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# A Time Series Forecast of COVID-19 Infections, Recoveries and Fatalities in Nigeria

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**Abstract:** The study investigated COVID-19 pandemic infections, recoveries, and fatalities in Nigeria to forecast future values of infections, recoveries, and fatalities and thus ascertain the extent to which the pandemic appeared to be converging with time. The prediction of COVID-19 infections, recoveries, and fatalities was necessitated by the impact that the pandemic had exerted in world economies since its outbreak in late 2019. The quantitative method was employed, and a longitudinal research design was applied. Data were obtained from the Nigeria Centre for Disease Control (NCDC). The least-squares test and autoregressive distributed lag (ARDL) tests were performed to forecast infections, recoveries, and fatalities. The results of the predicted infections for the last five months of the year (August–December 2020) shows that the cases of infections will narrow down within the period. The need for policymakers to implement complete unlocking of the economy for speedy economic recovery was suggested, among others.

**Keywords:** COVID-19 pandemic; COVID-19 infections in Nigeria; COVID-19 recoveries in Nigeria; COVID-19 fatalities in Nigeria; and COVID-19 convergence in Nigeria

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## 1. Introduction

The first evidence of coronavirus in human history manifested as viral diarrhoea in swine in 1946, but "a new coronavirus-like particle was detected by electron microscopic examination of intestinal or faecal samples from sick pigs in 1976 following the Belgian swine breeding farms with diarrheal problems" (Pensaet & Bouc, 1978) [1]). Severe Acute Respiratory Syndrome (SARS-CoV) and Middle East Respiratory Syndrome (MERS-CoV) are two animal infecting coronaviruses that were identified in southern China in 2003 and Saudi Arabia in 2012, respectively. It is reported that more than 1600 fatalities were associated with the two coronaviruses.

Despite not being the first coronavirus in human history, the COVID-19 pandemic is novel, owing to its contagion influence that saw virtually all countries across the globe enveloped within a few weeks of its emergence. The rate of fatality and disregard for the sophisticated health systems in industrially advanced countries was unprecedented. The COVID-19 pandemic is attributed to a novel coronavirus now called severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2; formerly called 2019-nCoV). It was first identified amidst an outbreak of respiratory cases of illness in Wuhan City, Hubei Province, China. The COVID-19 pandemic exposed the unpreparedness of many world leaders to respond to health challenges as the international response left much to be desired, thus leading to several deaths. As at Monday, 31 August 2020, there were twenty-five million, one hundred and eighteen thousand, six hundred and eighty-nine (25,118,689) confirmed cases of infections and eight hundred and forty-four thousand, three hundred and twelve (84,4312) deaths (WHO, 2020) [2].

The unprecedented rise in COVID-19 infections (INF) and fatalities (FT) in many countries overwhelmed the leaders of these countries, especially when the recoveries (RCV) in most of these countries did not appear to match the fatalities, thus making convergence of the pandemic seem impossible (See Figures 1–6). Given its unprecedented nature and the degree of devastations that have characterised it, anything that will enable policymakers to curb its spread was desirable. This perception may be responsible for the series of studies from diverse perspectives since the outbreak of the pandemic. The series of studies from diverse perspectives are based on the interests of these researchers.

