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Forecasts of the mortality risk of COVID-19 using the Markov-switching autoregressive model: a case study of Nigeria (2020–2022)

Idowu Oluwasayo Ayodeji[1]

Abstract

The global pandemic due to SARS-Cov-2 ravaged the world and killed more than 6 million people globally within two years. Studies predicting future occurrences are essential to effectively combat the virus. This study modeled daily fatality rate in Nigeria from March 23, 2020 to March 19, 2022 and forecast future occurrences using Markov switching model (MSM). MSM estimates segmented fatality rates into three states of low-, medium- and high-risks. Further, estimates revealed that as at 19th March, 2022, Nigeria remained at the low-risk regime in which 1 (95%CI: 0, 1) person, on the average, died of coronavirus daily; however, the most probable scenario in the nearest future was the medium-risk state in which an average of 4 (95%CI: 2, 5) persons would die daily with 48.7% probability. The study concluded that Nigerian COVID mortality risks followed a switching pattern which fluctuated within low-, medium- and high-risks; however, the medium-risk state was most likely in the future. Our results indicated that the quarantine measures adopted by the governments yielded positive results. It also underscored the need for governments and individuals to intensify efforts to ensure that the country remained at the low-risk zone till the virus would be eventually eradicated.

Key words: Nigeria, hidden Markov, autoregressive, coronavirus death rate.

1. Introduction

The novel coronavirus pandemic began in Wuhan, China on 8th December, 2019 (Ihekweazu, 2020) and sent shock waves around the world. Owing to its severity and rate of spread, the World Health Organization (WHO) declared it a public health emergency of international concern on the 30th January, 2020 (Ogundokun et al., 2020). None of the health institutions around the world was well prepared for its invasion as they were overwhelmed within few weeks of its arrival. Going by the way

[1] Obafemi Awolowo University, Ile-Ife, Nigeria. E-mail: ioayodeji@oauife.edu.ng, idowu.sayo@yahoo.com. ORCID: https://orcid.org/0000-0001-8671-5637.

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it affected the developed countries which were better placed in terms of health infrastructure, the pundits had speculated that Africa would not be able to withstand the effect of the pandemic (Ibrahim et al., 2021). Nigeria, being the most populous nation in Africa was expected to be the worst hit given the mode of transmission of the virus and the fact that several settlements within the country had no decent access to health facilities (Marbot, 2020). Worse still, the poor level of infrastructure in the country posed serious challenges to effective testing and treatment of coronavirus patients (Adekunle et al., 2020). Accordingly, the country was categorized by WHO as one of the 13 high-risk priority countries in Africa (Ihekweazu, 2020).

In order to effectively combat the virus, an accurate description and prediction of the associated risk would be essential. It could provide individuals and health practitioners with understanding of the fatality level and assist in anticipating its progression in the future. It could also offer useful insights to policy makers to make evidence-based decisions and strengthen their efforts in combating the spread. In addition, it could be used to assess the level of success of health' interventions made by governments and health organizations so far and assist in future projections.

The major objective of this study was to formulate a suitable model for COVID mortality rates in Nigeria which would be used to forecast future occurrences. Various methods had been used in previous studies to model coronavirus fatalities; the most commonly-used included the compartmental models (See Adekunle et al. (2020), Bagal et al. (2020) and Carcione et al. (2020), among others), and the time series processes (See Anne (2020), Khan and Lounis (2021), Pourghasemi et al. (2020), Singh et al. (2020), among others).

The time series specification was also predominant in existing prediction studies (Didi et al., 2021; Ibrahim and Oladipo, 2020; Ibrahim et al., 2021; Khan and Lounis, 2021; Li et al., 2022; Odekina et al., 2022). In addition to being able to describe the dynamics of epidemics, time series models could reveal the underlying data-generating process which could be used to forecast future patterns associated with the epidemics. However, relative to modeling studies, existing prediction studies on coronavirus were few and were mostly limited to short-term forecasts due to the type of time series models adopted.

A new variant of the time series model, namely the Markov-switching specification, had emerged in the late nineties which could be used to make accurate forecasts for long-term horizons because its forecasts were based on probabilities rather than some average values. Markov-switching model (MSM) was most appropriate to model and forecast series of ***time-varying*** nature such as the coronavirus fatalities owing to its switching features. What do we mean by time-varying nature? Consider Figure 1 which referred to coronavirus mortality rates in Nigeria from 23rd March, 2020-19th March, 2022. One obvious fact to be observed from the Figure was that the mortality risk was not constant over time but appeared to switch infrequently between the different states of low, medium and high risks. For instance, cases of medium and high mortality risk could be found under labels 1, 2, 4 and 5. Label 3, especially, corresponded to high mortality risk period, while the unlabeled sections appeared to be the low risk periods in Nigeria.

