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Do as your neighbours do? Assessing the impact of lockdown and reopening on the active COVID-19 cases in Nigeria

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ABSTRACT
This paper employs Autoregressive Integrated Moving Average (ARIMA) modelling and doubling time to assess the effect of lockdown and reopening on the active COVID-19 cases (ACC) based on a sample from 29 February to July 3, 2020. Two models are estimated: one with a sample covering post-lockdown period only and another spanning both post-lockdown and post-reopening periods. The first model reveals that the lockdown caused an immediate fall in the daily growth rate of the ACC by 14.30% and 33.26% fall in the long run. The parameters of the second model show that the lockdown had an impact effect of 8.56% and steady state effect of 20.88% reduction in the growth rate of the ACC. The effect of reopening on the ACC is insignificant. However, the doubling time of the ACC has increased after reopening. The study warns against complete reopening until sufficient post-reopening data series is available for exact estimation. The findings in this study can be useful in determining the hospitalisation needs and effectiveness of similar health-related policies.

1. Introduction

The emergence of Novel Corona Virus, otherwise known as COVID-19, in Wuhan, China and its eventual spread worldwide have caused panic across the international community. This development has resulted in the shutdown of social, religious and economic activities across the globe. As the COVID-19 is contagious (Cheng and Shan, 2020; Lauer et al., 2020; Shereen et al., 2020), policy makers across the globe have taken preventive measures such as shutdown of international flights, lockdown of cities including banning large gathering and enforcing social distancing. Developing countries like Nigeria, despite their differences from the developed countries, decided to ”copy and paste” similar measures to slow down the spread of the disease. Policy makers have begun to ‘live with the virus’ by opening up as the countries cannot cope with the continuous lockdown. This study focuses on the impact of lockdown and reopening on the active COVID-19 cases (ACC). The number of the ACC is an important factor in determining the hospitalisation need of a country. Hospitalisation need simply means the number of medical personnel, equipment and facilities needed to take care of the active COVID-19 patients. The government authorities implemented the lockdown measures in order to ‘flatten the curve’, but have to reopen because of unbearable social and economic conditions of the lockdown. Hence, empirical modelling of the impact of these measures on the ACC can give more insight on their outcomes. Thus, the outcome can help the authorities in making decisions whether to continue with the lockdown or reopen completely. The outcome can also help the authorities in taking the best measures when faced with similar incidence in the future.

Policy makers implement various measures to contain the spread of the COVID-19 from the unidentified infected to non-infected persons (Lau et al., 2020; Wilder-Smith and Freedman, 2020). By 20 March, the Nigerian government began to take certain measures in order to curb the spread of the disease. By 28 March 2020, the Nigerian government enforced a sweeping 14-day lockdown (otherwise known as quarantine) of three major cities, namely Lagos, Ogun and the Federal Capital Territory (FCT), that is the Nigerian Capital Abuja. Consequently, international and domestic flights were banned, a 24-h curfew was enforced and all social, religious, political and educational gatherings were cancelled.

A number of studies attempt to model the COVID-19 cases (Li et al., 2020; Ma, 2020; Read et al., 2020; Zhao et al., 2020a,b). Some of these studies use epidemiological models (Ahmed et al., 2020; Anastassopoulou et al., 2020; Isa Abdullahi Baba, 2020; Kucharski et al., 2020), correlation analysis (Zhao et al., 2020a,b), while other studies attempt to forecast the COVID-19 outbreak (Anastassopoulou, 2020; Roosa et al., 2020). Few studies also examine the effect of lockdown on various variables; Collivignarelli et al. (2020) analyses the effects of lockdown on air quality; Killesen and Kiware (2020) develops a simplified
2. Distribution of COVID-19 in Nigeria

Nigeria is the most populous country in Africa and is located on latitude 10°00′N and longitude 8°00′E. Fig. 1 presents the map of West Africa and Nigeria, while Fig. 2 shows the map of Nigerian States with the distribution of COVID-19 cases. It is obvious that Lagos, Kano and the FCT have the largest number of COVID-19 total confirmed cases.

