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## Article

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# Modelling the effect of Covid-19 mortality on the economy of Nigeria

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## ABSTRACT

**Objectives:** This paper is aimed at modelling the effect of COVID-19 mortality per population (CMP), a proxy for COVID-19 on the Gross Domestic Product (GDP) per capita per COVID-19 cases (RGDPC), a proxy for the economic wellbeing of a nation.

**Methods:** Nine models divided into three groups (Gaussian polynomial, other non-linear, and Gamma generalized polynomial models) were fitted for RGDPC data on CMP, collected from 1st June to 31st December 2020.

**Results:** The result showed that the gamma cubic model was selected as the best model out of the 9 competing models to predict the economic wellbeing of Nigeria. Predictions were made for the whole day in the year 2021.

**Conclusion:** It is therefore concluded that there is a non-linear relationship between COVID-19 mortality and the economic wellbeing of Nigerians. Thus, COVID-19 mortality has an adverse effect on the wellbeing of Nigerians. The economic wellbeing of Nigerians can be improved if COVID-19 mortality is stopped.

## 1. Introduction

Recently, an infectious disease called COVID-19, caused by a novel Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) (Adeniyi et al., 2020), which started in December 2019 from China (WHO, 2020), has infected people in all continents and countries of the world. The COVID-19 mortality rate varies from country to country. In Nigeria, the mortality rate is very low when compared to other countries in Europe and America. The recovery rate is very high in Nigeria, leaving a few active cases. This novel coronavirus was isolated on 7th January 2020 in China (Ekum & Ogunsanya, 2020). Currently, some countries have been able to manage cases with a high rate of recovery, while the body's immune system fights the illness (Are & Ekum, 2020). Just recently some laboratories have developed one vaccine or the other for COVID-19, and these vaccines have been distributed to some countries of the world, including Nigeria.

COVID-19 in Nigeria started with the case of an Italian Immigrant, who travelled from Milan to Lagos on the 28th February 2020. The first death in Nigeria was recorded on 26th March 2020. By 1st June 2020 the total COVID-19 induced deaths in Nigeria has increased to 299, and at the end of the year 2020, that is, 31st December 2020, the COVID-19 induced deaths had increased to 1,289 (NCDC, 2021; WHO, 2021). This COVID-19 mortality has crippled many aspects of the economy, thereby reducing the economic wellbeing of Nigeria. The Gross

Domestic Product per capita (RGDP) is not the real measure of the economic wellbeing of nations, but the RGDP per COVID-19 cases (RGDPC). This measure did not just take into account the population of a nation, but also take into account of the burden placed by COVID-19 mortality on the economy of a nation.

There are many types of research on COVID-19 already published in learned journals and there are many ongoing. The first set of notable researches on COVID-19 focused more on the spread and dynamics of the spread of the virus (Huang et al., 2020; Liu et al., 2020; Read et al., 2020; Zhao et al., 2020; Imai et al., 2020; Tang et al., 2020; Qun et al., 2020; Chen & Yu, 2020; Li et al., 2020; Ferguson et al., 2020; Kucharski et al., 2020; Wu et al., 2020; Roosa et al., 2020; Thomala, 2020; Xu et al., 2020; McMichael et al., 2020; Healy & Kovaleski, 2020; Chen et al., 2020; Hellewell et al., 2020; Yang et al., 2020).

The next set of researches on COVID-19 focused on how to flatten the curve and cases of asymptomatic (Wu & McGoogan, 2020; Oran and Topol, 2020; Adeniyi et al., 2020a, 2020b; Isere et al., 2020; Ekum & Ogunsanya, 2020; Ayinde et al., 2020; Ekum et al., 2020a; Subramanian et al., 2021). Today, many researchers on COVID-19 are studying the effect of COVID-19 on the economy of nations (see Abayomi et al., 2021; Hassan, Hashim, & Khan, 2020; Sornette, Mearns, Schatz, Wu, & Darcet, 2020; Cilliers et al., 2020; Chudik et al., 2020; Erokhin & Gao, 2020; Ivanaj & Oukhallou, 2020).

Nigeria is a mixed economy and emerging market, with expanding

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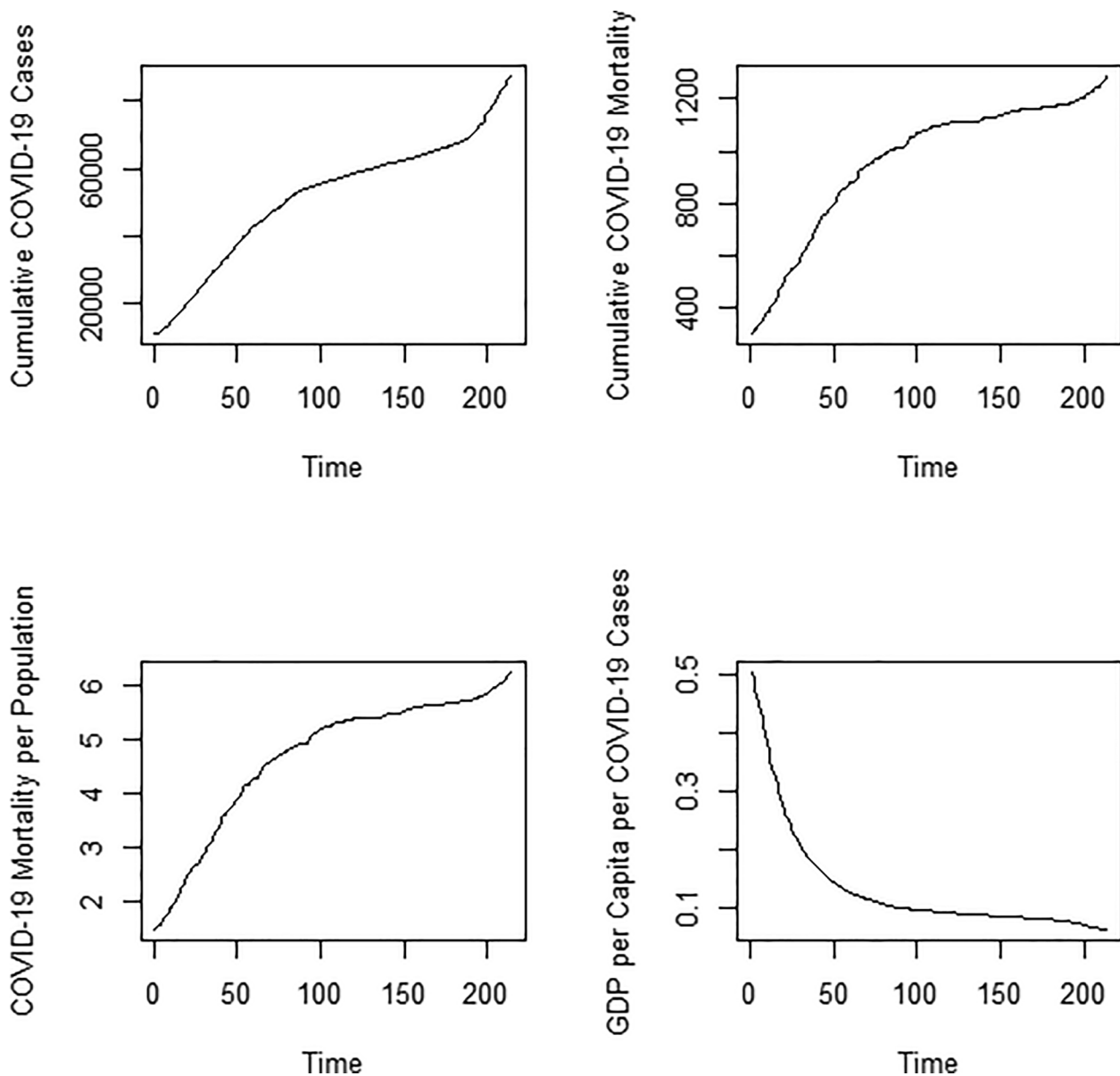


