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MODELLING POTENTIAL ECONOMIC IMPACT OF COVID-19 IN NIGERIA: EVIDENCE FROM GRAPH ANALYSIS

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Abstract: COVID-19 pandemic created a shockwave that can be felt across every sphere of society and the environment. The disease grew from a local event to a pandemic and the impacts are not the same everywhere. Therefore, there is a need to characterise the impact at different levels to ensure that initiatives to cushion the impacts are well-targeted. This study utilised graph analysis to examine the network attributes of Facebook Users' mobility during the pandemic in comparison with the baseline period before the pandemic to characterise the economic impact. Movement data were collated from the Facebook Data for Good platform while economic output and census data were collated from the National Bureau of Statistics. The result shows that economic output and baseline network attributes have a positive and highly significant relationship ($P<0.01$). Nodal efficiency was statistically different across the crisis and baseline periods while betweenness showed no difference. The sum of the difference from baseline values identified two extremes – Lagos State (most negatively impacted) and Kwara State (most positively impacted). The States adopted varying measures to combat the disease, these variations also emerged in the graph analysis results. Economic output from each State is related to its centrality and efficiency. It is therefore plausible that changes in network attributes will bring commensurate changes in the economic output of each State. States with high centrality and betweenness values had a greater decline in their network attributes. The study provided an insight into one aspect of the extent of the economic impact of the COVID-19 on each State. We recommend more investigations into the inclusion of local interactions in capturing intra-state movements and changes in modelling economic output.

Keywords: COVID-19, economic impact, graph analysis, complex systems, networks; mobility

1 INTRODUCTION

The novel Corona Virus of 2019 (COVID-19) pandemic created a shockwave that can be felt across every sphere of society and the environment. At the onset of the pandemic, different measures were adopted by various countries. However, lockdowns were quite common across the globe. When news of the outbreak emerged

(December 2019), the World Health Organisation (WHO) initially declared the outbreak a public health emergency of international concern and later upgraded it to a global pandemic as the spread intensifies. As of the first week of March 2021, the global total COVID-19 has surpassed 117 million while deaths are well over 2.6 million (Worldometer, 2021). This is unlike the previous outbreak of Severe Acute Respiratory Syndrome (SARS) in 2003 and Ebola in West Africa in 2014. With the disease growing from a local event to a pandemic affecting millions and many countries, many governments instituted a form of lockdown or other models of mobility restrictions to limit the spread of the disease. Thus, the stimulus to cushion the impacts of the social and economic downturn induced by the pandemic would be necessary. For this to be effective and bring about recovery, there is a need to evidence the extent and variation of the impact across places and regions across the country. The study examined the extent of the economic impact and their disparity across places using social network graph analysis and economic output data.

In Nigeria, the Federal Government of Nigeria instituted a nationwide lockdown on the 29th of March 2020 (Presidential Taskforce on COVID19, 2020). The lockdown was relaxed after five weeks to a nationwide night curfew, this continued till June 1 (the First Phase of eased lockdown) while the second phase started on the 2nd of June till August 6th but extended to September 3rd, 2020. The third commenced afterwards, lasting for four weeks and the country is still in this phase.

While lockdown offers a very potent tool for limiting the spread of the disease, it also presents a serious problem. Instituted restrictions and induced mobility reductions are likely to have negative socio-economic impacts, and this is likely to vary from place to place. While the use of a limited number of households in surveys could provide some indication, it is necessary to create models and indices that could provide a better indication of the impact of the pandemic on the social and economic condition of places across the country. The lack of such data and indices will hamper the design and implementation of initiatives meant to address the socio-economic impact of the pandemic across all the States in Nigeria. To adequately deal with the pandemic, there is a need to leverage available data, graph theory, machine learning, and statistical techniques to provide actionable insights on the socio-economic impacts of the disease and the lockdown on the people at different scales. Thus, by answering the questions of how much and where of the impacts (economic), evidence can be gathered to ensure that the country builds back better and improve the resilience of the society.

The impacts (especially economic and social) of the pandemic could be likened to that of a natural disaster (Khalid and Ali, 2019). Production, value chains, demand, supply, trade exchanges, social interactions, health, education, and services are heavily impacted when a disaster occurs. A few works have provided some estimates of the economic impact e.g. Fernandes (2020). It is thus evident that the mitigation measures taken by each country will determine the course of the pandemic (Anderson et al., 2020).