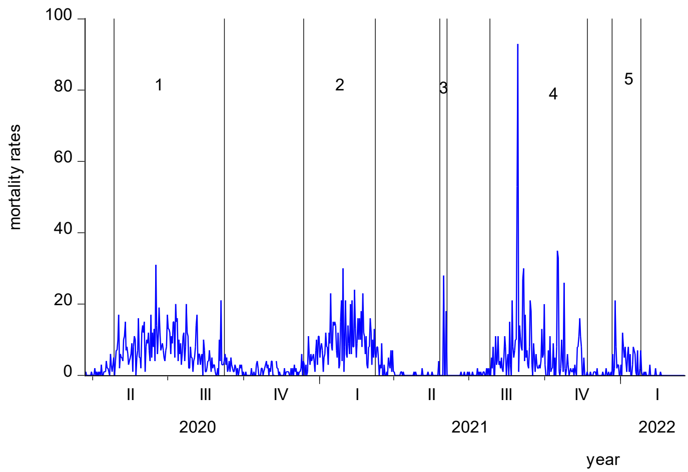

Figure 1: Coronavirus mortality rates in Nigeria (23rd March, 2020 – 19th March, 2022).

Owing to the peaks and troughs in Figure 1 therefore, the appropriate model for measuring and forecasting coronavirus mortality risk in Nigeria was the Markov-switching model (MSM) proposed by Hamilton (1989). In this context, MSM may be used to characterize mortality risks into different states that agreed with the realities in Figure 1. By design, MSM incorporates the Markov process into an autoregressive model such that the average mortality rate may vary across three (low, medium and high risks) unobserved states that evolved according to a first order Markov transition process.

In simple terms, MSM provided that the varying mortality rates seen in Figure 1 be modeled with a mixture of time series specifications whose transition was governed by a Markov process. This was in contrast with previous studies which employed a single model in forecasting. Ahlburg (1995) earlier noted that a combination of forecast models improve accuracy than a single model. Ibrahim et al. (2021) also provided empirical evidence in favour of multiple models.

MSM is especially applicable in the treatment of epidemics as it generates probabilities which can be used to measure the risks associated with the outbreak, as opposed to other time series variants which provide forecasts in form of some mean values. The probabilities obtained from MSM can be used to segment Nigerian coronavirus data into low-, medium- or high-risk state in line with the categorizations of WHO (Ihekweazu, 2020). It is noteworthy that few application studies had applied MSM to model COVID cases in United States (Oliveira et al., 2021) and South Africa (Mthethwa et al., 2022). They found that MSM outperformed other time series and growth models.

Overview of the paper was as follows: Section 2 contained literature review; in Section 3 we presented data and statistical techniques; Section 4 concerned results and discussions; and lastly, Section 5 contained conclusions and recommendations.

2. Literature Review

2.1. Evolution of Coronavirus in Nigeria and Governments' Interventions

The novel coronavirus was first discovered in Wuhan China on 8th December, 2019 (Ihekweazu, 2020). It was declared a public health emergency of international concern by WHO on 30th January, 2020 after 118,000 people had been infected globally (Ogundokun et al., 2020). The Nigeria Centre for Disease Control (NCDC) not being unaware of the enormous challenges involved immediately constituted rapid response teams across the 36 states and concluded their trainings in December 2019. NCDC also subscribed to plans to work with 22 state governors to establish emergency operation centers whose activities will be coordinated at the national centre (Ihekweazu, 2020). In addition, Nigeria also intensified surveillance at the international airports to prevent importation of the virus. However, despite all these efforts, its first index case from Italy was reported on the 27th February, 2020, and its first death on 23rd March, 2020 (Ileyemi, 2021). As at 24th March, 2022, there were 255,244 confirmed cases out of which 249,486 recovered and 3,142 died (Worldometer, 2022).