Fig. 1. Time Plots of Variables of Interest.

financial, service, communications, technology, and entertainment sectors. Nigeria was ranked 26th in the world in terms of nominal GDP and ranked 30th in 2013 before rebasing, ranked 40th in 2005 and 52nd in 2000, and is the largest economy in Africa based on the rebased figures announced in 2014. It is also on track to become one of the top economies in the world by 2020 (Okunnu et al., 2017). The GDP of Nigeria is affected by the large population figure, which has reduced the Gross Domestic Product per capita (RGDP) of Nigeria. According to World Bank statistics reported in 2016, the RGDP in Nigeria was 2,548.20 United States Dollar (USD) in 2015 with an estimated population of 181,100,000 persons but has reduced to 2,250.00 USD in 2020 with an estimated population of 206,000,000 persons, which is not unconnected to the surge created by COVID-19.

So, a measure of the wellbeing of Nigeria takes the susceptible population into consideration, and the population already infected by COVID-19. Thus, an index termed the GDP per capita per COVID-19 cases (RGDPC) is used as a proxy to measure the wellbeing of the people. The problem here is to determine the major factor that affects the RGDPC of a country like Nigeria. Some factors, such as COVID-19 mortality, population, etc., are factors considered. The problem of low

Gross Domestic Product Per Capita (RGDP) can be attributed to lack of adequate planning by the government (Ekum et al., 2020).

In this paper, we focused on the mortality rate per population and the non-linear effect on the economic wellbeing of Nigeria. The economy of Nigeria is proxy by Gross Domestic Product (GDP) per capita per COVID-19 confirmed laboratory cases (RGDPC) in Nigeria. The GDP per capita is one of the measures of the wellbeing of a people. It is further divided by the population that had suffered from COVID-19. RGDPC is the real measure of the economic well-being of people with infectious diseases. This is because, apart from the population affecting the GDP, the COVID-19 factor is also an extra burden to the wellbeing of the people. Different models were fitted, linear, non-linear and generalized linear models (glm) in this paper.

## 2. Methods and materials

Modelling the effect of one variable on another, where both variables are continuous requires a regression model. The relationship between the two variables can be linear or non-linear. It can be direct or indirect, and it can be strong or weak. Most often than not, we always want to

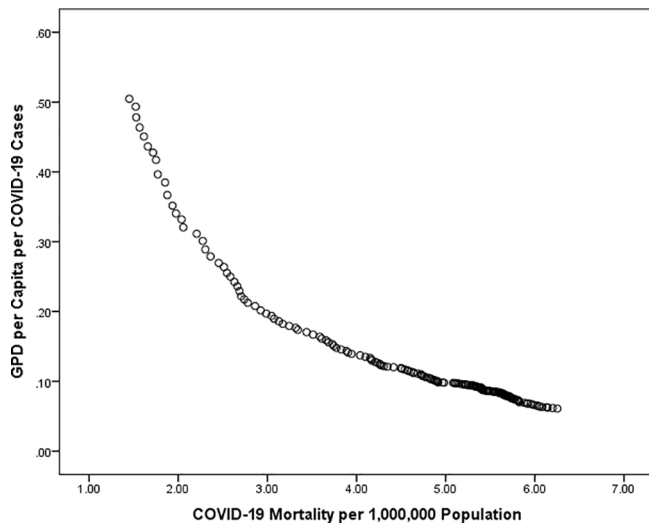


Fig. 2. Scatter Plot of GDP per Capita per COVID-19 on COVID-19 Mortality.

predict a random variable using another known random variable(s). In this case, we have only two variables, a dependent (RGDPC) and an independent (CMP), which can be related linearly or non-linearly, direct or indirect, weak or strong. The relationship will be modelled using curve estimation, which could be ordinary or generalized linear regression models, ordinary or generalized polynomial regression models, or other forms of non-linear models.

### 2.1. Data description

The data used in the analysis are daily data collected from World Health Organisation (WHO) from 1st June 2020 to 31st December 2020, spanning 214 datasets. The data include cumulative COVID-19 laboratory confirm cases, cumulative COVID-19 deaths, GDP per capita for the period, and Nigeria's population for the period under review. Two new variables used as dependent and independent variables were derived from the available known ones. The independent variable is a measure of COVID-19, termed COVID-19 Mortality per 1 million persons in the population (CMP), while the dependent variable is the GDP per capita per COVID-19 laboratory-confirmed cases (RGDPC). These two new variables are continuous variables (measurable), so the variation in them can be modelled with continuous distributions, like normal (Gaussian), Gamma, Weibull, Power, Pareto etc. The CMP is a proxy to measure COVID-19, while RGDPC is a proxy to measure the economic wellbeing of a country. If the RGDPC of a country is high, it implies that the economic wellbeing of that country is good, but if it is low, it implies that the economic wellbeing of the people is poor.

The CMP is given by

$$CMP = \frac{\text{Cumulative COVID19 Mortality}}{\text{Population}} \times K, \forall \text{Population} > 0$$

Where K can be 1,000 or 10,000 or 100,000 or 1,000,000, but in this paper, K = 1,000,000, and the RGDPC is given by

$$RGDPC = \frac{\text{GDPperCapita}}{\text{CumulativeCOVID19Cases}}, \forall \text{CumulativeCOVID19Cases} > 0$$

Table 1

Descriptive Statistics of COVID-19 Cases in Nigeria.

Variables	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
Cumulative Cases	10,578	87,607	51546.23	18744.314	-0.568	-0.436
Cumulative Mortality	299	1289	965.51	259.087	-1.134	0.122
COVID-19 Mortality per 1,000,000 Population	1.45	6.25	4.6838	1.25685	-1.134	0.122
GDP per Capita per COVID-19 Cases	0.06	0.50	0.1326	0.09194	2.334	5.041

These two measures can be included in demographic measures.