In the wake of the COVID-19 pandemic and the need to understand the impact of the disease, near real-time and big data platforms (social media, web mined datasets) could provide opportunities to get a closer look at the consequences on the social and economic facets of the society in Nigeria. For example, Wu and Brynjolfsson (2015) utilised google search engine data to predict future business activities. Hubbard (2011) showcased how web queries and other social network platforms can be used for tracking public opinion, economy, anxieties, etc. Lawal (2017) utilised Google search engine data to track attention to virtual security. Other issues that have been tackled using web queries and search engine data include syndromic surveillance, unemployment forecasts, economic indicators, and analysis of voters' roll-off, etc. These examples highlight the practical application of web queries, social media, text, and web mining for social and economic analyses. All these provided opportunities to capture socio-economic data which could offer insights into the disparity of the impacts of the pandemic on various places across the country.

Spatial interaction across places and among people creates economic output that generates wealth and economic development. Thus, such a system is an example of a complex network – characterised by the interaction between functionally segregated regions across the socio-eco-cultural-political landscape. Mellinger et al. (2000) reported that temperate coastal zones covering just about 8% of the total global landmass, inhabited by 23% of the total world population accounts for 53% of the world's GDP. While this might be wrongly misconstrued as the primacy of geography, the most important takeaway is that there is an intense level of spatial interaction (exchange of people, goods, and services) which ensures that such places dominate the total economic output. Tapping into this understanding can reveal the impact disruptions such as the pandemic could have on the economic output of places.

Complex networks are quite common across many areas of human and natural systems (Chen et al., 2012; Newman et al., 2006; Newman, 2012). They can be described as networks with irregular and complex structures that evolve dynamically over time (Borge-Holthoefer and Arenas, 2010). Graphs are networks and they provide an opportunity to represent complex structures of many systems. They possess non-trivial topological characteristics, unlike traditional networks. The analysis of these complex systems with non-trivial characteristics can be referred to as graph analysis and it has been utilised in the study of various systems such as social, biological, economic, physical, and engineering systems (Newman, 2012). The work of Erdos and Rényi (1960) presented the classical random graph theory. This has led to the growth in the number of works in the application of the model and theory to study complex networks. Despite this growth, there are still challenges in the extraction of useful and scientific understanding from medium and large-scale networks (Newman, 2012). However, various metrics have been developed to study small-scale structures in networks. The works of Albert and Barabási (2002), Newman (2003), Boccaletti et al. (2006), and many others provide an overview of the structure, dynamics, and attributes of complex networks.

Graphic analysis and understanding of complex networks have been used in gaining insight into various aspects of human and natural systems. Naimzada et al. (2008), provided extensive justification for the relevance of graph theory structuring the network of variables when studying economic or social phenomena. For example, in trying to provide new insight on the dynamics of economic development, Wang et al. (2012) utilised visibility graph analysis in exploring macroeconomic series. Their work revealed that there are relationships among government policy changes, community structures (across the three industries considered) of associated networks, and macroeconomic dynamics. They showed graph analysis can be used to examine the influence of government policies on economic output and adjustment across industries within the economy. Thus, showing that macroeconomic series could be examined from a complex network perspective. Foster (2005) had earlier explained why it is pertinent that economic analysis is approached as a network rather than the current approach of production and utility function, especially when dealing with a complex system. Thus, when dealing with the estimation or analysis of the economic impact of the pandemic, it would be necessary to address the analysis through the analysis of networks – whereby constraints in value generation (economic output) could be tied to the reduction of interaction (lockdown and mobility restriction). Re-examining the development of economic vulnerability and resilience indices, Bates et al. (2014) opined that many of the composite indices constructed at the national level are just fairly following the holistic view of sustainable development. They suggested the use of graph theory in understanding the structure of a network of variables capable of adequately depicting vulnerability and resilience. They identified two control dimensions (economic and political) and three contingency factors (social, environmental and the peripheral dimensions). To illustrate the usefulness of this approach, the method was tested using Singapore as an example. The results showed that the country has a resilience capacity that is higher than its vulnerability propensity. This strength was found to be rooted most especially in governance (control dimensions) as well the country's good insertion into global trade (thus enhancing its resilience capacity). The weaknesses were rooted in the environmental dimensions, and this aspect represents the only area where vulnerability surpasses resilience, thus identifying the need for Singapore to include environmental concerns as an issue in its development planning. Ji and Fan (2016) examined the global oil market using graph analysis and showed that adjacent countries or regions tend to interact more while South and North America as well as African regions are relatively stable. At the core of the network is the interaction between the US, Angola, and Saudi Arabia with higher betweenness centrality. Furthermore, the markets for East and Southeast Asian countries constitute the fringe of the network.