On 29th March, 2020, the Federal government imposed lockdown in Lagos state, being the epicenter of the virus. Ogun state was also included in the curfew arrangement because it shared border with Lagos. The lockdown also extended to the Federal capital territory (FCT), Abuja, being the region with second highest number of confirmed cases. Movement restrictions were also enforced by state governments of some other states which were not included in the federal-government-imposed lockdown (Odekina et al., 2022). By 23rd April, 2020, movement restrictions had been enforced in all thirty-six states of the federation and the FCT (Jacobs and Okeke, 2022).

In addition to the lockdown order, the Federal government also imposed restrictions on influx of people from thirteen countries which included China, Italy, United States, Iran, South Korea, United Kingdom, Spain, Netherlands, Japan, France, Norway, Switzerland and Germany on 8th March, 2020 (Ibrahim and Oladipo, 2020). 13 days later, the Abuja and Lagos international airports were totally shut down. As part of the safety measures, transport by rail was also suspended on 23rd March, 2020

(Ibrahim and Oladipo, 2020). Due to economic considerations, the Federal government began to ease lockdown and travel restrictions gradually on 4th May, 2020. However, other measures such as social distancing, contact tracing, source control, quarantine, administration of COVID vaccines and self-isolation were sustained (Jacobs and Okeke, 2022).

The quarantine measures and safety protocols notwithstanding, Nigeria continued to record casualties on daily basis. On Saturday, 28th August 2021, NCDC reported a record death of 53 Nigerians, the highest ever since the first confirmed case in February; and barely 24 hours later, 93 more people died of the same cause (Ileyemi, 2021). Though NCDC noted that the high number recorded was due to backlog of fatalities from Lagos state, however, most people were of the opinion that it was the sign of the third wave, and this had sparked fears afresh in the minds of the citizens (Ileyemi, 2021).

2.2. Review of Related Studies

The theory behind coronavirus infection and prognosis was multi-faceted. The occurrence of the virus had been linked with the black swan theory in the literature because it reflected the three characteristics of the theory; (i) it was an unexpected event; (ii) it had extreme impact; and (iii) it could not be predicted in advance, but its occurrence could be explained after it has occurred (Taleb, 2007). Accordingly, researchers had made several attempts to explain its occurrence since it was made public.

Sharifi et al. (2022) presented coronavirus as a syndemic which affected various aspects of human lives. The effect of COVID on people living with non-communicable diseases may differ from others who were not due to different precautionary regimens that were imposed during the pandemic. For instance, movement restrictions reduced physical activities and exercises which were crucial in the management of diabetes, obesity, and so on. Further, isolation of aged people may also increase loneliness and mental health issues such as depression.

Sociological theory and implications of COVID pandemic were presented in Bello and Amzat (2021). The study leaned heavily on the assumptions of George Simmel, Auguste Comte and Herbert Spencer to explain the effect of the pandemic on people's way of life. Based on Comte's theory, the study considered COVID-19 a cause of social instability and disruption to social and economic well-being. Quarantine measures such as social distancing and lockdown would cause a breakdown in social order and interactions; however, they would eventually make life better in the long run.

On the other hand, the decision to ease lockdown protocols at some point despite the pandemic followed Spencer's theory of "survival of the fittest". It is of economic and social advantage to accept that individuals would adapt and learn to live with the virus than to “lock them down” indefinitely. The consequences of long-term social and economic disorder outweighed that of coronavirus (Bello and Amzat, 2021).

Simmel’s theory was applicable to interpersonal relationship among individuals. Personal relationships among individuals had been restricted to virtual interactions through social media. Telemedicine replaced routine hospital visits in advanced countries (Sharifi et al., 2022) and people spent more time online than with one another. A different perspective to coronavirus incidence is contained in Simmel’s theories of secrecy and conflict, and how they affected social relationships during COVID (Bello and Amzat, 2021).

From the empirical viewpoint, most studies measuring the rate of coronavirus fatalities employed compartmental models (Adekunle et al., 2020; Bagal et al., 2020; Carcione et al., 2020) and time series processes (Anne, 2020; Khan and Lounis, 2021; Pourghasemi et al., 2020; Singh et al., 2020). Studies which employed the Markov switching variants in particular included Oliveira et al. (2021) and Mthethwa et al. (2022). Time series investigations conducted with Nigerian data were presented in Abdulmajeed et al. (2020), Chigbu et al. (2021), Li et al. (2022) and Odekina et al. (2022).