Fig. 3 depicts the fan plot of the total, active, recovery and death cases of COVID-19. The larger the sector of the fan plot, the larger the number of the respective case. The figure reports the extracts of the top four of each COVID-19 case. It is observed that Lagos leads in terms of each case, followed by Kano in terms of all but the number of active cases. The FCT comes second in terms of the number of active cases. The number of active cases for the FCT is larger than that of Kano because the number of recovery cases for the latter is 1.8 times larger than that of the former. Surprisingly, Kaduna, which is ninth in terms of the total confirmed cases (369), comes third in terms of the number of recovery cases. This moves its position down to twelfth on the scale of active cases. The State of Edo maintains its fourth position on both the scales of confirmed cases (125) and death cases (2), whereas the number of the new COVID-19 cases, the total, recovery and death cases. Implicitly, the number of active cases is also a function of the number of the new COVID-19 cases.

3. Data and methodology

3.1. Data

The data sets for this study are extracted from the daily Situation Reports by Nigeria Centre for Disease Control (NCDC). The link to the website is https://ncdc.gov.ng.

3.2. Definition of variables

The variables used in this study are defined as follows. The new cases refer to the daily laboratory record of COVID-19 patients, that is the number of new confirmed cases recorded daily. The total cases refer to the cumulative sum of new cases. Death cases refer to the total number of COVID-19-related deaths recorded over time. Recovery cases refer to the total number of COVID-19-infected persons that get recovered. The active cases refer to the number of COVID-19 patients currently on admission. The number of active cases is calculated as follows:

\[ A_t = T_t - R_t - D_t \]  

(1)

In Equation (1), \( A_t \) is the active COVID-19 cases, \( T_t \) is the total COVID-19 cases, \( R_t \) is the total number of recovery cases and \( D_t \) is the total number of death cases. The subscript \( t \) represents time in days. Explicitly, the number of active cases is determined by the number of total, recovery and death cases. Implicitly, the number of active cases is also a function of the number of the new COVID-19 cases.

3.3. ARIMA model

Autoregressive Integrated Moving Average (ARIMA) model was proposed by Box and Jenkins (1976) and Box et al. (2015). The ARIMA \((p,d,q)\) model is represented by Equation (2). The letters \( p \), \( d \) and \( q \) indicate the autoregressive order, order of integration and moving average order respectively.

\[ Y_t = \alpha_0 + \Gamma \varepsilon_t \]  

(2)

\( Y_t \) is the stationary dependent variable, \( \varepsilon_t \) is the white noise error term, \( \Gamma = 1 - \sum_{i=1}^{\infty} \alpha_i L^i \) and \( \Gamma = 1 - \sum_{i=1}^{\infty} \beta_i L^i \) and \( L \) is the lag operator defined as \( L^i Y_t = Y_{t-i} \) for \( i = 1, 2, \ldots, \infty \). For more details on ARIMA, see Enders et al. (1990), Enders (2015) and Akalpler et al. (2017). Therefore, the ACC can be modelled in terms of ARIMA as follows.

\[ Y_t = \alpha_0 + \beta d_t + \eta r_t + \Gamma \varepsilon_t \]  

(3)

The new variables \( d_t \) and \( r_t \) in Equation (3) stand for the dummy variables for periods of lockdown and reopening respectively. The ARIMA is used to model the ACC as it is most appropriate for intervention analysis (Enders et al., 1990).

4. Result

4.1. Plots of the variables

The time series plots of the number of active, death, recovery and total cases are shown in Fig. 4, while the descriptive statistics are reported in Table 1.

4.2. The ARMA estimate

The focus of this paper is on the impact of lockdown and reopening...
on the ACC. Therefore, only the ACC is modelled in this section. A new series \( a_t \) is created by taking logarithmic changes of the ACC. Specifically, \( a_t = \Delta \ln A_t \times 100 \), where \( \Delta = (1 - L) \). Therefore, \( a_t \) series can be interpreted as the daily growth rate of the ACC. The first task is to plot \( \{a_t\} \) in order to observe whether it is stationary. A cursory look at Fig. 6 shows that the mean is constant, but the variance changes over times. However, formal unit root tests Augmented Dickey Fuller (ADF), proposed by (Dickey and Fuller, 1979), and Phillips-Perron (PP), pioneered by (Phillips and Perron, 1988), show that \( a_t \) is stationary at level. In other words, \( a_t \) is I(0). The results of the unit root tests are reported in Table 2. This necessitates modelling \( a_t \) as an ARMA(p,q) process because it is stationary I(0).