### 2.2. Curve estimation models

There are different curve regression models in Statistics. To determine which model to use, it is necessary to plot the scatter diagram, which depicts the type of relationship that exists between the dependent and independent variables. If the variables appear to be linearly related, then a simple linear regression model is needed. When the variables are not linearly related, try transforming the data. When a transformation does not help, a more complicated model is needed. It could be a non-linear model or a generalized linear model or an even more complicated models. The scatterplot of the data will show a plot that resembles a mathematical function recognized, then fit the data to that recognized model. There are different types of models, but the ones used in this paper are explained.

### 2.3. Polynomial model

Let  $Y$  be a dependent variable and  $X$  be an independent variable. Polynomial regression is a special case of multiple regression, with only one independent variable  $X$  (Ostertagová, 2012), with the dependent variable  $y \in Y$  linearly depending on the powers of the single independent variable  $x \in X$ ,  $(x, x^2, \dots, x^k)$ . A one-variable polynomial regression model with  $k$ th order can be expressed as

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \dots + \beta_k x_i^k + e_i; i = 1, 2, \dots, n. \quad (1)$$

where  $k$  is the order of the polynomial, the  $\beta$ s are the unknown parameters to be estimated, and  $e$  is the error term.

If  $k = 1$ , then equation (1) becomes

$$y_i = \beta_0 + \beta_1 x_i + e_i; i = 1, 2, \dots, n. \quad (2)$$

Equation (2) is a simple linear model.

If  $k = 2$ , then equation (1) becomes

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + e_i; i = 1, 2, \dots, n. \quad (3)$$

Equation (3) is a quadratic model.

If  $k = 3$ , then equation (1) becomes

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \beta_3 x_i^3 + e_i; i = 1, 2, \dots, n. \quad (4)$$

Equation (4) is a cubic model. Equations (2) to (4) are polynomial models of order 1, 2, and 3 respectively.

### 2.4. Other non-linear model

A non-linear model can be transformed into a linear model. If the transformation is possible, such a model is called an intrinsically linear model, but if the transformation is not possible, it is called an intrinsically non-linear model. The power, growth, and exponential models are good examples of an intrinsically linear model. A good example of the intrinsically non-linear model is the Cobb-Douglas production model (Ekum & Ogunsanya, 2020).

### 2.5. Power regression model

The power model is given by

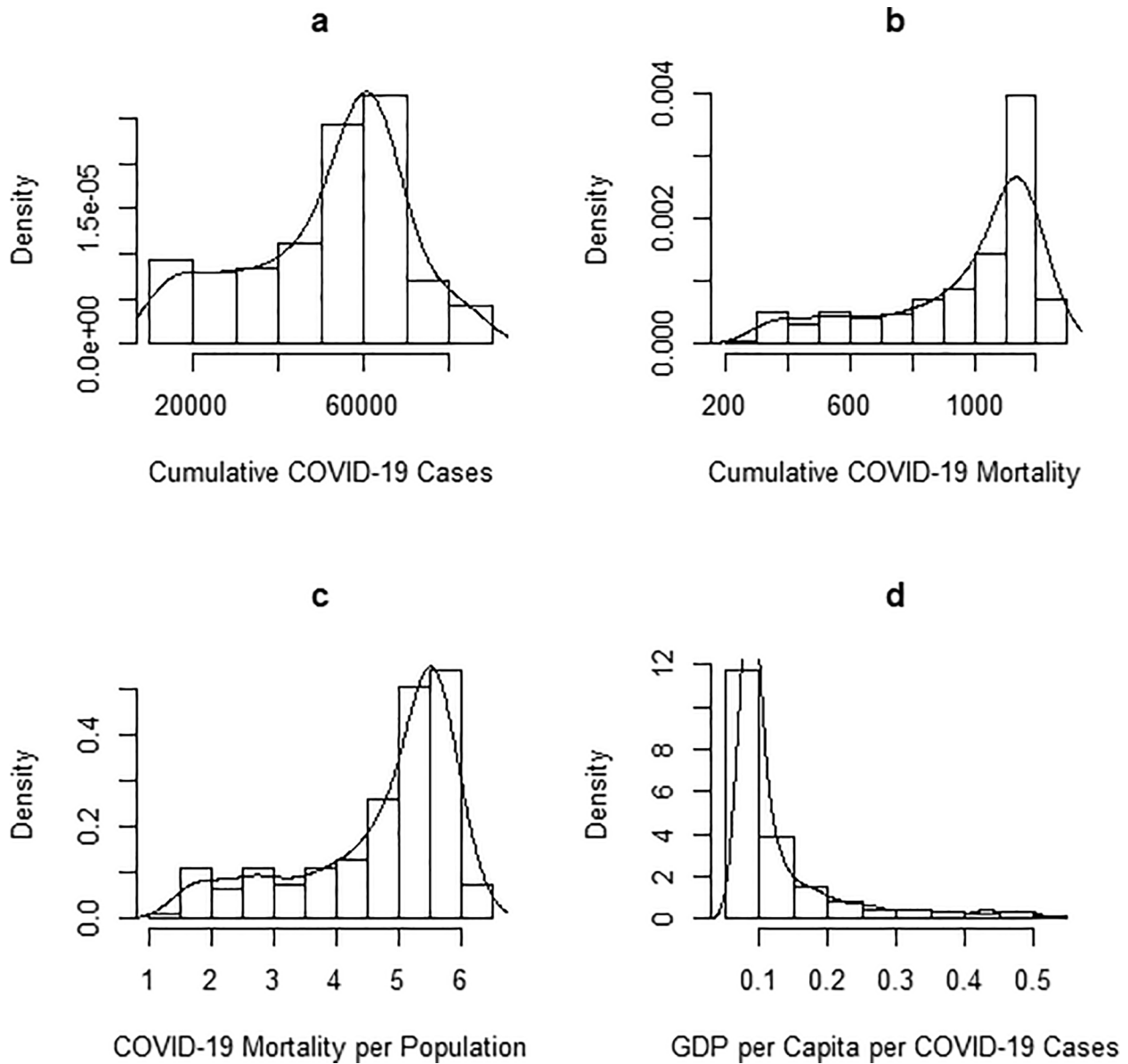


Fig. 3. Histogram with Curve of Data of Interest.

$$y_i = \beta_0 x_i^{\beta_1}; i = 1, 2, \dots, n. \quad (5)$$

Taking the log of equation (5) gives

$$\log y_i = \log \beta_0 + \beta_1 \log x_i; i = 1, 2, \dots, n. \quad (6)$$

So, equation (6) is the linear form of equation (5). Thus, the power model is intrinsically linear.

