulinskaya et al. (2021). Thirdly, in the area of demographic policies, governments can make appropriate projections for different groups of population. With the expected decline or moderate change in mortality rates in the BRICS countries, governments could pursue policies targeted at reducing infant mortality and expand family planning programs which could keep the population growth rate stable. Finally, reducing mortality rate per thousand per year would seem feasible and plausible in BRICS. Therefore, we predict further and broader economic growth in these countries.

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