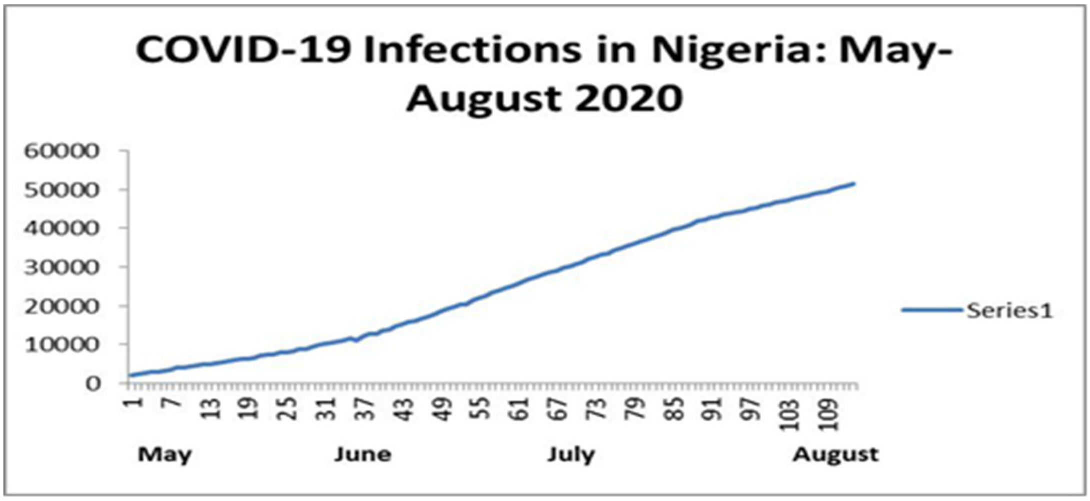


**Figure 1.** Total COVID-19 Infections in Nigeria from May 2020–August 2020.

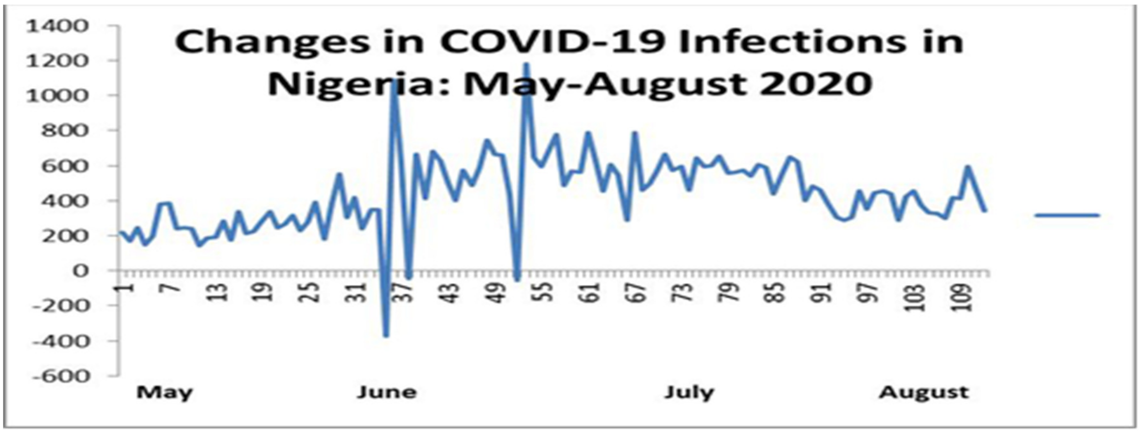


**Figure 2.** Changes in COVID-19 Infections in Nigeria from May 2020–August.

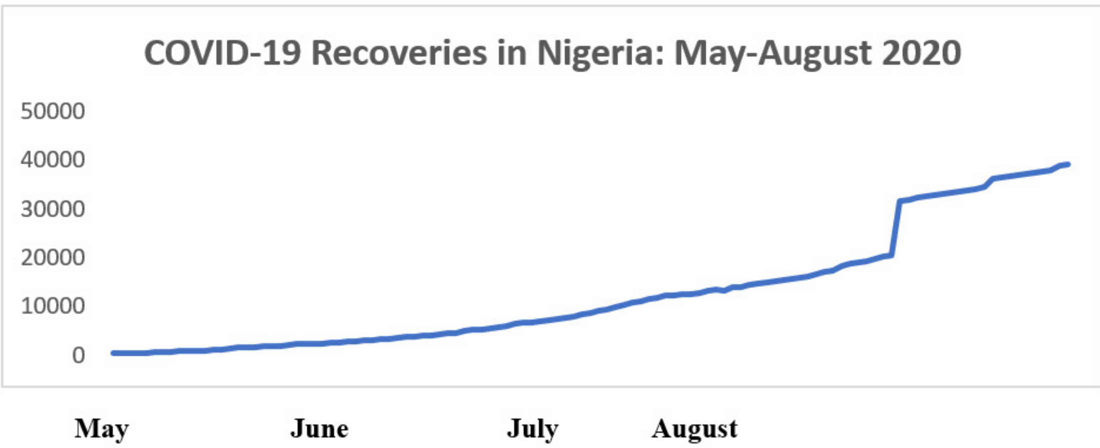


**Figure 3.** COVID-19 Infections in Nigeria (May–August 2020).


**Figure 4.** Changes in Cases of COVID-19 Recoveries in Nigeria from May–August 2020.


**Figure 5.** COVID-19 Fatalities in Nigeria (May–August 2020).

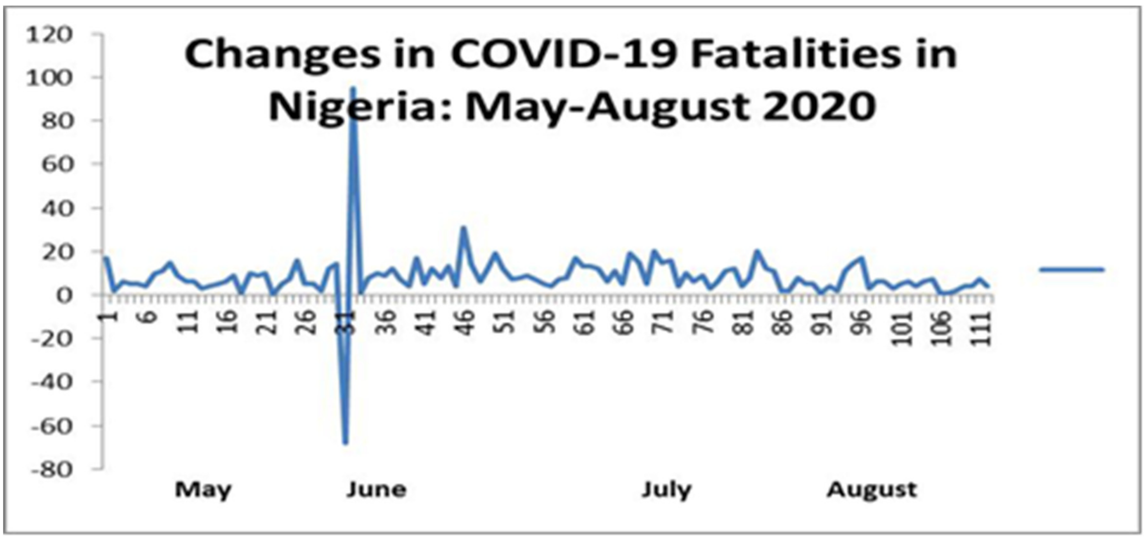


**Figure 6.** Changes in Nigeria's COVID-19 Fatalities (May–August 2020).

Owing to its topicality and perceived importance, the COVID-19 pandemic attracted research interest from various fields such as health, agriculture, and management, as well as education, and finance among others, owing to the implication of the pandemic on different sectors of the economy. Some of the studies include those conducted by Rahman & Bahar (2020) [3], Qian, et al., (2020) [4], Inegbedion (2020) [5], Inegbedion (2021), [6]), Ayinde et al., (2020) [7], and Oyinlola et al., (2020) [1]. Despite the numerous studies on the research problem within a short time only the studies of Ayinda et al., (2020) [7] and Oyinlola et al., (2020) [1] deliberately adopted a forecasting approach in Nigeria at the time, neither did the studies that employed forecasting technique examine the forecasting errors to determine the accuracy of such forecasts. In addition, the scope of coverage of the studies that employed forecasting techniques is restricted. These perceived shortcomings necessitated the conduct of this study. Consequently, this study sought to model the changes in INFs, RCVs and FTs of the COVID-19 pandemic in Nigeria using time series techniques in order to predict the possibility of convergence soon and thus provide insights for policymaking for the benefit of the entire citizenry. The rest of the paper is organised under the following subheadings: literature review, methodology, results, discussion of findings, policy implications and conclusion.

## 2. Literature Review

This section examines the concepts of coronavirus and some basic time series forecasting models that are used in the literature.

### 2.1. Coronavirus

The outbreak of the COVID-19 pandemic forced human and economic activities to be severely constrained for a reasonable part of the year 2020 as a result of the outbreak of the COVID-19 pandemic. The degree of contagiousness and the dimensions of transmission of the pandemic (contact and droplets, among others) made it very dreaded (He, et al., 2020) [8]. "Coronavirus causes acute and chronic respiratory, enteric, and central nervous system diseases in many species of animals, including humans" (Weiss et al., 2005) [9]. Host range and genome sequence within each group are used to identify viruses (Hoek et al., 2004) [10]. Some animals such as rodents, poultry birds, swine, domestic pets, and diary, among others, and humans have been associated with coronavirus.

Since this study focuses on the prediction of COVID-19 infections, recoveries, and fatalities, which are measured daily; the associated data are consistent with time series, and thus time series modelling techniques are appropriate. Some of the time series models are discussed in Section 2.2.

### 2.2. Time Series Models

A sequence of observations that are typically made up of successive measurements made over a time interval constitutes a time series dataset. The time intervals must be equal, such as daily, weekly, monthly, and annual, among others. Unlike cross-sectional data, which are collected at a single point in time, time series data are observed at different points in time. Data that are observed at equal time intervals can be subjected to time series analysis for useful prediction. However, because the points at which data are observed in time series are adjacent time periods, they are often susceptible to correlation between observations. To this end, "a key property of time-series is non-independence of values at consecutive time periods. This results in a statistical relationship between values at consecutive time periods and sometimes at different time lags, known as autocorrelation. Temporal autocorrelation is a fundamental characteristic of observations recorded over extended periods of time" (Ward et al., 2020) [11]. Such correlations can interfere with the forecasting precision. It is for this reason that various forecasting models are designed to make adjustments to the interruptions that may arise from correlations or other forms of interruptions that may be associated with time series data. There are different ways that non-stationary (NS) time series can occur; the major characteristics are possession of variable means ($\mu_t$), time-varying (TV) second moments fluctuating variance ($\alpha_t^2$), or both of these properties. The autoregressive integrated moving average models is a typical example of the class of homogeneous NS time series models. The discrepancies between the stationary and NS time series model can be bridged through useful differencing and variance stabilizing transformations. Three classes of time series models are examined below.