## 2.6. Growth regression model

The growth model is another intrinsically linear model. The growth model is given by

$$y_i = \exp(\beta_0 + \beta_1 x_i); i = 1, 2, \dots, n. \quad (7)$$

Taking the log of equation (7) gives

$$\log y_i = \beta_0 + \beta_1 x_i; i = 1, 2, \dots, n. \quad (8)$$

## 2.7. Exponential regression model

Finally, the exponential model is an intrinsically linear model given

by

$$y_i = \beta_0 \exp(\beta_1 x_i); i = 1, 2, \dots, n. \quad (9)$$

Taking the log of equation (9) gives

$$\log y_i = \log \beta_0 + \beta_1 x_i; i = 1, 2, \dots, n. \quad (10)$$

## 2.8. Generalized linear model (GLM)

The GLMs relate a dependent to independent variables about which information exists (Chen et al., 2020). The distribution of the dependent variable must be defined in GLM. The independent variables can be related to the dependent variable allowing for the random variation of the data (McCullagh & Nelder, 1989). GLMs are an extension of the classical linear model. Let  $Y$  be a dependent variable of  $n$  observations, which is randomly distributed with mean  $\mu$  and variance  $\sigma^2$  (Nelder & Wedderburn, 1972).

The general classical  $p$  variable linear model is used to study the relationship between a dependent variable and one or more independent variables (Ekum et al., 2015). The specification of such a model is given

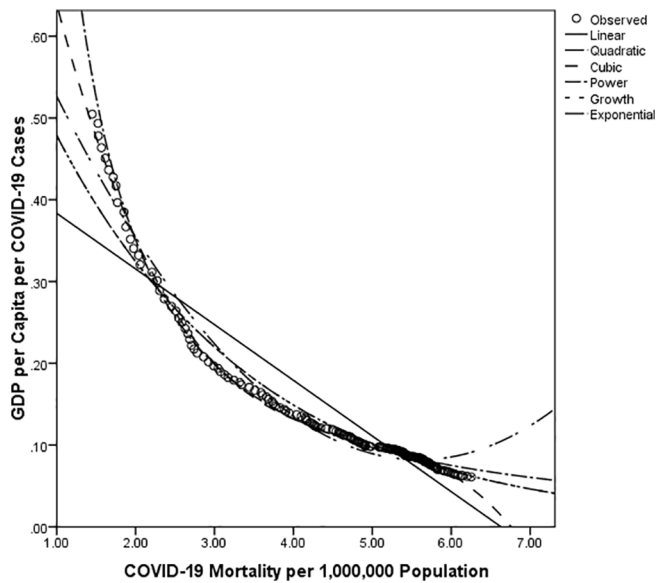


Fig. 4. Scatter Plots of the Effect of CMP on RGDP with Predicted Curves.

**Table 2**  
Gaussian Models Parameter Estimation and Model Selection Criteria.

Variables	Parameter Estimate (Standard Error)	F-Statistic	P-value	R <sup>2</sup>	MSE
Gaussian Linear Model	$\beta_0 = 0.452 (0.0089)$ $\beta_1 = -0.068 (0.0018)$	1378.04	0.000	0.867	0.001
Gaussian Quadratic Model	$\beta_0 = 0.741 (0.0106)$ $\beta_1 = -0.236 (0.0057)$ $\beta_2 = 0.021 (0.0007)$	3958.89	0.000	0.974	0.000
Gaussian Cubic Model	$\beta_0 = 1.106 (0.0097)$ $\beta_1 = -0.572 (0.0085)$ $\beta_2 = 0.114 (0.0023)$ $\beta_3 = -0.008 (0.0002)$	23805.45	0.000	0.997	0.000

**Table 3**  
Other Non-Linear Models Parameter Estimation and Model Selection Criteria.

Variables	Parameter Estimate (Standard Error)	F-Statistic	P-value	R <sup>2</sup>	MSE
Power Model	$\beta_0 = 0.928 (0.0140)$ $\beta_1 = -1.404 (0.010)$	21223.85	0.000	0.990	0.002
Growth Model	$\beta_0 = -0.347 (0.0170)$ $\beta_1 = -0.389 (0.0030)$	12739.51	0.000	0.984	0.004
Exponential Model	$\beta_0 = 0.707 (0.0120)$ $\beta_1 = -0.389 (0.0030)$	12739.51	0.000	0.984	0.004

**Table 4**  
Gamma Models Parameter Estimation and Model Selection Criteria.

Variables	Parameter Estimate (Standard Error)	LogL	AIC	BIC
Gamma Linear Model	$\beta_0 = -1.923 (0.0633)$ $\beta_1 = 2.442 (0.0200)$	234.32	-474.63	484.73
Gamma Quadratic Model	$\beta_0 = 0.447 (0.1155)$ $\beta_1 = 0.731 (0.0785)$ $\beta_2 = 0.245 (0.0111)$	135.25	-278.5	291.97
Gamma Cubic Model	$\beta_0 = -2.281 (0.2630)$ $\beta_1 = 3.621 (0.2694)$ $\beta_2 = -0.661 (0.0827)$ $\beta_3 = 0.086 (0.0078)$	58.45	126.91	143.74

as

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_p x_{pi} + e_i; i = 1, 2, \dots, n > 2p. \quad (11)$$

where  $p$  is the number of independent variables,  $n$  is the number of observations, the  $\beta$ s are the unknown parameters to be estimated, and  $e$  is the error term.

If  $p = 1$ , then equation (11) becomes a simple linear model given in equation (2). The systematic part of the model is a specification for the vector  $\mu$  in terms of  $\beta$ s. In the case of the ordinary linear model, the specification takes the form

$$E(y_i) = \mu_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_p x_{pi}; i = 1, 2, \dots, n > 2p. \quad (12)$$

Equation (12) is a special case of GLM, which is the ordinary linear model, with the expected value of  $y$  equal  $\mu$ , since  $Y$  has a Gaussian distribution. But if  $Y$  follows a distribution other than Gaussian, then the model in equation (12) will be written as

$$E(y_i) = g(\mu_i) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_p x_{pi}; i = 1, 2, \dots, n > 2p. \quad (13)$$

where  $g(\cdot)$  is called the link function. So, equation (13) is a generalization of equation (12).

In equation (12),  $Y$  is assumed to follow a Gaussian distribution, but in equation (13),  $Y$  can follow any other distribution in the exponential family.

The distribution in the class of the exponential family has a probability density function (pdf) that can be written in the form

$$f(y; \theta, \phi) = \exp \left\{ \frac{y\theta - b(\theta)}{a(\phi)} + c(y, \phi) \right\} \quad (14)$$

where  $a(\cdot)$ ,  $b(\cdot)$ , and  $c(\cdot)$  are known functions, provided  $\phi$  is known, and a canonical parameter  $\theta$  is known.