The most commonly-used method of forecasting was time series. Predictions on coronavirus status varied by outcome and dates: Chigbu et al. (2021) predicted values for Nigerian fatality and recovery rates from 25th August, 2020 to 31st January, 2021. The study predicted a gradual decrease in infection and fatality rates and an increase in recovery rate over the period of forecast. Li et al. (2022), in contrast to Chigbu et al. (2021), predicted an increase in infection and fatality rates in all the countries considered, including Nigeria, within 1st and 27th March, 2021; and Nigeria was expected to have the lowest prevalence rate among selected countries. Lastly, Mthethwa et al. (2022) predicted in South Africa 322 fatalities for 27th August, 2021 and expected the number to decrease over the next 10 days to 41.

3. Data collection and analysis

3.1. Data and study area

Daily counts of coronavirus deaths were reported on daily basis at the official website of the National Centre for Disease Control (https://covid19.ncdc.gov.ng/report/). They covered 23rd March, 2020, which corresponded to the death of the first index case, Suleiman Achimugu, to 19th March, 2022. The sample size was 727 observations. Details on the data collection process and other descriptions can be found at the website.

3.1. The Markov Switching Model

Denote d_t the daily death rate of coronavirus in Nigeria. The Markov switching model can be written as (Hamilton, 1989):

$$d_t = \mu_{S_t} + \sum_{i=1}^{p} \beta_{i,S_t} d_{i,t-1} + \varepsilon_t,\ S_t = 1,2,\cdots,m;\ t = 1,2,\cdots,T. \tag{1}$$

For mathematical tractability, it was assumed that d_t was normally distributed with means μ and variances σ^2 in the different possible states. A similar assumption was made in Engel and Hamilton (1990). The variance σ^2 varied alongside the mean so that the hidden Markov model could capture the peaks and troughs in Figure 1. At each different states S_t of the coronavirus fatality rate, a variance was computed. The autoregressive term d_{t-1} was included to capture serial correlation that may exist in the data. Following WHO categorization (Ihekweazu, 2020), the study adopted $m = 3$ in the 3 different states, which, in this context, may be denoted $S_t = 1$ for low-risk fatality rate, $S_t = 2$ for medium-risk fatality rate, and $S_t = 3$ for high-risk fatality rate. The Markov process employed was such that the state at any time t was determined randomly and only depended on the state at time $t - 1$.

Transition from one state to the other was determined by the transition probabilities P_{ij}. The closer the value of P_{ij} to 1 the longer it took for the system to transit to the next state. The probability of being in state i tomorrow given that death rate was in state i today was $P_{ii} = \Pr(S_t = i|S_{t-1} = i), i = 1,2,\cdots,m$. In general, $P_{ij} = \Pr(S_t = j|S_{t-1} = i)$ and

$$\sum_{j=1}^{m} P_{ij} = 1; j = 1,2,\cdots,m \text{ and for all } i. \tag{2}$$

The loglikelihood equation corresponding to System (1) - (2) can be written as (Engel and Hamilton, 1990):

$$\log L = \sum_{t=1}^{T} \log f(d_t|S_t) \tag{3}$$

where

$$f(d_t|S_t) = \frac{1}{\sigma_{S_t}\sqrt{2\pi}} \exp\left\{\frac{1}{2\sigma_{S_t}^2}\left(d_t - \mu_{S_t}\right)^2\right\} \tag{4}$$

S_t was not directly observable hence following Engel and Hamilton's (1990) we rewrote $f(d_t|S_t)$ as

$$f(d_t, S_t|\upsilon_{t-1}) = f(d_t|S_t, \upsilon_{t-1})P(S_t|\upsilon_{t-1}) \tag{5}$$

and

$$f(d_t|\upsilon_{t-1}) = \sum_{S_t=1}^{m} f(d_t|S_t, \upsilon_{t-1})P(S_t|\upsilon_{t-1}) \tag{6}$$

where υ_{t-1} was the information available up to time $t-1$.

The loglikelihood equation (3) was then updated as follows:

$$\log \mathrm{L} = \sum_{t=1}^{T} \log \sum_{S_t}^{m} f(d_t|S_t, \upsilon_{t-1})P(S_t|\upsilon_{t-1}) \tag{7}$$

Following Hamilton (1989), model parameters were estimated from Equation (7) using the maximum likelihood approach. We also drew probabilistic inference in form of a nonlinear iterative filter and smoother, popularly referred to as filtering and smoothing probabilities, respectively in econometrics literature. Expected length or duration of state i was computed as (Engel and Hamilton, 1990):

$$E(D) = \frac{1}{1-P_{ii}} \tag{8}$$

For more comprehensive details about the method, interested reader may refer to Hamilton (1989).