From the foregoing, the relevance and application of graph theory, complex systems, and graph analysis have shown significant evidence of providing new insight into the study of various systems. To this end, this study leverages these in indicating the level of pre-COVID inter-state economic interaction and the potential economic impact of COVID-19 on the States in Nigeria using network attributes.

2 DATA AND METHODS

2.1 Study Area

Nigeria has 36 states and Abuja as the Federal Capital Territory (FCT) (Figure 1). The States are further divided into 774 LGA spreads over an area of 923,768 square kilometres, including about 13,000 km^2 of water. The work of Lawal and Anyiam (2019) provides more details about the study area.

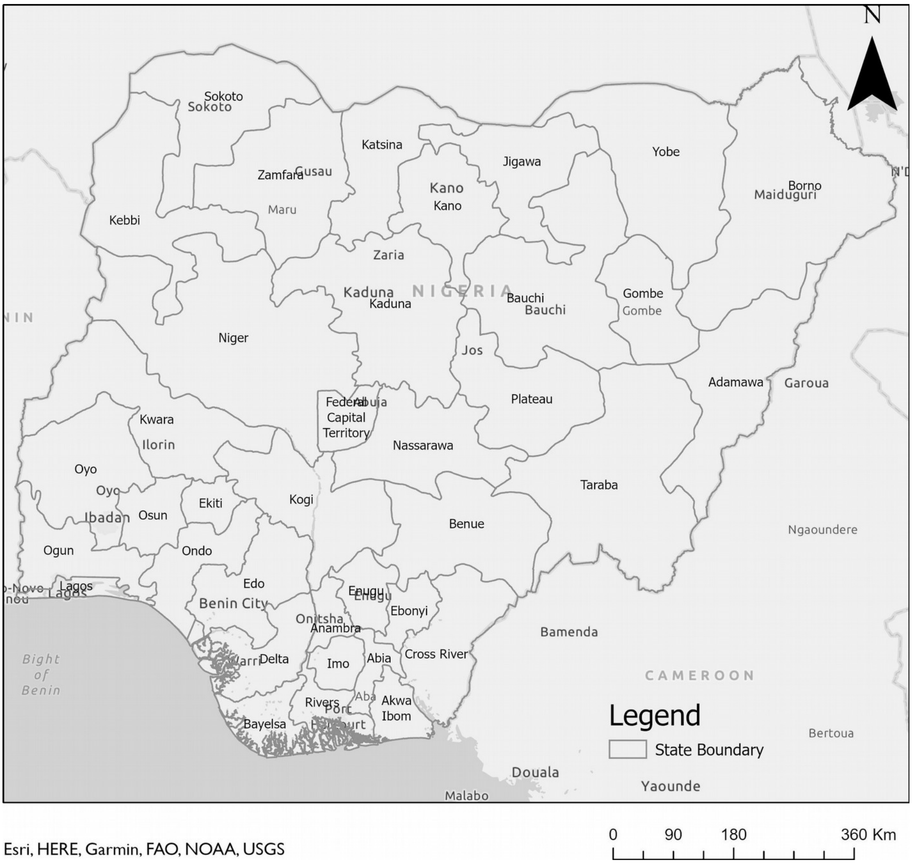

Figure 1 Nigerian States and neighbouring countries

2.2 Data

The mobility data were collated from Facebook Data for Good Platform (Facebook, 2020a). The dataset is made up of anonymised movement data over time and space. For this study, we utilised the “Movement between Administrative Regions” dataset with data for Nigeria available from 7th April 2020. This provided data on which pairs of administrative regions are people moving over a specific period, i.e., the total number of people using the Facebook application (with location data capturing enabled) who moved between a pair of States in Nigeria. The movement data were aggregated to 0:00, 08:00, and 16:00 hours of the day. This interaction between pairs of States constitutes the vertices used for the network analysis while the individual States constitute the nodes within the network. Baseline data was generated using data from 45 days before when the map generation was kicked off, a further description can be found on Facebook (2020b)

Gross Domestic Product (GDP), an indicator of economic output was sourced from the National Bureau of Statistics database (NBS, 2021). The data captured the total economic output (in Billion dollars) of each State for 2007 in Purchasing Power Parity (PPP). One of the States (Enugu) had no GDP value. In addition, socio-economic and demographic data from the 2006 Census were also collated from the same source. This was done to examine the relationship between the census-derived data and the economic output and to use such an association to create a predictive model for the missing GDP.