## 2.9. Generalized linear model (GLM)

If  $Y$  follows a gamma distribution with shape and scales parameters  $\alpha$  and  $\beta$  respectively, then the pdf of  $Y$  is given by

$$f(y) = \frac{\beta^\alpha}{\Gamma(\alpha)} y^{\alpha-1} e^{-\beta y}; \alpha, \beta > 0, y \geq 0 \quad (15)$$

Gamma written in the exponential family form is given by

$$f(y) = \exp \{ (\alpha - 1) \log y - [\log \Gamma(\alpha) - \alpha \log \beta] - \beta y \} \quad (16)$$

Comparing equation (16) with the exponential family pdf in equation (14) gives the following:

$$\theta = (\alpha - 1), \quad b(\theta) = [\log \Gamma(\alpha) - \alpha \log \beta], \quad c(y, \phi) = -\beta y, \quad a(\phi) = 1, \quad E(y) = \mu(\theta) = -1/\theta \quad \text{and} \quad V(\mu) = \mu^2. \quad \text{The sufficient statistics is } \log y.$$

Thus, the gamma GLM is written thus

$$-1/\mu_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_p x_{pi} \quad (17)$$

So, that equation (16) is written as

$$\mu_i = -1/(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_p x_{pi}) \quad (18)$$

## 3. Results and discussion

The data applied is the Nigeria COVID-19 data, comprising cumulative cases, cumulative deaths, GDP per capita, and population of Nigeria. The dependent variable is the RGDP. It is the GDP per capita divided by COVID-19 cases. The independent variable is CMP. The COVID-19 data is daily data, collected from 1st of June 2020 to 31st of December 2020, spanning 214 days. Estimated Nigeria's population figure for this period was 206,139,587 persons and the GDP per capita was 2,250.00 USD. The dependent and independent variables are continuous data.

Fig. 1 shows that the cumulative COVID-19 cases curve was almost



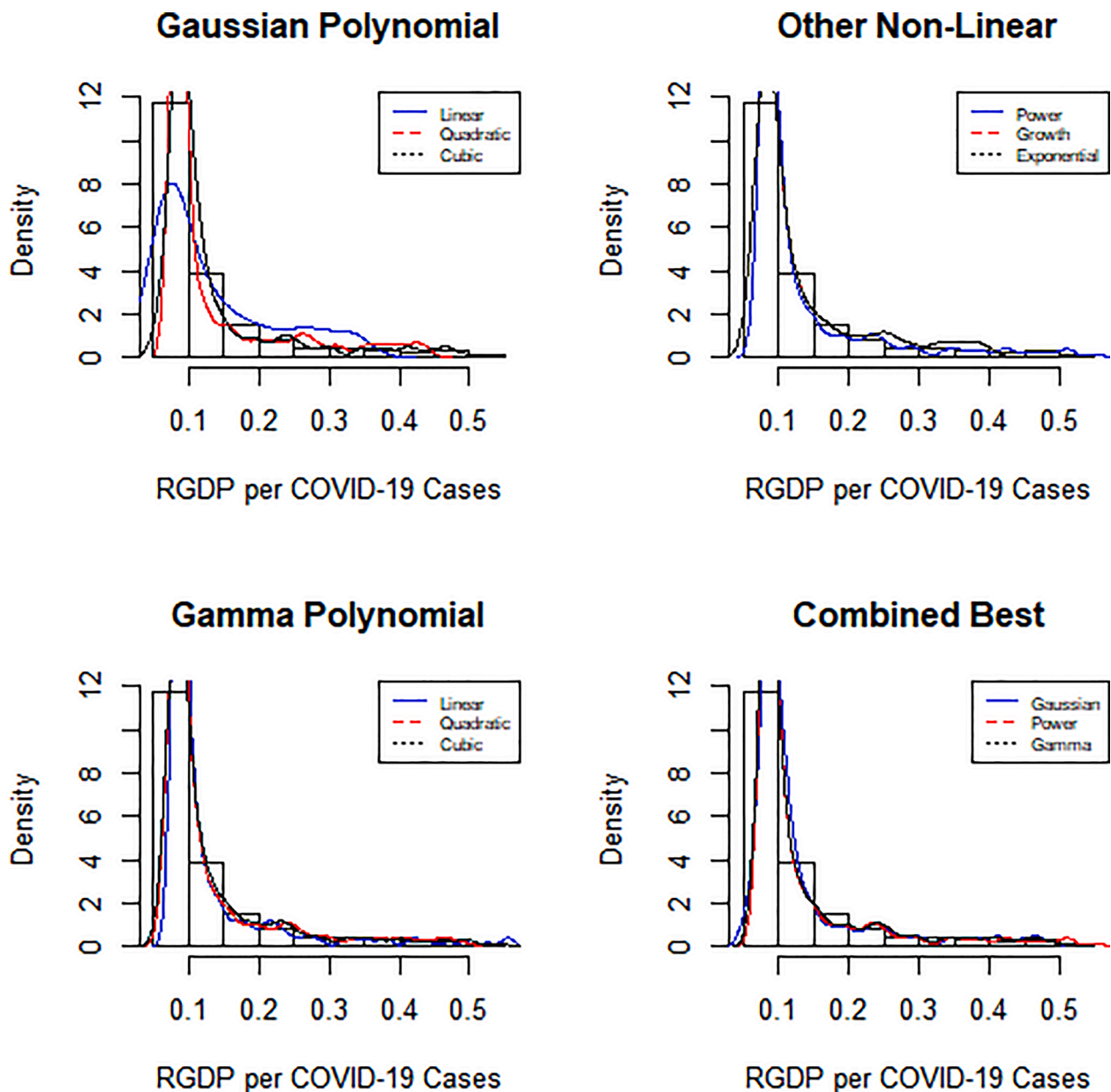


Fig. 5. Histogram and Fitted curves of Competing Models.

**Table 5**  
Best Models Parameter Estimation and Model Selection Criteria.

Models	Parameter Estimate (Standard Error)	Residual Sum of Squares
Gaussian Cubic Polynomial Model	$\beta_0$ 1.106 (0.0097)	0.000024669
	$\beta_1$ = -0.572 (0.0085)	
	$\beta_2$ = 0.114 (0.0023)	
	$\beta_3$ = -0.008 (0.0002)	
Power Non Linear Model	$\beta_0$ = 0.928 (0.0140)	0.000052190
	$\beta_1$ = -1.404 (0.010)	
Gamma Cubic Polynomial Model	$\beta_0$ = -2.281 (0.2630)	0.000002814
	$\beta_1$ = 3.621 (0.2694)	
	$\beta_2$ = -0.661 (0.0827)	
	$\beta_3$ = 0.086 (0.0078)	

flattened but trended upward again as new more cases were recorded towards the end of the year 2020. The cumulative COVID-19 mortality curve was almost flattened as well but trended upward again as new deaths were recorded towards the end of the year 2020. The CMP curve

has the same trend as the COVID-19 mortality curve since the population figure available was almost constant for the period. However, the RGDP decreased exponentially with time.