#### 2.2.1. Autoregressive (AR) Models, Moving Average (MA) Models, and the Autoregressive Integrated Moving Average (ARIMA) Models

An autoregressive (AR) model forecasts the future behaviour of a given set of data on the bases of the past data's behaviour. AR models are very useful in forecasting when the time series data are sufficiently autocorrelated. Autoregressive models are used to describe the nature and degree of relationships between past and current data as well as between current and future observations in TS. Thus, autoregressive models are useful in determining the portion of the observed TS that previous values of the data can explain based on the behaviour of the data. Time series can be classified as simple AR, ARMA and ARIMA models. Each of these models differ in the manner that their previous values in the TS predict or relate with future values (Wang, 2018) [12]. Basically, a linear model whose regression terms are lagged values of the same TS is an autoregressive model. However, MA models use lagged values of forecast errors, while ARMA models combine the properties of MA and ARIMA. The ARIMA models require a first difference to become stationary, thus they are integrated of order one.

#### 2.2.2. Vector Autoregressive Model (VAR)

The Vector Autoregressive model is a multivariate Time Series technique flexible and is useful in describing the dynamic behaviour of specific time series data; that is, a vector of time series. This type of forecast is predominant in economics and financial analysis. In VAR system, one equation is considered for the dependent variable with constant and lags. "Each variable is assumed to influence each other in the system, which makes direct interpretation of the estimated coefficients very difficult" (Hyndman & Athanasopoulos, 2014) [13]. In contrast, to the VAR model, the structural VAR (SVAR) model, adds coefficients to capture the direction and size of contemporaneous relations (Bultee et al., 2016) [14].

#### 2.2.3. Vector Error Correction (VEC) Model

The VEC model is used in modelling the relationship between time series variables when all the variables are integrated of order one that is I(0) and cointegrated. Thus, only variables that are stationary at first difference and which are cointegrated are suitable for the vector error correction model. It is pertinent to mention that each VAR model equation is an autoregressive distributed lag model. To this end, the VEC model is a variant of a VAR model that has cointegration constraints because there is a cointegration relationship in the VEC model; "when there is a large range of short-term dynamic fluctuation, VEC expressions can restrict long-term behaviour of the endogenous variables and be convergent to their cointegration relation" (Zou, 2018) [15]. A basic assumption of the VECM method of estimation is the cointegration of the underlying variables, meaning that all the variables are stationary at first difference, I(1) while the error term should be stationary, I(0) (Inegbedion et al., 2020) [16].

#### 2.2.4. Autoregressive Distributed Lag System (ARDL)

Another time series model that belongs to the autoregressive group is the ARDL. However, unlike the VEC model, the ARDL does not require that all the variables be stationary at first difference. It is more suitable when the TS data consists of a mixture of I(0) and I(1) variables; that is, a mixture of variables that are stationary at level and those that are stationary at first difference. The existence of a single long run relationship often revealed by the presence of cointegration of the underlying variables makes the model robust (Nkoro & Uko (2016)) [17].

### 2.3. Theoretical Framework

Consistent with the definition of multivariate TS models as consisting of multiple time-series that make meaningful contribution to forecasting, this study employs multivariate TS models as its theoretical framework. The study chose the multivariate TS model based on the multiple models of forecasting involving infections, recoveries, and fatalities as well as to make provision for long-run relationships between the variables being studied since the existence of such long-run relationships are critical to making the series amenable to TS analyses, even when the individual series are NS at the level. The fact that it is possible to have mixed stationarity statuses of the variables is also supportive of n multivariate analysis (Frees, 2004) [18]. "The multivariate extension of the univariate auto-regression is the vector autoregression (VAR), in which a vector of time-series variables, $Y_{t+1}$, is represented as a linear function of $Y_t, \ldots, Y_{t-p+1}$, perhaps with deterministic terms (an intercept, or trend)" (Smelser & Bates, 2001) [19].

In addition, "the possibility of cointegrating variables in VARs which is not present in univariate autoregressions makes VARs unique because such an occurrence will make the variables still exhibit the properties of stationarity. Based on the properties of VARs especially the Vector error correction model and autoregressive distributed lag system" (Inegbedion et al., 2020) [16]. In line with TS data analysis, the data analysis method employed in analysing the COVID-19 data took cognisance of the stationarity statuses of the variables (whether at level, or first difference or second difference or whether it is a mixture of level and first difference). Specifically, the ARDL technique was used, owing to the mixture of the order of integration of the underlying variables (COVID-19 infections, recoveries, and fatalities).

### 2.4. Empirical Review

The empirical literature on COVID-19 pandemic is very rich despite the fact that the pandemic was not prolonged. The abundant literature on the problem was informed by the degree of interest generated globally as a result of the concern that it caused people and governments across global divide. Oyinlola et al., (2020) [1] conducted an empirical investigation of the confirmed cases of COVID-19 in Nigeria to enable them to predict and evaluate the implications of such forecasts. Consequently, their study focused on the nature of the pandemic such as the shape of the COVID-19 growth curve. They also sought to forecast INF in Nigeria. The Poisson, Negative Binomial, as well as Wallinga and Teunis' modelling techniques served as the data analysis methods. Their analysis led to projections of the pandemic from the two standard models. The projections suggested that there was a possibility that INFs may start reducing before the beginning of the third quarter and will, thereafter, stabilise in the third quarter of 2020. They predicted that the development would precipitate large sacrifices that would result in the depletion in potential Gross Domestic Product (GDP) and bring about the need for government and other stakeholders to intervene by implementing some proactive measures to reduce the negative consequences so that they can reduce the span of the resultant economic recession.

Qian et al., (2020) [20] studied "fighting against the common enemy of COVID-19 through building a community with a shared future for mankind". They noted that the biological characteristics of the COVID-19 pandemic, regarding its name, severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), coupled with its speed of spread as well as the unprecedented pattern of transmission were majorly responsible for the delayed inability of people to curtail the pandemic. They also opined that China was on the right course as the public health measures implemented were proving to be effective and successful. However, given the fact that on the average, the world had not done well in combating the pandemic, they suggested that the international community should be more purposeful in their quest to curtail the pandemic through the development of better strategies as well as consolidate their coordination, cooperation, and strong solidarity in the joint efforts of fighting against COVID-19 spread.