4. Results

4.1. Model fitting

Following our observations in Figure 1, we estimated System (1)–(2) using 3 states[2]. Subsequently we categorized Nigeria as low-, medium- or high-risk country. The simplest Markov-switching autoregressive specification AR(1) has been shown to perform well in forecasting (Engel and Hamilton, 1990) hence it was adopted here. Table 1 referred to maximum likelihood estimates of the parameters in System (1)–(2).

Table 1: Maximum likelihood estimates of MSM

Parameter	States		
	1	2	3
μ	8.160* (-4.308, 12.011)	0.163* (0.104, 0.221)	3.329* (2.611, 4.046)
σ	9.137*	0.376*	3.187*
P_{ii}	0.125	0.834	0.694

95% confidence interval in parentheses *significant at the 5% level.

From our result, State 1 was identified as the high risk state where an average of 9 ($p<.05$) deaths were recorded on daily basis; State 2 as the low risk state where an average of 1 ($p<.05$) death was recorded on daily basis; and State 3 as the medium risk state where an average of 4 ($p<.05$) deaths were recorded on daily basis.

[2] We also experimented with 1 and 2 states, however, result, not displayed here for lack of space, showed that the 3 states model described the realities in Figure 1 better than the two other alternatives. Note that for only 1 state, MSM reduced to the conventional autoregressive (AR) model.

The estimated standard deviations σ showed that the number of deaths recorded in the high risk state varied more than in the other states. This implied that the deaths in high risk state were more difficult to predict compared to the remaining states.

Lastly, from the $\mathrm{P_{ii}}$ row we observed that the probability of remaining in low-risk state once the system was in it was the highest followed by the medium-risk and lastly the high-risk. Consequently, the expected durations for the three states were computed as 2, 4, and 7 days for high-, medium- and low-risk states, respectively. This implied that the high risk state was estimated to last for only 2 days at a stretch while the low-risk period was expected to last for 7 days whenever the system transited into the state.

The remaining transition probabilities were shown in the matrix,

$$\widehat{\mathrm{P}} = \begin{pmatrix} 0.125 & 0.088 & 0.787 \\ 0.024 & 0.834 & 0.142 \\ 0.192 & 0.114 & 0.694 \end{pmatrix}$$

Since these probabilities were within (0,1), we can infer that the system was transitive however the likelihood of transiting from one state to the other varied. Out of the three states, the highest likelihood of transition (78.7%) was from the high-risk state directly to the medium-risk state; whereas there was only an 2.4% chance of moving to a high-risk regime at the expiration of a low-risk mortality period.

Again, following Engel and Hamilton (1990) we tested the null hypothesis that the three states did not differ from one another. Wald's test statistics and corresponding p-values were presented in Table 2. The results showed that the three states were different both in the means and variances. This confirmed our observations in Figure 1 that the mortality risks varied over time.

Table 2: Test of hypotheses

Null hypothesis	Wald's statistic
$\mu_1 = \mu_2 = \mu_3$	110.9974 (0.0000)
$\sigma_1^2 = \sigma_2^2 = \sigma_3^2$	1150.423 (0.0000)

p-values in parentheses

Figure 2 displayed the filtered probability plots of the three states (regimes) superimposed with the daily death rates. We followed the conventional assumption in econometrics literature (Engel and Hamilton, 1990) that the system had switched from one state to the other when the probability exceeds 0.5. It was evident from the plot that Markov switching model efficiently captured all the high-, medium- and low-risk mortality periods between 23rd March 2020 and 19th March, 2022 in Nigeria. The fatality rate switched infrequently among the three risk states; it switched severally between low- and medium-risk zones in the periods between the third and fourth quarters in 2020 whereas the high-risk regime dominated the third quarter of 2021. We recalled that Nigeria recorded 53 and 93 deaths in 2 consecutive days within August 2021 in the third quarter of 2021.