2.3 Methods

The research utilised mobility as a proxy to capture the consequences of the pandemic on the economy and society. Leveraging understanding from the Graph theory, mobility dataset was examined to deduce the connectivity across spatial units and thus provide an insight into changes in connectivity across spatial units before and during the pandemic. This captured intrinsic characteristics of the network of mobility during the pandemic. Network data were processed in R (R Core Team, 2020), using the packages *igraph* (Csárdi and Team, 2020a) and *brainGraph* (Watson and Team, 2020a). An edge attribute (Betweenness) was computed for each of the 37 spatial units for both baseline and crisis periods. Furthermore, to capture the efficiency of the nodes within the network, nodal efficiencies were computed for both periods.

For the graph analysis, a node is represented by a State. Thus, the vertices are the link between each State i.e., the direction of movement of people from one State to the other. The number of people moving in each direction was used to weigh the vertices. When there were multiple links between the same nodes, such were collapsed by summing their weights.

To study the efficiency-related topological characteristics of the State-level Facebook user mobility network graphs, we computed the graph metric of nodal efficiency. To identify hub regions in the functional network, we determined each node's degree of centrality as a measure of its relative importance for network interaction. Nodal efficiency was computed using the approach documented in Watson and Team (2020b). From this, nodal efficiency was computed as the inverse of the average shortest distance between node i and all other nodes j of the graph.

Betweenness relates to the extent to which a node can be found between other nodes in a network (how often a node is in-between others). Thus, capturing the connectivity to neighbouring nodes. Nodes serving as bridges to other nodes will have higher betweenness values. Vertex and edge betweenness can be defined by the number of shortest paths going through a vertex or an edge. We computed vertex betweenness because edge betweenness could give false values for graphs with multiple edges (Csárdi and Team, 2020b) as found in our study. The computation follows the approach documented in Csárdi and Team (2020b).

In the analyses, the crisis period refers to the period between April 2020 and December 2020 for which the study collated data. Comparison of the network attributes during the pandemic with baseline values, the study characterised the extent to which the mobility restriction (lockdown) impacted the network attributes. The aggregated mobility dataset was analysed to reveal the geographic pattern of the impact.

3 RESULTS AND DISCUSSION

3.1 Modelling of Economic Output

GDP varies considerably across the Federation, with the highest figure recorded in Lagos and the lowest in Yobe State. The State average for the year stood at just over $ 8B with a standard deviation of well over $ 6.6B. The distribution is positively skewed (Table 1), indicating there are more States with GDP less than the mean and with a value greater than $ 1B, thus showing that the distribution is highly skewed.

Table 1 Distribution of GDP for 2007 across the States in Nigeria

Statistics	GDP(PPP) Billion $
Minimum	2.01
Maximum	33.68
Mean	8.37917
Std. Deviation	6.61405
Skewness	1.968
Skewness – SE	0.393

N = 36, SE – Standard Error, Std. – Standard

Source: Authors' computation

The State-level GDP values were compared to census data summaries for the States using Person Product Moment Correlation. The results showed that the number of people with the attribute HQ0403 (Main Construction material used for flooring – Cement/Concrete), and HQ0504 (Main construction materials used for the walls of dwelling – Cement/Block Bricks) are the most highly and statistically significant correlates of GDP across the States (Table 2).

Table 2 Correlation results for GDP versus State-level census variables (top ten)

Variables	Pearson Coeff.	Sig. Level
HQ0403	0.924	**
HQ0504	0.908	**
HQ1504	0.901	**
HQ1602	0.885	**
HQ0407	0.875	**
HQ0806	0.866	**
HQ1001	0.865	**
HQ1103	0.857	**
HQ0802	0.853	**
HQ0406	0.852	**

N = 36, ** Correlation is significant at the 0.01 level (2-tailed)

Source: Authors' analysis

This indicated that it is plausible to use the values from either of these two attributes to derive the missing GDP value. In this case, a regression analysis was carried out to develop a model representing the relationship between GDP and HQ0403. The regression model utilised HQ0403 as the independent variable and GDP values for the available State as the dependent. The regression analysis produced a model with an adjusted R Square of 0.849 and the summary ANOVA results (Table 3) indicated that the model is statistically significant. The coefficient (0.00001881) was also found to be highly significant ($P<0.01$). From these results, the model showed a high explanatory power (high adjusted R Square value).