Ayinde et al., (2020) [7] investigated the "daily confirmed cases, recoveries and fatalities of the COVID-19 pandemic in Nigeria". The design was a longitudinal survey of the major COVID-19 variables. The data were analysed using curve estimation statistical models which came in three forms, the simple, quadratic, cubic, and quartic forms. Based on the results of the curve estimation analysis, they found "the best models to be quartic linear regression model with an autocorrelated error of order 1 (AR (1)); and found the ordinary Least squares, Cochrane Orcutt, Hildreth–Lu, and Prais-Winsten and least absolute deviation (LAD) estimators useful to estimate the models' parameters". Consequently, the study suggested the need to use LAD estimator for the daily cumulative forecast of INFs, RCVs and FTs for May and June 2020 at the 99% confidence level.

Inegbedion (2020) [5] examined "COVID-19 Lockdown: Implication for food security" in order to draw the attention of policymakers to a possible food crisis and possible food insecurity in the near future if appropriate steps were not proactively taken to forestall the occurrence, especially as the index case and the attendant implementation of lockdown coincided with the planting season in Nigeria. The cross-sectional survey design was used to select farmers online through the Facebook medium. The study employed a questionnaire with Likert scale question-response format as the research instrument while the *t*-test and least squares technique were used to analyse the data. It was found that COVID-19 lockdown could jeopardise food security as it could significantly constrain the trio of farm labour, transportation, and security.

Rahman and Bahar (2020) [21] conducted a literature review of "the COVID-19 pandemic and its devastating consequences on global economies since its commencement". The design was a narrative of the pandemic's causes, spread, and consequences. To this end, the narration basically examined the symptom, diagnosis, and effective strategies for its management. Their evaluation revealed that the virus had defied all forms of treatment as it had no existing form of treatment or vaccine at the time; a development which made INF prevention practice the best. Ogundokun et al., (2020) [4] sought to forecast COVID-19 cases in Nigeria in order to determine the influence of travelling history and contacts on the spread of COVID-19 in Nigeria. They employed an ex-post facto research design on INF for the period March-May, 2020. The data were analysed using the least-squares technique. The results of the diagnostic checks conducted revealed that the model fitted well to the dataset. The travelling history and contacts made were observed to increase the likelihood of infection by eighty five percent and eighty-eight percent respectively.

In line with Arksey and O'Malley's scoping review of 2020, Adhikari et al., (2020) [22] investigated "epidemiology, causes, clinical manifestation and diagnosis, as well as prevention and control of coronavirus disease (COVID-19) during the early outbreak period". They employed 65 articles that were published before the end of January in 2020. Most of the articles were observed to have investigated the causes of the COVID-19 pandemic and a significant percentage of the studies were published by Chinese scholars. "Studies thus far have shown that the virus' origination is in connection with a seafood market in Wuhan, but specific animal associations have not been confirmed" (Adhikari et al., 2020). The major reported symptoms of the COVID-19 pandemic were fever, cough, fatigue, pneumonia, headache, diarrhoea, haemoptysis, and dyspnoea while the major suggestions identified as likely to reduce transmission were the "use of face masks, practices of hand hygiene, social/physical distancing, case detection, contact tracing, and quarantines".

Nadeem (2020) [23] discussed some articles on the COVID-19 pandemic by various journals and companies globally with the hope of updating the article as events concerning the pandemic unfold and more articles are published to reflect theses unfolding events.

As a result of the above mentioned, the following null hypotheses were tested:

- $H0_1$ The COVID-19 infections in Nigeria are not related to time
- $H0_2$ The COVID-19 infections and fatalities in Nigeria are not significantly related to the recoveries
- $H0_3$ The COVID-19 infections and recoveries in Nigeria are not significant related to the fatalities

## 3. Methodology

The study investigated the major COVID-19 indicators such as the infections, recoveries, and deaths in order to have an understanding of the pandemic's trend and thus permit a useful forecast of the indicators (infections, recoveries, and fatalities) that will not deviate significantly from the actual values. Such a near accurate forecast will provide insights that will assist policymakers to adopt adequate measures to tackle the pandemic. The daily data on the target variables which were the major COVID-19 indicators (infections, recoveries, and deaths) were studied for four months consecutively. Thus, the design of the study was longitudinal and ex-post facto. Longitudinal because the data constituted a sequence of observations that were successively measured over a one-day time interval for four months. It was ex-post facto because the researcher had no ability to influence the data. The data were obtained from the daily updates of COVID-19 records of the Nigeria Centre for Disease Control (NCDC) (2020) [24] for May 2020 to August 2020 (113 days). The data were obtained online from the NCDC Website. The data were examined for outliers using the SPSS software's Analyse-descriptive, explore-outliers' option but there was no outlier.

### *3.1. Measurement of Variables*

The values of the COVID-19 infections, recoveries, and deaths have absolute zeros and are characterised by the existence of equal intervals between neighbouring points, which is consistent with ration measurement. To this end, the studies' variables are ratio. Thus, the dependent and independent variables were ratio measured. COVID-19 infections served as the dependent variable in one of the models with time as the independent variable; COVID-19 recoveries served as the dependent variable in the second model with time, infection, and fatalities as the independent variables while COVID-19 Fatalities served as the dependent variable in the third model with time, infections, and recoveries as the independent variables. The time (T) is also ratio measured but specifically in days.

### *3.2. Method of Data Analysis*

In order to know whether linear models will be suitable to the data, the data were tested for linearity. The linearity tests were accomplished through the use of line charts; thereafter, linearity tests were performed through the use of the scatter plot dialog box in SPSS software. The results of the linearity tests established consistency of the data with linearity characteristics. Consequently, further tests were conducted; they include the percentage tests and least-squares test. The percentage tests served to demonstrate how the infections and recoveries arising from the COVID-19 cases change with time. Lastly, two tests of significance of data, the least square and the autoregressive distributed lag system (ARDL) test were performed to determine how the COVID-19 infections relate with time in Nigeria (time measured in days), how recoveries relate with time (days), infections and deaths as well as the relationships between the COVID-19 fatalities, time (days), infections and recoveries.

#### 3.2.1. Model Specifications

This section presents the models of the study. Three specific models are presented:

$$\mathrm{CINF} = \theta_0 + \theta_1\,\mathrm{TM} + \mathrm{e} \tag{1}$$

$$\mathrm{CRCV} = \delta_0 + \delta_1 \mathrm{TM} + \delta_2 \mathrm{CINF} + \delta_3\,\mathrm{CFT} + \mathrm{e} \tag{2}$$

$$\mathrm{CFT} = \varphi_0 + \varphi_1 \mathrm{TM} + \varphi_2\,\mathrm{CINF} + \varphi\,\mathrm{CRV} + \mathrm{e} \tag{3}$$

where

CINF = infectious cases of COVID-19
TM = the time (days) from May to August 2020
CRCV = COVID-19 recoveries from confirmed cases
CFT = COVID-19 fatalities from confirmed cases

$\theta_0$ = Part of the changes experienced in COVID-19 infections that is not traceable to the changes in time
$\theta_1$ = Part of the changes in COVID-19 infections that variation in time can account for
$\delta_0$ = The portion of the changes in COVID-19 recoveries that cannot be traced to the changes in the independent variables
$\delta_i - \delta_3$ = coefficients of the independent variables
$\varphi_0$ = the aspect of the changes in COVID-19 deaths that is not caused by the independent variables
$\varphi_1 - \varphi_3$ = coefficients of the independent variables
e = Random error associated with the measurement of the variables.