The convention of an intervention analysis is to estimate the ARMA model over sample before or after the intervention (that is lockdown or reopening in this case). The lockdown measure in Nigeria began around March 20, 2020. The sample prior to the lockdown is not included because it is smaller than the sample for the post-lockdown period. Hence, the initial estimation sample of the ARMA model for \( \{a_t\} \) series ranges from March 20, 2020 to July 3, 2020. The dummy for the lockdown (\( d_t \)) is a series of zeros for period prior to March 20, 2020 and unity otherwise. That is, \( d_t = 0 \) for all \( t < \) March 20, 2020 and \( d_t = 1 \) for all \( t \geq \) March 20, 2020. Similarly for the reopening dummy, \( r_t = 0 \) for all \( t < \) June 10, 2020 and \( r_t = 1 \) for all \( t \geq \) June 10, 2020. After determining the best ARMA model, a new model is re-estimated which includes the
lockdown and reopening variables as described in Enders et al. (1990) and Enders (2015). The steps are illustrated in Fig. 5 below:

The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) in Fig. 7 help in identifying the probable models. The significant lags of the PACF indicate the probable AR order (p), while the significant lags of the ACF suggest the probable MA order (q). It is observable that the probable models include AR(2), MA(2), MA(3), MA(4), ARMA(1,2), ARMA(2,1), ARMA(2,2) and so on. All the probable models are estimated and then compared against each other in terms of the values of $R^2$, Akaike Information Criterion (AIC) (Akaike, 1973, 1974, 1981), Schwarz Information Criterion (SIC) (Schwarz, 1978), and residual diagnostics. The $R^2$ is used to measure the explanatory power of the regressors, the SIC is preferred over the AIC as it selects the most parsimonious model. The AIC and SIC are given as $AIC = 2ln(\Omega) + 2k$ and $SIC = 2ln(\Omega) + ln(n)k$, where $k$ is the number of regressors, $n$ is the number of estimated residuals and $\Omega$ is the likelihood function. Parsimony is the idea that the lower the number of regressors in a model, the better. Fig. 8 reports the ARMA criteria graph of the top 20 models in ascending order of their SIC values. Although AR(3) has the lowest SIC value, ARMA (1,2) is used to estimate the $a_t$ series as it contains no redundant parameters, no autocorrelation, and Fig. 9 shows that its actual correlogram resembles the theoretical correlogram well. The following ARMA(1,2) model is estimated with a sample ranging from March 20, 2020 to June 10, 2020 to cover the lockdown period only.

$$a_t = 20.83 + 0.57a_{t-1} - 0.79 \epsilon_{t-1} + 0.63\epsilon_{t-2} - 14.30d_{t}$$
$$T = 83 \quad R^2 = 0.45 \quad AIC = 6.79 \quad SIC = 6.97 \quad \hat{\sigma} = 6.93$$

(4) (t – statistics in parentheses)

Another ARMA(1,2) model is estimated with a sample spanning February 29, 2020 to July 3, 2020 to include both post-lockdown and post-reopening periods.

$$a_t = 14.72 + 0.59a_{t-1} - 0.42 \epsilon_{t-1} + 0.31\epsilon_{t-2} - 8.56d_{t}$$
$$T = 125 \quad R^2 = 0.24 \quad AIC = 7.76 \quad SIC = 7.89 \quad \hat{\sigma} = 11.43$$

(5) (t – statistics in parentheses)