Table 3 ANOVA results from the regression analysis of GDP against HQ0403

Statistics	Sum of Squares	df	Mean Square	F	Sig.
Regression	1306.399	1	1306.399	197.676	.000
Residual	224.699	34	6.609		
Total	1531.098	35			

N = 36

Source: Authors' analysis

Thus, using this model, the 2007 predicted GDP for Enugu stood at \$ 9.883B (Standard Error [SE] = \$ 0.44B). The standard error (SE) of the prediction for all the other States ranges between \$ 0.429B and \$ 0.699B, except for Lagos with SE of \$ 2.001B. This high SE of prediction is an indication of the extremity of the GDP value obtained for Lagos in comparison to other States.

Examination of the distributions (Table 4) showed that the mean values are very close (difference of 0.041). The comparison (Table 4) also indicated that the minimum values are close, while the maximum values are considerably different (predicted is much higher than measured). Moreover, the prediction showed less dispersion compared to the measured data while the skewness remained positive. Based on these attributes, the predicted GDP value for Enugu was taken forward in subsequent analyses.

Table 4 Comparison of the distribution of measured and modelled GDP

Statistics	Measured GDP ($ B)	Predicted GDP ($ B)
Minimum	2.010	1.913
Maximum	33.680	35.867
Mean	8.379	8.420
Std. Deviation	6.614	6.029
Skewness	1.968	2.734
Skewness Std. Error	0.393	0.388
N	36	37

Source: Authors' analysis

3.2 Comparison of Network Attributes

3.2.1 Exploring Baseline Network Attributes across States

Network attributes computed were averaged for the year 2020 for each State (baseline and crisis period). From the baseline values, the mean nodal efficiency for the States shows (Figure 2a) that the average shortest path length is longest for the North-eastern States while the length decreases towards the south and the western parts of the country. Nasarawa and Lagos have, among other States, the shortest average shortest path length (most efficient nodes).

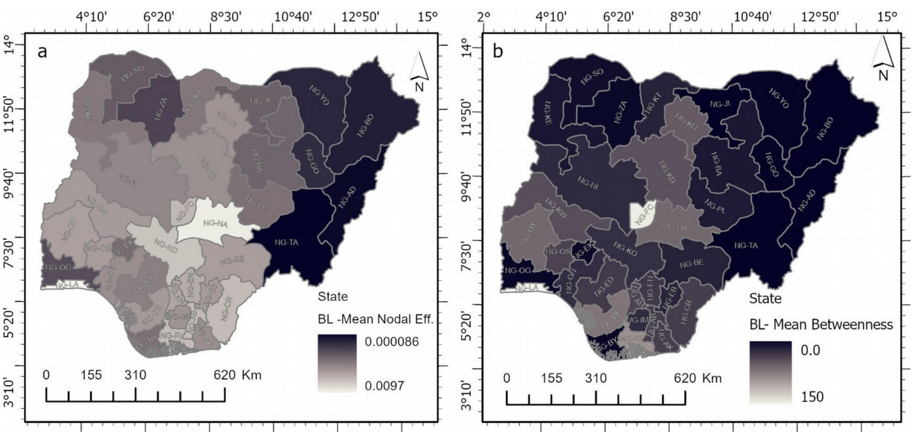

Figure 2 Distribution of baseline means for centrality and efficiency across the Nigerian States

In the case of betweenness (Figure 2b), mean values were generally lower for States on the periphery, and this occurred mostly in the North-Western and North-Eastern States. However, Ogun, Ekiti, and Bayelsa State exhibited similar attributes in the southern part of the country. Lagos and FCT (Abuja) have the highest mean centrality. Centrality values showed that there is an element of regional clustering across the country.

3.2.2 Comparing Baseline with Crisis Period Network Attributes

T-test analysis was carried out to compare the baseline against the crisis period betweenness and nodal efficiency values across the States. The descriptive analysis result (Table 5) showed that the average centrality (betweenness) across the two periods differs only slightly (0.07%). However, there was an increase in dispersion (higher SD) of the values during the crisis period. For nodal efficiency, the average value increased (20%) for the crisis period when compared to the baseline. Perfunctory examination indicated better nodal efficiency during the crisis period in comparison to the baseline, which is counterintuitive as such further examination was carried out.

Table 5 Descriptive statistics summary for network attributes

Network Attributes	Mean	Std. Deviation
Betweenness Baseline	32.23201	68.855
Betweenness Crisis	32.20941	69.461
Nodal Efficiency Baseline	0.00517	0.005
Nodal Efficiency Crisis	0.00646	0.006

N=29,859

Source: Authors’ analysis

To ascertain that the differences are statistically significant, paired-sample T-test analysis was carried out and the result (Table 6) showed that there is no statistically significant difference between the crisis and the baseline period in terms of the centrality of the nodes (States).