Consistent with Inegbedion et al., (2020), Equations (1)–(3) are used to capture the models, which indicate how COVID-19 infections and time (days) relate in the long run, how COVID-19 recoveries and the predictors relate in the long run, as well as how COVID-19 deaths and the independent variables relate in the long run. These equations can be adjusted to enable them to reflect the short-run dynamic adjustment mechanism. This can be done as presented below:

$$\delta\ \mathrm{CRCV}_{t,j} = \theta_0 + \sum_{i=1}^{m1} \theta_{1i,j}\delta\ \mathrm{CRCV}_{t-1,j} + \sum_{i=0}^{m2} \theta_{2i,j}\delta\ \mathrm{FTL}_{t-1,j} + \sum_{i=0}^{m3} \theta_{3i,j}\delta\ \mathrm{CIN}_{t-1,j} + \sum_{i=0}^{m4} \theta_{4i,j}\delta\ \mathrm{CFT}_{t-1,j} + \rho_{t-1,\ i} + \mu_t \quad (4)$$

where:

$\delta$ is the "change in" is the change of differencing operator,
$m_i$ ($i$ =1, 3, ... 5) = represents the number of lags,
$\rho_{t-1}$ is the error term.

A fundamental assumption in this estimation technique is that the variables are cointegrated, but the error term is assumed to be stationary, i.e., I(0). "But if the variables in (1), instead of exhibiting I(I), they have a combination of I(1) and I(0) then another method of co-integration (ARDL) is employed; this technique is that of Pesaran, Shin and Smith (2001)". By combining the lagged variables linearly $\rho_{t-1}$ in (2) is replaced with its equivalent in (5).

Solving (2) and lagging the result by one period and substituting (4) yields (5).

$$\delta\ \mathrm{CRCV}_{t,j} = \pi_0 + \sum_{i=1}^{n1} \pi_{1i,j}\delta\ \mathrm{CRCV}_{t-1,j} + \sum_{i=0}^{n2} \pi_{2i,j}\delta\ \mathrm{TM}_{t-1,j} + \sum_{i=0}^{n3} \pi_{3i,j}\delta\ \mathrm{CINF}_{t-1,j} + \sum_{i=0}^{n4} \pi_{4i,j}\delta\ \mathrm{CFT}_{t-1,j} + \pi_5\mathrm{TM}_{t-1} + \pi_6\mathrm{CINF}_{t-1} + \pi_7\mathrm{CFT}_{t-1} \quad (5)$$

### 3.2.2. Test for Normality and Significance of Forecast Errors

After forecasting infections, recoveries, and fatalities, it became necessary to forecast the errors in order to determine the accuracy of forecasts. The forecast errors were computed using the formula; e = Forecast − actual. Thereafter, a test for normality was performed on the forecast errors using the one sample Kolmogorov Smirnov statistic. Furthermore, a test for significance was performed for the forecast errors to determine whether the errors are significantly different from one percent, because one per cent deviation of the forecast errors was assumed not to be significant.

## 4. Findings

In order to determine the appropriate statistic to employ in the test for significance of data, stationarity test was performed using the augmented Dickey Fuller statistic. In addition, a cointegration test was also performed to ascertain whether a long-run relationship exist between the variables. The results of the stationarity test and cointegration test are presented in Sections 4.1 and 4.2.

### *4.1. Stationarity and Cointegration Tests*

The results indicate the variables was stationary at level, but all were stationary at the first difference (see the results in Table 1).The cointegration test results indicate that the variables are not cointegrate, thus ruling out the possibility of any long-run relationship (see the results in Table 2).The results prompted the choice of the ARDL for the test for significance of data.

**Table 1.** Augmented Dickey Fuller Test for Unit Root.

| S/N | Variable | $p$ Value at Level | $p$ Value at First Diff. | Significant at |
|---|---|---|---|---|
| 1 | Infections | 0.9917 | 0.030 | First Difference |
| 2 | Recoveries | 0.7877 | <0.01 | First Difference |
| 3 | Fatalities | 0.3745 | <0.01 | First Difference |

**Table 2.** Cointeration Test.

| Hypothesized | | | 0.05 | |
|---|---|---|---|---|
| Number of Coffs. | Eigenvalue | Trace | Critical Value | Sig. Prob |
| None | 0.4253 | 113.8462 | 95.7537 | 0.0016 ** |
| At most 1 | 0.3738 | 78.9463 | 61.8189 | 0.0078 ** |
| At most 2 | 0.3097 | 49.4564 | 47.8561 | 0.0352 * |

Note: * means significant t five per cent (5%); ** means significant at one percent (1%).

### *4.2. Estimation of the Infections, Recoveries and Fatalities of COVID-19*

The first model was that of infections and time. The results of the test revealed the specific forecast model of infections is:

$$\text{CINF} = 195.2 + 0.96\ \text{CINF}\ (-1) + 19.42\text{TM}$$

The t-statistics for the test of significance of the coefficients and the $p$ values were 3.91 ($p < 0.001$), 4.07 ($p < 0.001$) and 9.80 ($p < 0.001$) for constant, one period lagged value of infections, and time respectively. Thus, there is a statistically significant positive relationship between the infections and time. This explains the surge in the cases of infections. One period lagged values of infection also exhibited a significantly positively relationship with infections. In other words, lagged values of infections significantly influence future values. The goodness of fit test presented an adjusted R squared value of 0.996; this implies that 99.6% variance in infections is due to the variance in time. Furthermore, the D-W statistic had a computed value of 1.8634, which is within the acceptable limits of the Durbin Watson statistic at a 5% level. Thus, the stochastic error terms are not serially correlated (Table 3).

**Table 3.** Infections as a Function of Time.

| Variable | Coefficient | Standard Error | t | Sig P |
|---|---|---|---|---|
| Infections | (−1) 0.963 | 0.0101 | 9.795 | 0.000 ** |
| Time (T) | 19.8419 | 4.8778 | 4.068 | 0.0001 ** |
| C | 195.17 | 49.949 | 3.91 | 0.0002 * |
| Adjusted R-square | 0.9960 | Durbin-Watson Statistic | | 1.8634 |

Note: * means significant t five per cent (5%); ** means significant at one percent (1%).

The recoveries against infection and fatalities yielded the following forecast model:

$$\text{CRCV} = 381.4 + 0.93\ \text{CRCV}\ (-1) + 0.21\text{CINF} - 7.87\ \text{CFT}$$

The $t$-test for regression coefficients with the $p$ values were 1.02 (0.31), 30.3 ($p < 0.001$), 2.16 (0.033) and −1.804 (0.074) for the constant, lagged value of recoveries, infections, and fatalities, respectively. Consequent upon the $p$ values, the lagged values of recoveries and infections have statistically significant positive relationships with recoveries. In addition, fatalities had a negative but statistically insignificant relationship with recoveries Thus, recoveries have a significant positive relationship with infections in Nigeria. The significant direct association between COVID-19 recoveries and infections is responsible for the persistent increase in the cases of COVID-19 recoveries with increases in the cases of infections (See Table 4).