Fig. 2 shows that there is a negative non-linear relationship between GDP per Capita per COVID-19 and COVID-19 mortality. The higher COVID-19 mortality, the lower the RGDP, and vice versa.

Table 1 shows that the minimum cumulative cases for the period under review are 10,578 cases, while the maximum is 87,607 cases and it is negatively skewed. The minimum cumulative mortality for the period under review is 299 cases, while the maximum is 1,289 cases and it is also negatively skewed. The CMP has a minimum of 1.45 deaths per 1 million persons and the maximum is 6.25 deaths per 1 million persons, and it is negatively skewed. The minimum RGDP is N0.06 per person per case and the maximum is N0.5 per person per case, but it is positively skewed.

Fig. 3 shows that Figures a to c are negatively skewed, while Figure d is positively skewed as explained in Table 1. This implies that all the datasets are not normally distributed. So, there is a need for a normality confirmatory test especially for the dependent variable of interest (see

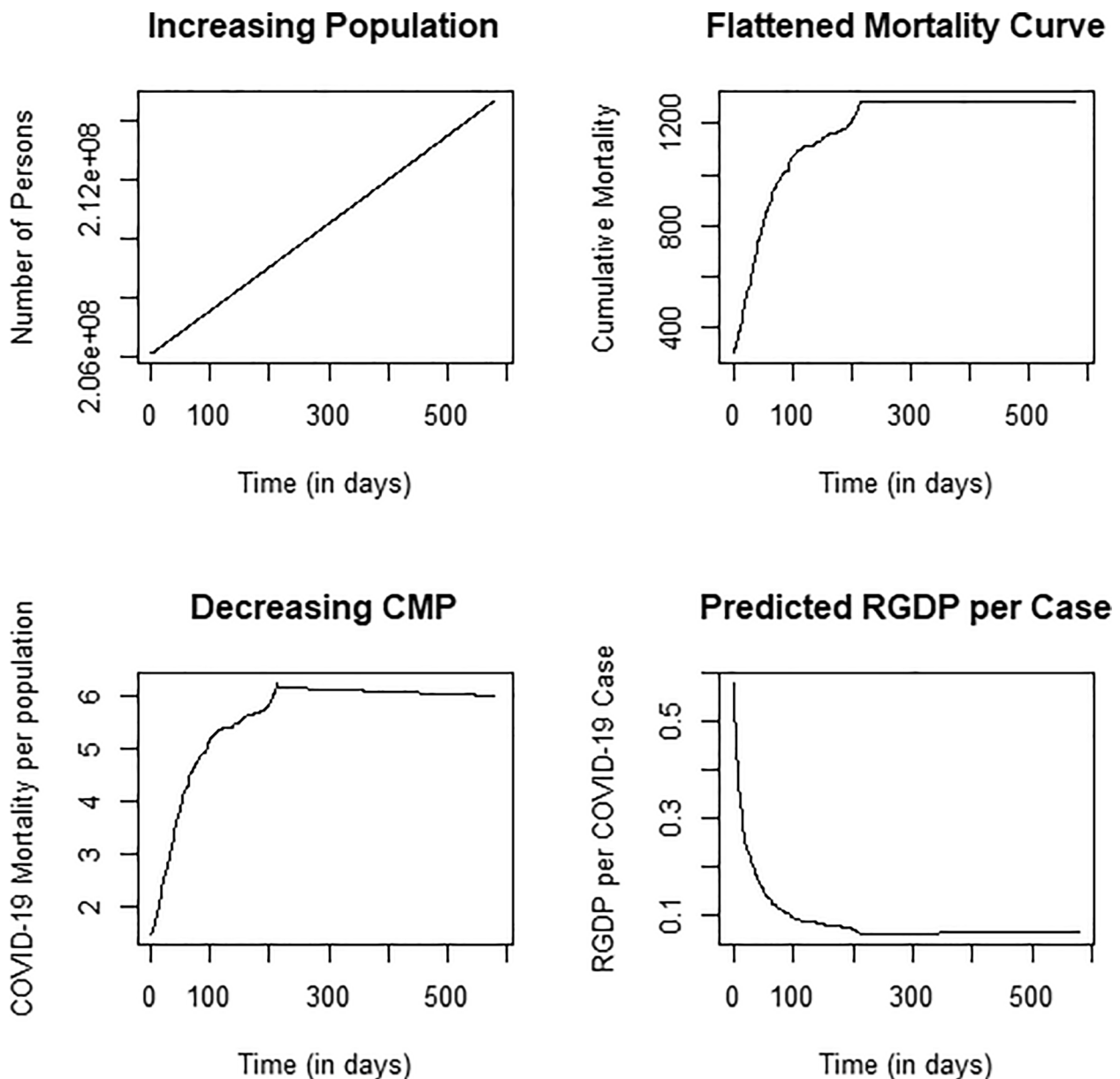


Fig. 6. Time Plots of Data of Interest.

Fig. 4).

Table 2 shows that the cubic model is the best based on the predictive power measured by the coefficient of determination ( $R^2$ ). This implies that there is a cubic polynomial relationship between RGDP and CMP, but the relationship is a strongly negative one.

Table 3 shows that the power model is the best based on the predictive power measured by the coefficient of determination ( $R^2$ ). This implies that there is a non-linear (power) relationship between RGDP and CMP, but the relationship is a strongly negative one.

Table 4 shows that the cubic model of the gamma GLM is the best based on the AIC and BIC criteria. This implies that there is a cubic polynomial relationship between RGDP and CMP, but the relationship is a strongly negative one.

Fig. 5 shows that all the models are a good fit for the data under consideration, except the linear model of the Gaussian family. This is because the RGDP data is not normally distributed based on the histogram showing positive skewness and supported with the descriptive statistics in Table 1. All the gamma models show a good fit, including the gamma linear model. Even all the other non-linear models are good fits

to the data of interest.

Table 5 shows that the cubic model of the gamma GLM is the best based on the models' predictive power selection criteria using the residual sum of squares (RSS). The RGDP is then forecasted to see the effect of CMP on RGDP.

Fig. 6 shows that if the population is increasing at a constant rate of 0.00006986 per day, that is, 2.55% per annum in 2021 (NPC, 2021), with a flattened COVID-19 mortality curve, that is, no more COVID-19 induced death, then the CMP will begin to decrease, thereby resulting to increasing RGDP. Fig. 6 depicts what would have happened in 2021 if there is no more COVID-19 mortality with an increasing population at a constant rate.