However, there was a statistically significant difference between the baseline and crisis periods for nodal efficiency. The results showed that the nodal efficiency declined during the crisis period and the difference is significant when compared to the baseline. The results provided a piece of evidence indicating the negative impact of the pandemic and lockdown implemented on the efficiency of exchange and movement across the spatial units (States) across the country.

3.3 Relationship between Economic Output and Baseline Network Attributes

The association between GDP and the baseline network attributes was examined using correlation analysis. The analysis utilised betweenness and nodal efficiency averaged over the year 2020 for each State. The result (Table 7) showed that the mean centrality and nodal efficiency during the baseline period were positively associated with GDP. The associations observed were medium and highly significant ($P<0.01$). The measure of dispersion for centrality also showed a medium, positive, and highly significant relationship with the GDP, while GDP showed a positive but weak and statistically significant association with the dispersion measure of the nodal efficiency.

Table 6 Comparison of baseline against crisis period network attributes

Statistics		Betweenness Baseline VS Betweenness Crisis	Nodal Efficiency Baseline VS Nodal Efficiency Crisis
Paired Differences		0.0226	-0.0013
Std. Deviation		12.9839	0.0021
Std. Error Mean		0.0751	0.0000
95% Confidence Interval of the Difference	Lower	-0.1247	-0.0013
	Upper	0.1699	-0.0013
	t	0.3010	-108.4400
	Sig. (2-tailed)	0.7640	0.0000

df. = 29,858

Source: Authors' analysis

Table 7 Correlation analysis summary for the association between network attributes and GDP

Variables (Baseline)	Rho
Mean Betweenness	0.662**
SD – Betweenness	0.688**
Mean – Nodal Efficiency	0.535**
SD – Nodal Efficiency	0.360*

** Correlation is significant at the 0.01 level (2-tailed), * Correlation is significant at the 0.05 level (2-tailed), N = 37

Source: Authors' analysis

The positive relationship suggests increasing centrality is associated with increasing GDP, and increasing GDP is associated with increasing nodal efficiency. Thus, with the instituted lockdown, it is plausible that each of the States would have their economic output depressed potentially to the extent by which their network attributes were negatively impaired (i.e., when compared to baseline).

3.4 Exploring changes in Network Attributes and Implications for Economic Output

To capture changes in the network attributes computed, the difference between the baseline and the crisis period was computed. The result identified the changes across the States of the Federation (Figure 3a and 3b). Using quartile classification, the differences for betweenness indicated that Abia, Akwa-Ibom, Bayelsa, Delta, Edo, Kaduna, Kano Lagos, Oyo, and Rivers witnessed the worst changes in centrality (Figure 3a). Most of the States in the north-eastern and north-western parts of the country formed a group with slight to no changes in centrality. Bauchi and Niger States were unique (increased centrality) compared to other States in the Northern part of the country. These two States shared similar traits with other States like Cross River, Ebonyi, Anambra, Imo, Osun, and Ekiti. Kastina State is more like an outlier in the Northern region concerning centrality changes – having a considerable increase in its centrality. Similar traits were recorded for Kwara, Kogi, Ondo, Benue, FCT, Nasarawa, Benue, and Plateau States.

For nodal efficiency (Figure 3b), ten States witnessed a relatively big decline in their nodal efficiency – these group includes Kano, Lagos, and FCT (some of the States with the highest CIVID-19 cases in Nigeria). The next group recorded a decline in nodal efficiency albeit to a lower extent than the earlier mentioned group. The States in this group spread from the north-central part of the country (Kastina, Jigawa) through the middle-belt (Nasarawa and Kogi) to parts of the Southern and Southwestern regions of the Country. Extending from the north-eastern part of the country down to Benue State, as well as two States from the north-western corner and Ekiti belongs to the least impacted in respect to changes in nodal efficiency because of the pandemic. The results from the change analysis (i.e., the difference between baseline and crisis period) showed that the impact varies across the State and the impact also exhibited some clustering across regions with some outliers showing up across certain regions.

Summing the differences indicated the group membership of the States in the characterisation of the level of impacts due to the COVID-19 pandemic. Figure 4 showed that 16 out of the 37 spatial units considered recorded a slight (0.010) to high (5.160) improvement (over the baseline) for the combined network attributes. In this group, Kwara stands out. States like Taraba, Adamawa, Yobe, Borno, Gombe, Zamfara, Kebbi, Jigawa showed no difference from baseline when the differences from baseline for the network attributes were summed. The remaining States witnessed a negative change from baseline ranging from -0.010 recorded in Sokoto to -10.550 recorded in Lagos. In this group, Lagos was in a class of its own, followed by Oyo State. The result shows that while there are three major groups, there are subgroups within each of them.