**Table 4.** Recoveries as a function of Infections and Fatalities.

| Variable | Coefficient | Standard Error | t | Sig P |
|---|---|---|---|---|
| COVID-19 Recoveries | (−1) 0.93 | 0.0310 | 30.2649 | 0.000 ** |
| COVID-19 Infections | 0.2082 | 0.0964 | 2.1596 | 0.033 * |
| COVID-19 Fataliti | −7.869 | 4.3629 | −1.8037 | 0.074 |
| C | 381.40 | 376.39 | 1.0156 | 0.3120 |
| Adjusted R-square | 0.9237 | Durbin-Watson Statistic | | 2.0539 |

Note: * means significant t five per cent (5%); ** means significant at one percent (1%).

Furthermore, lagged values of recoveries were significant, which means that lagged values of recoveries have significant influence on the future values. Nevertheless, fatalities had no significant influence on recoveries. The value of the adjusted coefficient of determination was 0.927, which indicates that 92.7% variance in recoveries is attributable to variances in the predictors. Finally, the D-W statistic of 1.8634 is within permissible limits at the 5% level, thus indicating that the error terms are not serially correlated (See Table 4).

The test of Fatalities against infection and recoveries showed that the forecast model of recoveries is:

$$CFT = 14.71 + 1.04\ CFT\ (-1) + 0.0007\ CINF - 0.000122\ CRCV$$

The t-statistics and $p$ values were 16.5 ($p < 0.01$), −1.17 (0.24), −0.74 (0.46) and 2.91 (0.044) for the constant, lagged value of fatalities, infections, and recoveries, respectively. Thus, lagged values of fatalities are significant. Infections and recoveries have insignificant inverse relationships with fatalities. To this end only the lagged fatalities are significant predictors of fatalities. The adjusted R squared value of 0.986 indicates that variations in the independent variables account for 98.6% variations in fatalities. Lastly, the computed D-W statistic of 1.94 is within permissible limits, thus indicating that the stochastic error terms are okay (Table 5).

**Table 5.** Fatalities with Infections and Recoveries as predictors.

| Variable | Coefficient | Standard Error | t | Sig P |
|---|---|---|---|---|
| COVID-19 Fatalities | (−1) 1.0373 | 0.0256 | 16.53 | 0.000 ** |
| COVID-19 Infections | −0.00066 | 0.0056 | 1.173 | 0.2434 |
| COVID-19 Recoveries | −0.000122 | 0.00017 | −0.734 | 0.4646 |
| C | 14.706 | 1.9607 | 2.911 | 0.0044 ** |
| Adjusted R-square | 0.9864 | Durbin-Watson Statistic | | 1.9419 |

Note: ** means significant at one percent (1%).

The obtained model in Table 3 was used to test for the adequacy of the forecasts of infections (see Table 6). Similarly, the models obtained from Tables 4 and 5 were used to test the adequacies of the forecasts of recoveries and fatalities respectively (See Tables 7 and 8).

**Table 6.** Cases of COVID-19 Infections in Nigeria (May–August, 2020).

| T | Date | Forecasted Infections CI = 195.17 + 0.963CI (−1) + 19.84T | Actual Infections | Deviation | % Change | Absolute % Change |
|---|---|---|---|---|---|---|
| | | 1932 | | | | |
| **1** | **01/05** | 2147 | 2170 | −23 | −1.1 | 1.1 |
| **7** | **07/05** | 3363 | 3526 | −163 | −4.6 | 4.6 |
| **14** | **14/05** | 5087 | 5162 | −75 | −2.37 | 2.37 |
| **21** | **21/05** | 7042 | 7016 | 26 | 0.37 | 0.37 |
| **28** | **28/05** | 9161 | 8915 | 246 | 2.76 | 2.76 |
| **31** | **31/05** | 10,300 | 10,162 | 136 | 1.36 | 1.36 |
| **32** | **01/06** | 10,597 | 10,578 | 19 | 0.18 | 0.18 |
| **38** | **07/06** | 12,730 | 12,846 | −116 | −0.9 | 0.9 |
| **45** | **14/06** | 16,190 | 16,085 | 105 | 0.65 | 0.65 |
| **52** | **21/06** | 20,302 | 20,244 | 56 | 0.29 | 0.29 |
| **59** | **28/06** | 24,551 | 24,567 | −16 | −0.07 | 0.07 |
| **61** | **30/06** | 25,609 | 25,694 | −85 | −0.33 | 0.33 |
| **62** | **01/07** | 26,169 | 26,484 | −315 | −1.19 | 1.19 |
| **68** | **07/07** | 29,471 | 29,789 | −318 | −1.07 | 1.07 |
| **75** | **14/07** | 33,610 | 33,616 | −6 | −0.018 | 0.018 |
| **82** | **21/07** | 37,670 | 37,801 | −131 | −0.35 | 0.35 |
| **89** | **28/07** | 41,617 | 41,804 | −187 | −0.45 | 0.45 |
| **92** | **31/07** | 43,130 | 43,151 | −21 | −0.05 | 0.05 |
| **93** | **01/08** | 43,595 | 43,537 | 58 | 0.13 | 0.13 |
| **99** | **07/08** | 45,729 | 45,687 | 42 | 0.092 | 0.092 |
| **106** | **14/08** | 48,634 | 48,445 | 189 | 0.39 | 0.39 |
| **113** | **21/08** | 51,516 | 51,304 | 212 | 0.41 | 0.41 |

**Table 7.** COVID-19 Recoveries in Nigeria within the period 1 May–23 August 2020.

| Date | Forecasted Recoveries CR = 381.4 + 0.96CR(−1) +0.21CI−7.87CF | Actual Recoveries | Infections | Fatalities | Dev. | % Δ | ∣% Δ∣ |
|---|---|---|---|---|---|---|---|
| | | 319 | | | | | |
| **01/05** | 539 | 352 | 2170 | 68 | 187 | 53 | 53 |
| **07/05** | 607 | 601 | 3526 | 107 | 6 | 0.991 | 0.99 |
| **14/05** | 1146 | 1180 | 5162 | 167 | −33.77 | −2.86 | 2.86 |
| **21/05** | 1853 | 1907 | 7016 | 211 | −54 | 0.03 | 0.03 |
| **28/05** | 2542 | 2501 | 8915 | 259 | 40 | 1.6 | 1.6 |
| **31/05** | 3023 | 3007 | 10,162 | 287 | 16 | 0.53 | 0.53 |
| **01/06** | 3141 | 3122 | 10,578 | 299 | 19 | 0.61 | 0.61 |
| **07/06** | 3946 | 3959 | 12,846 | 354 | −13 | −0.33 | 0.33 |