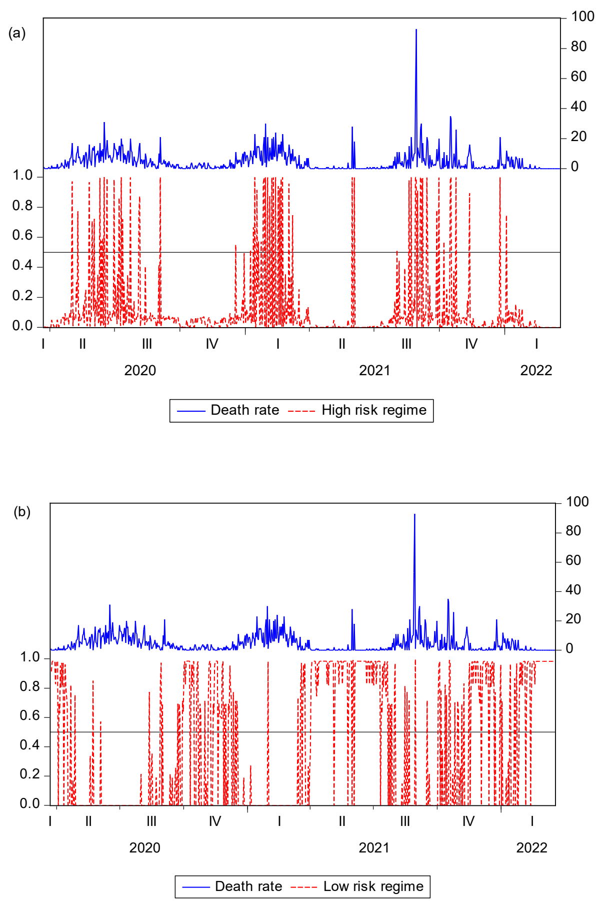

Figure 2: Filtered probability plots by states superimposed with death rates.

4.2. Forecast

We compared three specifications of MSM, namely the 1-state case, 2-state case and 3-state case using various metrics and graphics. The details were available in the

Appendix. The highlight of the result was that the 3-state model outperformed the other two in all the measures employed; hence, it was used for forecast.

Given

$$\widehat{\mathrm{P}} = \begin{pmatrix} 0.125 & 0.088 & 0.787 \\ 0.024 & 0.834 & 0.142 \\ 0.192 & 0.114 & 0.694 \end{pmatrix}$$

the probability P_{12} that if the system was in the high-risk zone today, it would transit to low-risk zone the following day was approximately 0.09. In other words, given the current realities, if 9 deaths, on the average, were recorded today, the probability that the fatality rate would reduce to 1, on the average, tomorrow was just 9%. In 2 days' time, the probability increased to 17.4%:

$$\widehat{\mathrm{P}}^2 = \begin{pmatrix} 0.169 & 0.174 & 0.657 \\ 0.050 & 0.714 & 0.236 \\ 0.160 & 0.191 & 0.649 \end{pmatrix}$$

In 3 days' time, it increased to 23.5%:

$$\widehat{\mathrm{P}}^3 = \begin{pmatrix} 0.152 & 0.235 & 0.614 \\ 0.069 & 0.627 & 0.305 \\ 0.149 & 0.247 & 0.604 \end{pmatrix}$$

The value continued to improve until it gradually converged to 39.6%, and this convergence only occurred after 30 days:

$$\lim_{\mathrm{n}\to\infty} \widehat{\mathrm{P}}^{\mathrm{n}} = \begin{pmatrix} 0.118 & 0.396 & 0.487 \\ 0.118 & 0.396 & 0.487 \\ 0.118 & 0.396 & 0.487 \end{pmatrix}$$

Thus, given the state of health facilities and all forms of government's interventions, if the system was in the high-risk zone today, it was expected that the fatality rate would decrease to the barest minimum within 30 days with probability 0.396. In the same vein, the probability that the fatality rate would remain high could be computed in like manner.

Figure 3 below displayed the forecast probabilities that the system would remain in the high-, medium- and low-risk zones; and that it would transit from high-risk state to low-risk. We inferred from the Figure that in the nearest future, the most probable scenario in Nigeria was the medium-risk zone in which 4 persons, on the average, died of coronavirus on daily basis with 48.7% probability, followed by the low-risk zone in which 1 Nigerian, on the average, died of coronavirus on daily basis with 39.6%, probability and lastly the high-risk regime in which 9 persons, on the average, died of coronavirus on daily basis with 11.8% probability.