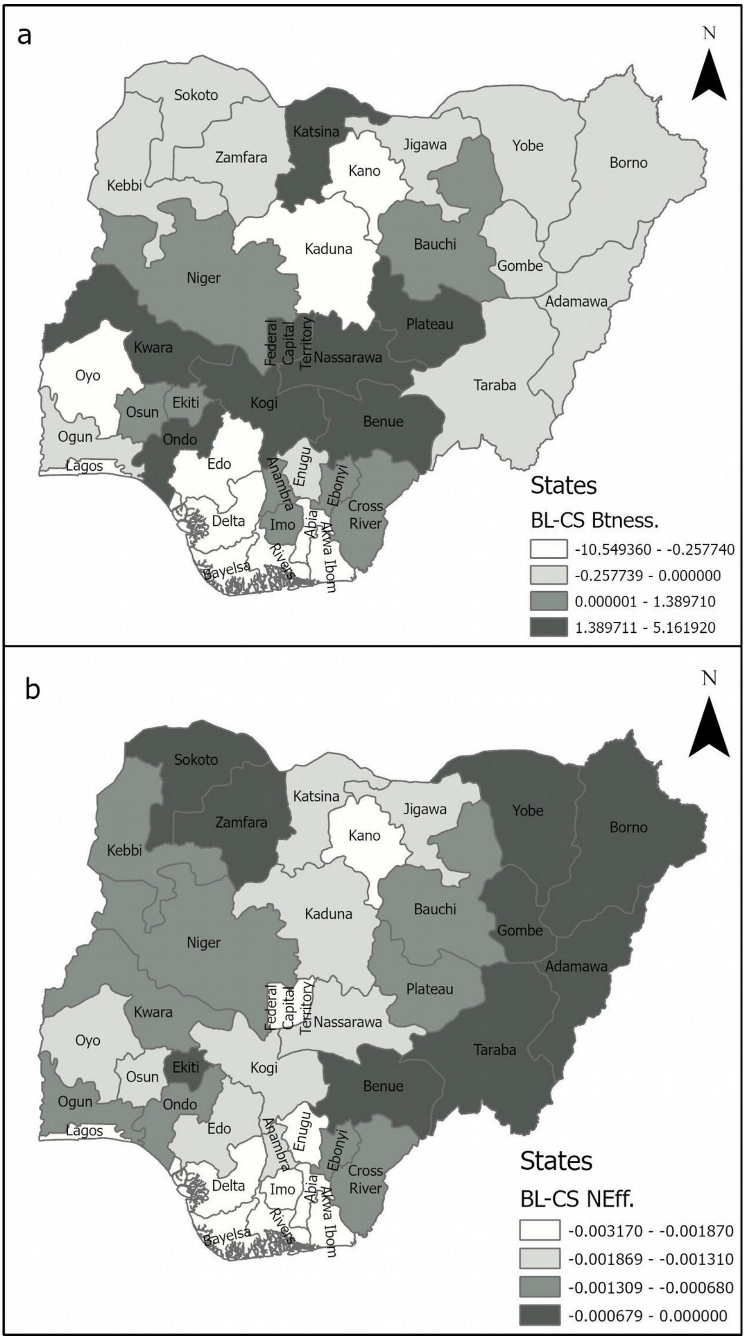

Figure 3 Changes between baseline and crisis period network attributes (a) centrality, (b) nodal efficiency