**Table 7.** *Cont.*

| Date | Forecasted Recoveries CR = 381.4 + 0.96CR(−1) +0.21CI−7.87CF | Actual Recoveries | Infections | Fatalities | Dev. | % Δ | ǀ % Δ ǀ |
|---|---|---|---|---|---|---|---|
| **14/06** | 5216 | 5220 | 16,085 | 420 | −5 | −0.096 | 0.096 |
| **21/06** | 6804 | 6879 | 20,244 | 518 | −75 | −1.09 | 1.09 |
| **28/06** | 9115 | 9007 | 24,567 | 565 | 108.17 | 1.2 | 1.2 |
| **30/06** | 9878 | 9746 | 25,694 | 590 | 132 | 1.4 | 1.4 |
| **01/07** | 10,258 | 10,152 | 26,484 | 603 | 106 | 1.04 | 1.04 |
| **07/07** | 12,532 | 12,108 | 29,789 | 669 | 424 | 3.5 | 3.5 |
| **14/07** | 13,752 | 13,792 | 33,616 | 754 | −39.91 | −0.29 | 0.29 |
| **21/07** | 16,244 | 15,677 | 37,801 | 805 | 567 | 3.62 | 3.62 |
| **28/07** | 19,258 | 18,764 | 41,804 | 869 | 534 | 2.85 | 2.85 |
| **31/07** | 20,446 | 19,565 | 43,151 | 879 | 881 | 4.5 | 4.5 |
| **01/08** | 20,389 | 20,087 | 43,537 | 883 | 302 | 1.5 | 1.5 |
| **07/08** | 32,769 | 32,637 | 45,687 | 936 | 132 | 0.41 | 0.41 |
| **14/08** | 34,805 | 35,998 | 48,445 | 973 | −1193 | −3.31 | 3.31 |
| **21/08** | 38,256 | 37,885 | 51,304 | 996 | 371 | 0.98 | 0.98s |

**Table 8.** COVID-19 Fatalities in Nigeria within the period 1 May–23 August 2020.

| Date | Forecasted Fatalities CR = 14.5 + 0.90CF (−1) +0.0024CI − 0.0008CR | Actual Fatalities | Recoveries | Infections | Dev. | % Δ | ǀ % Δ ǀ |
|---|---|---|---|---|---|---|---|
| | | 58 | | | | | |
| **01/05** | 66 | 68 | 352 | 2170 | −2 | −2.94 | 2.94 |
| **07/05** | 110 | 107 | 601 | 3526 | 3 | 2.8 | 2.8 |
| **14/05** | 173 | 167 | 1180 | 5162 | 6 | 3.6 | |
| **21/05** | 205 | 211 | 1907 | 7016 | −6 | −2.84 | 2.84 |
| **28/05** | 363 | 259 | 2501 | 8915 | 4 | 1.54 | 1.54 |
| **31/05** | 276 | 287 | 3007 | 10,162 | −11 | −3.83 | 3.83 |
| **01/06** | 296 | 299 | 3122 | 10,578 | −3 | −1 | 1 |
| **07/06** | 352 | 354 | 3959 | 12,846 | −2 | −0.56 | 0.56 |
| **14/06** | 417 | 420 | 5220 | 16,085 | −3 | −0.71 | 0.71 |
| **21/06** | 518 | 518 | 6879 | 20,244 | 0 | 0 | 0 |
| **28/06** | 568 | 565 | 9007 | 24,567 | 3 | 0.53 | 0.53 |
| **30/06** | 582 | 590 | 9746 | 25,694 | −8 | −1.4 | 1.4 |
| **01/07** | 600 | 603 | 10,152 | 26,484 | −3 | −0.50 | 0.50 |
| **07/07** | 670 | 669 | 12,108 | 29,789 | 1 | 0.15 | 0.15 |
| **14/07** | 754 | 754 | 13,792 | 33,616 | 0 | 0 | 0 |
| **21/07** | 810 | 805 | 15,677 | 37,801 | 5 | 0.62 | 0.62 |

**Table 8.** *Cont.*

| Date | Forecasted Fatalities CR = 14.5 + 0.90CF (−1) +0.0024CI − 0.0008CR | Actual Fatalities | Recoveries | Infections | Dev. | % Δ | ǀ % Δ ǀ |
|---|---|---|---|---|---|---|---|
| **28/07** | 869 | 869 | 18,764 | 41,804 | 0 | 0 | 0 |
| **31/07** | 886 | 879 | 19,565 | 43,151 | 7 | 0.80 | 0.80 |
| **01/08** | 887 | 883 | 20,087 | 43,537 | 4 | 0.45 | 0.45 |
| **07/08** | 937 | 936 | 32,637 | 45,687 | 1 | 0.11 | 0.11 |
| **14/08** | 972 | 973 | 35,998 | 48,445 | −1 | −0.1 | 0.1 |
| **21/08** | 997 | 996 | 37,885 | 51,304 | 1 | 0.1 | 0.1 |

Source: Author's computation

Lastly, owing to the fact that infections were solely dependent on time, the relationship between infection and time was analysed using least-square technique. This is because the ARDL was not suitable. The predicted infections were 51,304, 55,329, 59,970, 65,216 and 71,067 for 31 August, 30 September, 31 October, 30 November, and 31 December, respectively. The predicted recoveries were 52,791, 54,767 and 67,509 for October, November, and December, respectively, while the predicted Fatalities were 1099, 1266 and 1315 for October, November and December, respectively.

*4.3. Discussion of Findings*

The study's first objective sought to investigate the relationship between time and COVID-19 infections. The corresponding null hypothesis was tested, and a statistically significant positive association was established between time and infections based on the *p* values. The implication is that time is a significant predictor of the COVID-19 infections in Nigeria. This outcome suggests two likely implications. The first implication of the finding is that as the number of people tested increases, which is a function of time, the possibility of more infections increases. The other implication is that in the short run, more people get infected as a result of exposure by contacts with time; thus, time is very critical to the changes in infections whether due to the increase in the number of people tested or due to the likelihood of exposure to infected people as a result of contacts. The bottom line of the first objective is that infectious cases increase with time. The results are not different from the points of view of Ogundokun et al., (2020) as well as Ayinde et al., (2020).

The study's second objective sought to ascertain how the COVID-19 infections and fatalities affect recoveries. The associated null hypothesis was tested to find out the nature of the influence of infections and fatalities on COVID-19 recoveries. Based on the asymptotic significant probabilities, lagged values of COVID-19 recoveries had statistically significant association with current values and COVID-19 recoveries had a statistically significant association with infections. However, despite exhibiting a negative relationship with COVID-19 recoveries, the fatalities did not have a statistically significant relationship with COVID-19 recoveries. To this end, increased COVID-19 infectious cases stimulate increases in recoveries because the number of recoveries is a function of the number of infections cases that are treated. In other words, the number of recoveries depend of the number of people infected that are treated. This being the case, as long as recovery is possible, no matter how low the recovery rate is, the number of recoveries must increase as the number of infections increase, because every new case of infection has the chance to recover. The results support the findings of Ayinde et al., (2020).