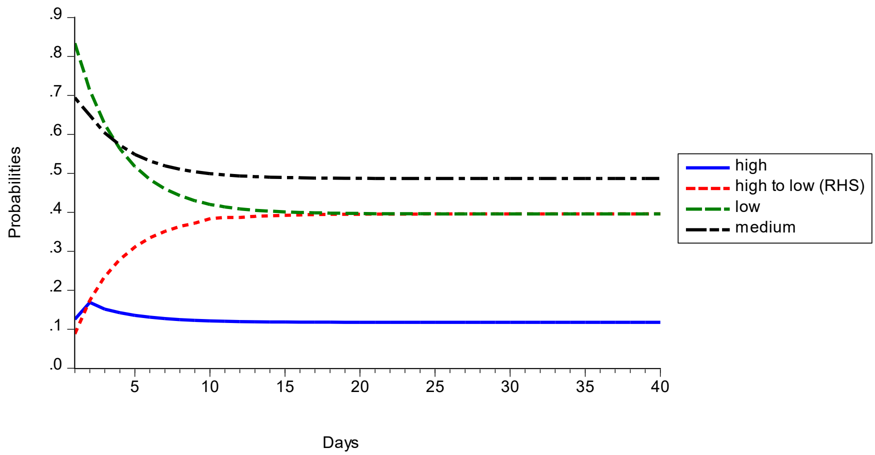

Figure 3: Forecast probabilities.

4.3. Discussion

We developed a Markov switching model for the coronavirus fatality rates in Nigeria. Our results showed that Nigerian death rates switched infrequently among three states of low-, medium- and high-risk within 2020 and 2022. In particular, the system remained in the medium-risk state in which an average of 4 (CI=2, 5) deaths/day were recorded most of the time in the fourth quarter of 2020 though pockets of low- and high-risk transitions were also recorded within the time. This finding agreed with Chigbu et al. (2021) who predicted an average of 3 deaths per day from August 25, 2020 to January 31, 2021.

Further, our results showed that the medium-risk regime was dominant from March 1, 2021 to March 27, 2021. This was in contrast with Li et al. (2022) who predicted an average of 14 (CI= 12, 16) deaths per day. Our results indicated that the system was in the medium-risk state in which an average daily mortality risk of 4 (CI=2, 5) was expected. It is noteworthy that the actual observations of new deaths reported by the NCDC within the stipulated period averaged 5 deaths per day, which supported our findings. .

We also observed that the high-risk regime dominated the third quarter of 2021 in which an estimated 9 persons were expected to die daily of coronavirus in Nigeria. Though Nigeria recorded its highest number of coronavirus casualties within the third quarter of 2021, these were significantly less than the number of fatalities predicted in South Africa within the same time frame; (see Mthethwa et al. (2022)). Thus South Africa was the indeed the epicenter of the virus in Africa.

As at 19th March, 2022, Nigeria no longer belonged to the high-risk group; our result showed that the country had transited to and settled in the low-risk regime in which an average of 1 person was expected to die of coronavirus daily. This was an indication that individuals indeed adapted and learnt to live with the virus over time. We recall that Bello and Amzat (2021) had earlier observed that the government's decision to ease lockdown while the pandemic was still on followed Spencer's theory of "survival of the fittest". In addition, the fact that the mortality rate has significantly reduced was also an indication that the various government policies and interventions yielded the desired results. In addition, it also bore testament to the fact that quarantine measures could effectively flatten the curve as it did in developed countries such as Germany and South Korea (Jacobs and Okeke, 2022).

We noted earlier in section 2.2 that the virus caused huge disruptions to the social, economic and health aspects of human lives. It led to social order breakdown, limited human interpersonal relationships to virtual mode and also prevented people living with various non-communicable diseases to access treatments at their convenience. Ensuring that normalcy returned as soon as possible should be a priority, not for the government alone, but for everyone.

3. Conclusions

The Markov switching model was employed to model and forecast the fatality rate scenarios of coronavirus in Nigeria. The highlight of the results was that Nigeria, as at 19th March, 2022, which was earlier categorized by WHO as a high-risk country had transited from that state to a low-risk one in which 1 person was expected to die of coronavirus daily. This indicated that the various health intervention programs and policies instituted by the government to combat the virus yielded positive results; however, all things given, the most probable scenario in Nigeria was the medium-risk level in which an average of 4 persons would die daily; hence the need to sustain the fight against the virus.

The study concluded that Nigerian COVID mortality risks followed a switching pattern which fluctuated within low-, medium- and high-risks; however, the medium-risk state was most likely in the future. The findings from this study gave an accurate description of the fatality level which could assist in anticipating its progression in the future. It offered useful insights to aid policy makers in making evidence-based decisions and strengthen their efforts in reducing and eventually eradicating coronavirus deaths. In addition, it also assessed the level of success of health' interventions the government and health organizations have made so far and concluded that the efforts had yielded positive results. Our findings also underscored the need to sustain and intensify efforts with the quarantine measures that have been adopted and also embark on awareness programs for individuals to be more responsible for their safety so as to completely eradicate the virus.