Fig. 7 shows the actual RGDP data from 1st June 2020 to 31st December 2020, where 1st of June is taken to be the 1st day of the series and 31st of December the 214th day of the series. The forecast starts from 1st January 2021 to 31st December 2021. The RGDP, which measures the wellbeing of a nation begins to increase 2021 from 0.0602 USD in 1st January to 0.0646 USD on 31st December 2021 even at a constant GDP for the year 2021. This implies that, even if Nigeria's GDP



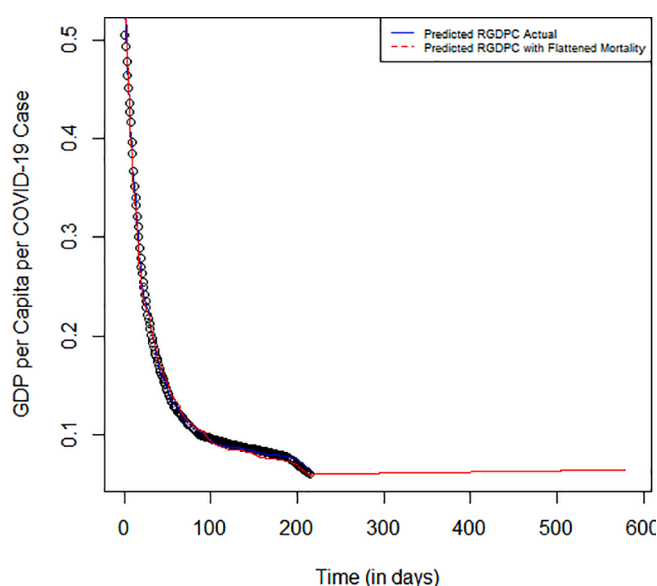


Fig. 7. Prediction of RGDP per COVID-19 Case.

per Capita remains unchanged in the year 2021, but with no COVID-19 case, then the economic wellbeing of Nigerians will begin to appreciate in the year 2021. This would have been possible if there are no more COVID-19 cases and COVID-19 mortality.

#### 4. Conclusion

The spread of COVID-19 in Nigeria is a thing of concern to the Nigerian government and the Nigeria Centre for Disease Control (NCDC). The plot of COVID-19 and COVID-19 mortality per population on time plot depict an upward trend, with some inherent pattern within some days, but the RGDP depicts a downward trend. This RGDP depends on some factors, such as COVID-19 mortality, population, etc., which is believed that COVID-19 mortality can be a major cause of the downward trend, even with a constant GDP per capita. Nine models divided into three groups were fitted for RGDP on CMP. The result of the analysis showed that the cubic model of the gamma GLM is selected as the best model to predict the RGDP in Nigeria. The model was used to forecast RGDP for the whole day in the year 2021 for a flattened cumulative COVID-19 mortality curve with an increasing population at a constant rate. The result shows that RGDP will increase provided all other factors remain constant. This is possible if all the states in Nigeria comply with NCDC directives. The major way to stop the trend of spread of COVID-19 is to abide by the NCDC recommendations of at least 1-metre physical distance, wearing face masks in crowded places, inculcate a high level of hygiene based on NCDC recommendations.

#### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

#### References

- Adeniyi, M.O., Ekum, M.I., Iluno, C., Ogunsanya, A.S., Akinyemi, J.A., Oke, S.I., & Matadi, M.B. (2020). Dynamic Model of COVID-19 disease with exploratory data analysis. *Scientific African*, 9, Article e00477. doi: 10.1016/j.sciaf.2020.e00477.
- Abayomi, A., Odukoya, O., Osibogun, A., Wright, O., Adebayo, B., Balogun, M., et al. (2021). Presenting symptoms and predictors of poor outcomes among 2,184 patients with COVID-19 in Lagos State, Nigeria. *Int. J. Infectious Disease*, 102, 226–232. <https://doi.org/10.1016/j.ijid.2020.10.024>.