For the sake of comparison, Equations (6) – (8) report the estimates of AR(3,0), AR(3,1) and AR(1,3) respectively. These equations use the same sample as Equation (4). It is observed that Equation (4) is the best model because it does not contain redundant regressors.
For this reason, Equation (5) is chosen as the best model. The aim of this study is to examine the impact of lockdown and reopening on the active COVID-19 cases (ACC). Two models are estimated as in Equations (4) and (5). Equation (4) provides the estimates of best ARMA(p,q) model for sample spanning lockdown period only. The post-lockdown average daily growth rate of the ACC is 48.44 \(( \lambda_{48} = \frac{20.83}{0.41} = 48.44)\) and the value of \( \lambda \) is -14.30. This implies that the impact effect of the lockdown is the reduction of the ACC daily growth rate by 14 per cent. Given that \( \alpha_{1} = 0.5727 \), the long run (steady-state) effect of the lockdown is the reduction of the ACC daily growth rate by 33.26 per cent (\( \frac{\lambda_{33.26}}{1-\lambda} = \frac{14.30}{0.30} = -33.26 \)). Equation (5) estimates \( \alpha_{1} \) including both post-lockdown and post-reopening periods. Based on Equation (5), the post-lockdown mean daily growth rate of the ACC is 35.90 \(( \lambda_{35.90} = \frac{14.73}{0.20} = 35.90)\), while the value of \( \lambda \) is -8.56. Therefore, the lockdown caused an immediate fall in the ACC daily growth rate by 8.56 per cent. In the long run, the lockdown reduced the ACC daily growth rate by 20.88 per cent (\( \frac{\lambda_{20.88}}{1-\lambda} = \frac{8.56}{0.20} = -20.88 \)). The difference between the estimates of Equations (4) and (5) is due to the difference in

\[
\begin{align*}
\alpha_{1} &= 17.91 - 0.21 a_{0} + 0.32 a_{-3} + 0.61 a_{-1} - 10.58 d_{\alpha} \\
T &= 83 \quad R^{2} = 0.48 \quad AIC = 6.76 \quad SIC = 6.93 \quad \hat{\sigma} = 6.78 \quad (t - \text{statistics in parentheses})
\end{align*}
\]

\[
\begin{align*}
\alpha_{1} &= 18.02 - 0.25 a_{0} + 0.32 a_{-3} + 0.63 a_{-1} + 0.04 e_{-1} - 10.75 d_{\alpha} \\
T &= 83 \quad R^{2} = 0.47 \quad AIC = 6.78 \quad SIC = 6.98 \quad \hat{\sigma} = 6.82 \quad (t - \text{statistics in parentheses})
\end{align*}
\]

\[
\begin{align*}
\alpha_{1} &= 18.65 + 0.88 a_{0} - 1.15 e_{-1} + 0.79 e_{-2} - 0.29 e_{-3} - 11.60 d_{\alpha} \\
T &= 83 \quad R^{2} = 0.46 \quad AIC = 6.81 \quad SIC = 7.01 \quad \hat{\sigma} = 6.97 \quad (t - \text{statistics in parentheses})
\end{align*}
\]
the sample size. It is obvious that, the longer the sample size, the smaller the effect of the lockdown on the growth rate of the ACC. This shows that the lockdown is effective in reducing the daily growth rate of the ACC, but the effect diminishes with time.

6. Conclusion

This study has examined the “copy-paste” policies of lockdown and reopening to control the spread of COVID-19 in Nigeria. The ARIMA modelling is used to estimate the daily growth rate of the ACC. The lockdown measures have led to the reduction of daily percentage rate of growth of the ACC. Even though the lockdown policy is successful, the big question is whether the benefit of this policy outweighs its cost. This question is difficult to answer as it is not easy to quantify the economic losses due to the lockdown or place economic value on the success of the lockdown policy.

The reopening measures are difficult to assess as the post-reopening data series is too short for exact estimation. However, the doubling time of the ACC indicate that it takes more days for the ACC to double after the reopening than before. Doubling time is calculated as $DT = \frac{n}{r}$, where $n$ is the growth proportion. The result is not reported, but it is available upon request. The implication of this is that Nigeria can continue with its reopening policy as it does not reduce the doubling time of the ACC.

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