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Appendices

We compared three specifications of MSM, namely the 1-state case (which corresponded to the conventional autoregressive model), 2-state case and 3-state case using various statistical techniques including (i) information criteria; (ii) error measurements (the maximum absolute error and the mean square error); and (iii) visual aid.

Table A1 comparing the models by information criteria showed that the 3-state case performed better than the other two specifications as it had the lowest Akaike and Bayesian information criteria values.

Table A1: Model comparison by information criteria

Model	AIC	BIC
1-state	6.445	6.458
2-states	5.025	5.075
3-states	4.663	4.757

Further we compared the three models by prediction errors from in-sample we assumed that the system is in the high-risk state whenever P_{11} exceeded 0.5, at such times, coronavirus death rates in Nigeria were best described by the equation $\hat{d}_t = 8.16 + 1.07d_{t-1}$; at other times when P_{33} exceeded 0.5, we assumed that the system was in the medium-risk state and was best modeled as $\hat{d}_t = 3.33 + 0.26d_{t-1}$. Finally when P_{22} exceeded 0.5, the corresponding state space was the low-risk state and in such cases, $\hat{d}_t = 0.16 + 0.01d_{t-1}$ provided the best fit for the system. Table A2 showed prediction error analysis by model. We observed that the 3-state case again provided the best fit for the death rates.

Table A2: Model comparison by prediction errors

Model	Max. abs. error	Mean square error
1-state	66.738	36.662
2-states	61.436	28.240
3-states	18.544	11.780

In addition, we plotted the observed against the predictions from the 3 candidate models in Figure A1 below. In agreement with the results presented in Tables A1 and A2, we observed that the 3-state model provided the best fit to the observed data. In all the daily predictions, the 1-state model could not reproduce the minimum death rate as its minimum estimated value was 2.38.

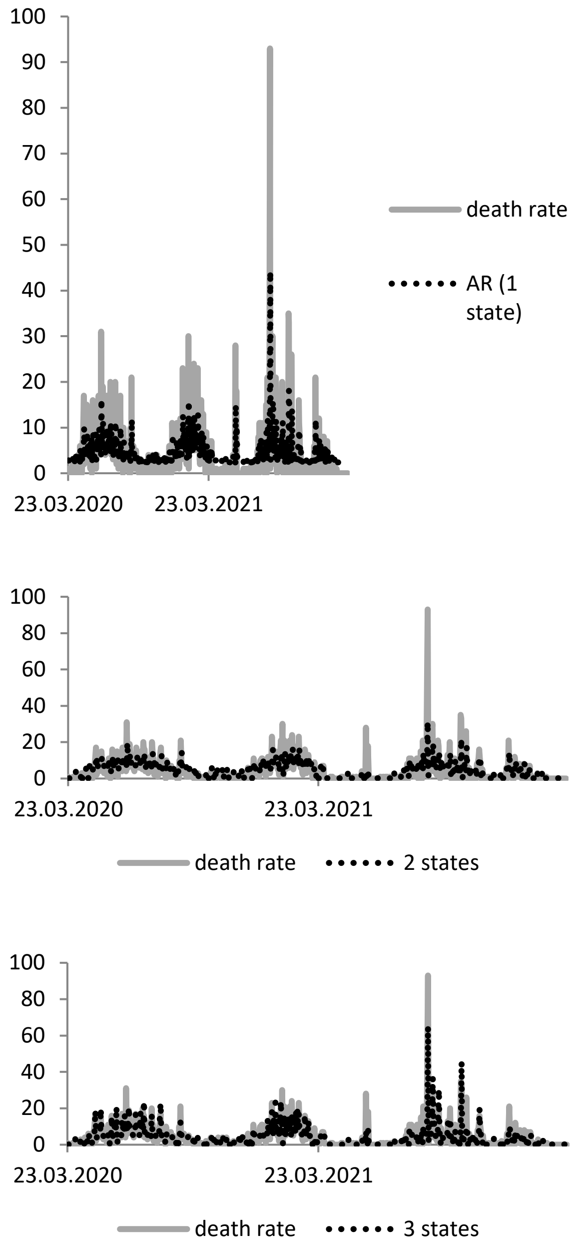

Figure A1: Predicted versus observed by models