- Are, S. O., & Ekum, M. I. (2020). COVID-19 pandemic data visualization with moment about midpoint: exploratory and expository analyses. *Asian J. Probability Statistics*, 8 (4), 15–37. <https://doi.org/10.9734/AJPAS/2020/v8i430212>.
- Ayinde, K., Lukman, A. F., Rauf, R. I., Alabi, O. O., Okon, C. E., & Ayinde, O. E. (2020). Modeling Nigerian Covid-19 cases: a comparative analysis of models and estimators. *Chaos Solitons Fractals*, 138, 109911. <https://doi.org/10.1016/j.chaos.2020.109911>.
- Chen, T.-M., Rui, J., Wang, Q.-P., Zhao, Z.-Y., Cui, J.-A., & Yin, L. (2020). A mathematical model for simulating the phase-based transmissibility of a novel coronavirus. *Infect. Dis. Poverty*, 9(1). <https://doi.org/10.1186/s40249-020-00640-3>.
- Chen, X., & Yu, B. (2020). sss two months of the 2019 Coronavirus Disease (COVID-19) epidemic in China: real-time surveillance and evaluation with a FFF derivative model. *Glob. Health Res. Policy*, 5, 7.
- Cilliers, J., Oosthuizen, M., Kwasi, S. Alexander, K., Yeboua, K. Moyer, J.D., 2020. Exploring the impact of COVID-19 in Africa: a scenario analysis to 2030. Embargoed until 16:00 SAST on 25 June 2020.
- Chudik, A., Mohaddes, K., Pesaran, M.H., Raissi, M., Rebucci, A., 2020. Economic consequences of COVID-19: A counterfactual multi-country analysis. Research-based policy analysis and commentary from leading economists. Available at <https://voxeu.org/article/economic-consequences-covid-19-multi-country-analysis>.
- Ekum, M. I., Akinmoladun, O. M., & Ogunsanya, A. S. (2020). Stochastic modelling of COVID-19 closed cases in Nigeria. *J. Nigerian Assoc. Mathematical Phys.*, 2020(11).
- Ekum, M.I., Ogunsanya, A.S., 2020. Application of Hierarchical Polynomial Regression Models to Predict Transmission of COVID-19 at Global Level. *Int. J. Clin. Biostat. Biom.* 6:027, 6(1), 1-18. doi: 10.23937/2469-5831/1510027.
- Ekum, M. I., Akinmoladun, O. M., Aderole, O. R., & Esan, O. A. (2015). Application of multivariate analysis on the effects of world development indicators on GDP Per Capita of Nigeria (1981–2013). *Int. J. Sci. Technol.*, 4(12), 524–534.
- Erokhin, V., Gao, T., 2020. Impacts of COVID-19 on Trade and Economic Aspects of Food Security: Evidence from 45 Developing Countries. *Int. J. Environ. Res. Public Health* 2020, 17(16), 5775; doi: 10.3390/ijerph17165775 .
- Ferguson, N., Laydon, D., Nedjati-Gilani, G., Imai, N., & Ainslie, K., 2020. Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand. Imperial College COVID-19 Response Team.
- Hassan, Z., Hashim, M. J., & Khan, G. (2020). Population risk factors for COVID-19 deaths in Nigeria at sub-national level. *Pan African Med. J.*, 35(2), 131. <https://doi.org/10.11604/pamj.supp.2020.35.2.25258>.
- Healy, J., & Kovaleski, S. (2020). *The Coronavirus's Rampage through a Suburban Nursing Home*. The New York Times.
- Hellewell, J., Abbott, S., Gimma, A., Bosse, N., & Jarvis, C. (2020). Feasibility of controlling COVID19 outbreaks by isolation of cases and contacts. *The Lancet Global Health*, 8, E488–E496.
- Huang, C., Wang, Y., Li, X., Ren, L., Zhao, J., Hu, Y.i., ... Cao, B. (2020). Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. *The Lancet*, 395 (10223), 497–506.
- Imai, N., Cori, A., Dorigatti, I., Baguelin, M., & Christl, A. (2020). Report 3: Transmissibility of 2019-nCoV. Imperial College London.
- Ivanaj, E., Oukhallou, Y., 2020. The Economic and Institutional Determinants of COVID-19 Mortality. Munich Personal RePEc Archive. Available at <https://mpra.ub.uni-muenchen.de/103895/> MPRA Paper No. 103895, posted on 15 Jan 2021 00:09 UTC.
- Isere, E.E., Adejagbagbe, A.M., Oladoyin, V., Abiona, S. & Omorogbe, E.N., 2020. Pre-symptomatic and asymptomatic COVID-19 cases in Nigeria amidst prevailing socio-cultural beliefs and practices: Implication for COVID-19 transmission and way forward. *Archives of Preventive Medicine*. Available at <https://www.peertechzpublications.com/articles/APM-5-118.php>.
- Kucharski, A. J., Russell, T. W., Diamond, C., Liu, Y., Edmunds, J., Funk, S., et al. (2020). Early dynamics of transmission and control of COVID-19: A mathematical modelling study. *Lancet Infect. Dis.*, 20(5), 553–558.
- Li, R., Pei, S., Chen, B., Song, Y., Zhang, T., Yang, W., & Shaman, J. (2020). Substantial undocumented infection facilitates the rapid dissemination of novel coronavirus (SARS-CoV2). *Science*, 368(6490), 489–493.
- Liu, Y., Gayle, A., Wilder-Smith, A., & Rocklöv, J. (2020). The reproductive number of COVID-19 is higher compared to SARS coronavirus. *J. Travel. Med.*, 27, 21.
- McMichael, T. M., Clark, S., Pogosjans, S., Kay, M., Lewis, J., Baer, A., et al. (2020). COVID-19 in a long-term care facility – King County, Washington, February 27–March 9, 2020. *MMWR Morb. Mortal Wkly Rep.*, 69(12), 339–342.
- NCDC (2021). NCDC Coronavirus COVID-19 Microsite: COVID-19 Nigeria. <https://covid19.ncdc.gov.ng/>.
- Okunnu, M. A., Ekum, M. I., & Aderole, O. R. (2017). the effects of macroeconomic indicators on economic growth of Nigeria (1970–2015). *Am. J. Theoretical Appl. Statistics*, 6(6), 325–334. <https://doi.org/10.11648/j.ajtas.20170606.19>.
- Oran, D. P., & Topol, E. J. (2020). Prevalence of asymptomatic SARS-CoV-2 infection. *Ann. Intern. Med.*, 173(5), 362–367. <https://doi.org/10.7326/M20-3012>.
- Ostertagová, E. (2012). Modelling using polynomial regression. *Procedia Eng.*, 48, 500–506.
- Li, Q., Guan, X., Wu, P., Wang, X., Zhou, L., Tong, Y., ... Feng, Z. (2020). Early transmission dynamics in Wuhan, China, of novel coronavirus-infected pneumonia. *N. Engl. J. Med.*, 382(13), 1199–1207.
- Read, J.M., Bridgen, J.R.E., Cummings, D.A.T., Ho, A., Jewell, C.P., 2020. Novel coronavirus 2019-nCoV: Early estimation of epidemiological parameters and epidemic predictions. medRxiv.
- Roosa, K., Lee, Y., & Luo, R. (2020). Real-time forecasts of the COVID-19 epidemic in China from February 5th to February 24th, 2020. *Infect. Dis. Model.* 5, 256–263.
- Roosa, K., Lee, Y., Luo, R., Kirpich, A., Rotherberg, R. (2020). Short-term forecasts of the COVID-19 epidemic in Guangdong and Zhejiang, China. February, 2020. *J. Clin. Med.* 9, 596, 13-23.

- Sornette, D., Mearns, E., Schatz, M., Wu, K.e., & Darcet, D. (2020). Interpreting, analysing and modelling COVID-19 mortality data. *Nonlinear Dyn.*, 101(3), 1751–1776. <https://doi.org/10.1007/s11071-020-05966-z>.
- Subramanian, R., He, Q., Pascual, M., 2021. Quantifying asymptomatic infection and transmission of COVID-19 in New York City using observed cases, serology, and testing capacity. *Proc. Natl. Acad. Sci. U.S.A.* 118 (9) e2019716118; doi: 10.1073/pnas.2019716118.
- Tang, B., Wang, X., Li, Q., Bragazzi, N. L., & Tang, S. (2020). Estimation of the transmission risk of 2019-nCoV and its implication for public health interventions. *J. Clin. Med.*, 9, 462.
- World Bank Databank sources (2016). International Financial Statistics and data files and OECD GDP estimates. Balance of Payments databases. International Debt Statistics. IMF, World. Economic Outlook, October 2016.
- World Health Organization. (2020). There is a current outbreak of coronavirus (COVID-19) disease.
- Wu, J. T., Leung, K., & Leung, G. M. (2020). Nowcasting and forecasting the potential domestic and international spread of the 2019-nCoV outbreak originating in Wuhan, China: a modelling study. *The Lancet*, 395(10225), 689–697.
- Wu, Z., & McGoogan, J. F. (2020). Asymptomatic and Pre-Symptomatic COVID-19 in China. *Infectious Diseases of Poverty*, 9, 72. <https://doi.org/10.1186/s40249-020-00679-2>.
- Xu, B.o., Gutierrez, B., Mekaru, S., Sewalk, K., Goodwin, L., Loskill, A., et al. (2020). Epidemiological data from the COVID-19 outbreak, real-time case information. *Sci Data*, 7(1). <https://doi.org/10.1038/s41597-020-0448-0>.
- Yang, S., Cao, P., Du, P., Wu, Z., Zhuang, Z., 2020. Early estimation of the case fatality rate of COVID-19 in mainland China: A data-driven analysis. *Ann. Transl. Med.*, 8, 128.
- Zhao, S., Lin, Q., Ran, J., Musa, S. S., Yang, G., Wang, W., ... Wang, M. H. (2020). Preliminary estimation of the basic reproduction number of novel coronavirus (2019-nCoV) in China, from 2019 to 2020: a data driven analysis in the early phase of the outbreak. *Int. J. Infect. Dis.*, 92, 214–217.