The study's third objective sought to investigate the extent to which COVID-19 infections and recoveries influence fatalities. Accordingly, the corresponding null hypothesis was "there is no significant relationship between COVID-19 infections and fatalities" as well as "there is no significant relationship between COVID-19 recoveries and fatalities". Based on the asymptotic significant probability of the test, the results revealed that lagged values of

COVID-19 fatalities had a statistically significant influence on current values. The results also indicated that COVID-19 infections had a negative but insignificant relationship to fatalities, and that COVID-19 recoveries did not significantly influence fatalities. The findings suggest that COVID-19 infections do not predict fatalities neither do recoveries predict fatalities. Consequently, the results were used to make projection of COVID-19 infections. The projected cases on infections indicate that the COVID-19 infections will be constant in the last five months of the year (August–December). The projections suggest that the curve of infections will flatten within the period. The projected flattening of the curve suggests that there will be a slow and gradual convergence of the infection in Nigeria given a sustenance of the current trend. The results support the finding of Oyinlola et al., (2020).

The results of the normality tests (See Table 9), autocorrelation, and test for significance of forecast errors (See Table 10) are suggestive of accurate forecasts and that the study's models are very adequate (See Table 11). Table 12 shows how the forecasted indicators compared with the actual cases for October–December 2020. Based on the results of the study it is evident that the forecasts did not deviate significantly from the actual parameters.

**Table 9.** Test for Normality of the Forecast Errors (Kolmogorov Smirnov Test).

| Variable | Z | Significant P | Remark |
|---|---|---|---|
| Infections | 0.561 | 0.911 | Normal |
| Recoveries | 1.261 | 0.083 | Normal |
| Fatalities | 0.599 | 0.865 | Normal |

**Table 10.** Test for Significance of the Forecast Errors.

| Variable | Mean | t | Significant P | Remark |
|---|---|---|---|---|
| Infections | −16.682 | −0.517 | 0.610 | Not Significant |
| Recoveries | 109.61 | 1.348 | 0.192 | Not Significant |
| Fatalities | −0.061 | 1.191 | 0.850 | Not Significant |

**Table 11.** Results of the Autocorrelation tests of the Forecast Errors.

| | Box Ljung Statistic and Asymptotic Probabilities | | | |
|---|---|---|---|---|
| Variable | Lag 1 | Lag 2 | Lag 3 | Lag 4 |
| COVID-19 Infections | 0.094 (0.76) | 2.95 (0.23) | 3.01 (0.31) | 3.22 (0.52) |
| COVID-19 Recoveries | 0.23 (0.63) | 0.62 (0.73) | 2.74 (0.48) | 2.51 (0.64) |
| COVID-19 Fatalities | 0.06 (0.81) | 1.45 (0.49) | 1.52 (0.68) | 2.25 (0.69) |

**Table 12.** Actual versus Forecasted COVID-19 parameters.

| | | COVID-19 Infection | COVID-19 Recoveries | COVID-19 Fatalities |
|---|---|---|---|---|
| **October**: | Actual | 62,853 | 58,675 | 1144 |
| | Forecast | 59,969 | 52,791 | 1099 |
| | Deviation | −2884 (−4.59%) | −5904 (−10.06%) | −45 (−3.93%) |
| **November**: | Actual | 67,557 | 63,282 | 1173 |
| | Forecast | 65,216 | 54,767 | 1265 |
| | Deviation | −2341 (−2.47%) | −8515 (−13.5%) | 92 (7.8%) |
| **December**: | Actual | 86,576 | 73,322 | 1278 |
| | Forecast | 71,067 | 67,509 | 1314 |
| | Deviation | 15,509 (17.9%) | 5813 (7.9%) | 36 (2.03%) |

This study has made a significant contribution to knowledge in management science research through the modelling of the trend of COVID-19 infections, recoveries, and fatalities in Nigeria using standard forecasting methodology. The prediction of infections has provided useful insights about the COVID-19 pandemic that is useful for policymaking on mitigation of the infections as well as what to do in the post-pandemic era. This study, to the best of the author's knowledge, is the first study to investigate the research problem in this magnitude in Nigeria considering the volume of data and the indicators employed as well as the variables studied and the combination of forecasting techniques employed. These factors, to a significant extent, make the work novel.

Despite the contributions of the study, it was not without limitations. The study's major constraint is the restriction in testing. The testing capacity in Nigeria was very low, thus making the proportion of infectious cases tested to the total number of infectious cases insignificant. This was due to Nigeria's restricted testing capacity. The restricted testing capacity was a source of constraint to the reported cases of infections. There is a probability that some infected cases who were not tested may not have been declared infected and thus not counted among the infected cases because they were not tested. To this end, it is evident that the published cases of infection did not reflect the actual cases of infection. The observed constraint does not vitiate the results of the test of significance of the relationship between infection and time because the tested people represent the population and as the number of tests increase, the proportion of infections increase, when everyone is eventually tested the parameters of the indicators should not differ significantly from the statistics of the indicators.

### 4.4. Implications for Policy

The findings of the study have significant implications for policymaking. To this end, policymakers in government, labour union leaders in the health sector, health workers and other major stakeholders will find the results useful for policymaking for the COVID-19 pandemic as well as for other health challenges. There is no doubt that the COVID-19 pandemic got major stakeholders overwhelmed, but the results of this study indicate that the government efforts at managing the pandemic have paid off since the rate of infections and fatalities are expected to converge in the near future. The prediction that the curve of infections will flatten in the last five months of the year suggests that policymakers in the three tiers of government strategize on the possible containment strategies that will not constrain a total unlocking of the system. This will facilitate the restoration of full economic and social activities in a post-COVID-19 era. The restriction in economic activities during the COVID-19 lockdown adversely affected the economy. To this end the policymakers should, as a matter of urgency, make plans to fully unlock the economy for full restoration of economic activities. Efforts should be made to plan for lost grounds to enable the students meet up in line with the educational curriculum. Thus, policymakers should forthwith give the reopening of educational institutions top priority to enable them to commence academic activities and thus complete the uncompleted academic sessions.

## 5. Conclusions

The infections arising from the COVID-19 pandemic were initially rising uncontrollably, but, even at that, Nigeria witnessed a significantly higher recovery rate than the rate of fatality. The higher recovery rate than the rate of infection gives credence to the policies put in place by the three tiers of government in Nigeria to manage the COVID-19 pandemic. In view of the problem definition and the research findings, the study concludes that the cases of infections arising from the COVID-19 pandemic in Nigeria are fizzling out, raising hopes of an imminent convergence due to the study's predicted flattening of the curve in the last five months of the year. The COVID-19 recovery rate is significantly higher than the rate of fatalities and infections. This means that if the current policies on COVID-19 management are sustained the convergence of the pandemic in Nigeria will occur within the shortest possible time and put paid to restrictions in all sectors.

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**Informed Consent Statement:** Informed consent was not necessary as human participants were not involved.

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