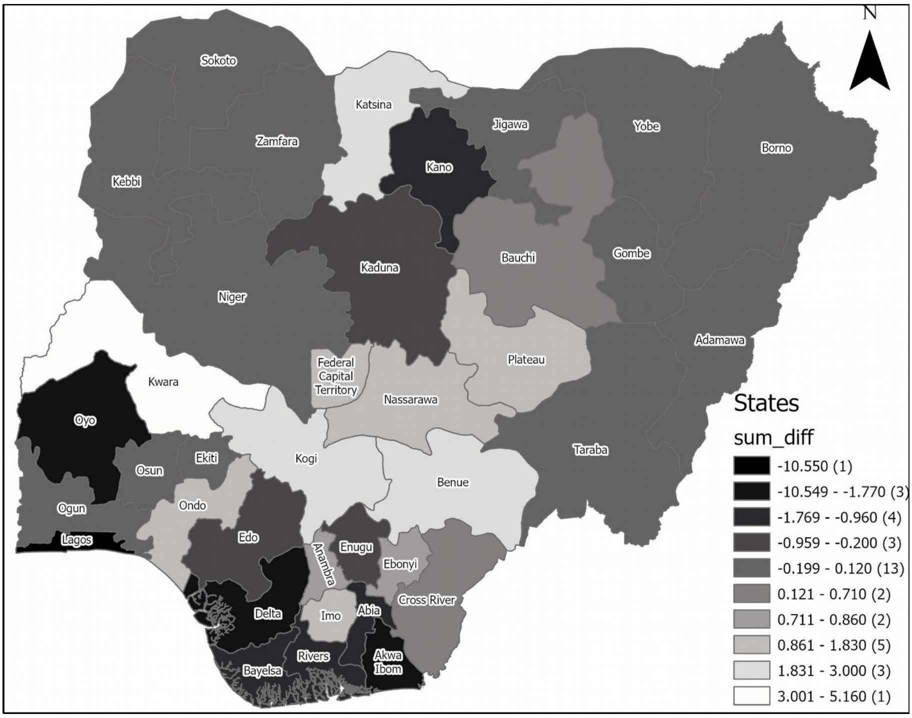

Figure 4 Distribution of sum of differences from baseline for betweenness and nodal efficiency

3.5 Discussion

3.5.1 Comparison of Network Attributes: Baseline vs Crisis Period

Centrality values showed that the baseline and the crisis periods are not statistically different from one another, however, the nodal efficiencies for the two periods were statistically different. Therefore, the efficiency of interaction among the spatial units (States) was negatively impacted by the pandemic. This is in line with the expectation that as mobility is restricted and people are afraid of contracting the virus interaction will be constrained and the efficiency of such interactions would be hampered. This was observed on the annual and monthly levels of aggregation. This was in line with the findings of Lawal and Nwegbu (2020) which showed that there were huge reductions in mobility towards place categories such as retail, recreation, grocery, pharmacy, parks, and transportation hubs during the pandemic.

3.5.2 Association between GDP and network attributes

Aggregated GDP values for each State were found to have a positive and highly significant relationship with the baseline network attributes. The betweenness and nodal efficiency displayed a moderate association with GDP figures. This is understandable since these attributes capture some aspects of spatial interaction which generate economic outputs. Just as human mobility is one of the facilitators of spatial interactions, its increase or decrease is bound to impact economic activities and consequently economic output (GDP). For example, the understanding from the gravity model (Ravenstein, 1885) showed that some places will attract more activities than others and the distance decay will play a role in the manifestation of such. Thus, places with higher gravitational pull (in this case economic pull) will have higher levels of interactions thus a higher level of economic output than those further away. This has been shown for labour productivity – isolated places have lower productivity (Battersby, 2006); economic size, and international trade (Battersby and Ewing, 2005; Beronilla et al., 2016; Brodzicki et al., 2015). Further to this is the conclusion from Midelfart (2004) showing that higher incomes could be attributed to higher activity density rather than education and skills across territorial units in Norway.

There was an indication that States with higher centrality and nodal efficiency values also have higher economic output. Thus, starting at the lower end of the rung (lower centrality, lower nodal efficiency) or the top (higher centrality and higher nodal efficiency) could dictate the extent of the impact on the economic output of the States. Essentially, irrespective of where each State starts, changes in economic output will likely be commensurate with the changes in network attributes.

3.5.3 Assessment of Differences in Network Attributes and Implications for the Economy

Results from Figures 4a and b indicate the variability of the impacts of the pandemic the network attributes across States in Nigeria. Thus, the disparity is wide-ranging and thus gives a reflection of the already established economic hierarchy across the country. States with higher centrality and nodal efficiency seem to witness the highest level of impact (i.e., the decline in network attributes). Thus, the attributes (high spatial interaction, economic power and pull) that made them successful (economically) are now contributing to their vulnerability to the pandemic. As mobility becomes depressed, States which enjoyed a greater proportion of economic activity (highly urbanised) across the country were the most impacted. Stier et al. (2020) showed that COVID-19 infection rates in the United States increase with increasing city size, thus highlighting how the attributes of cities or urbanised areas (huge population, the economy of scale, high productivity, etc.) can also bring about significant negative impacts (especially in the case of the current pandemic). As local and regional travels are restricted, such highly urbanised States (economically powerful) will most likely witness a significant negative impact on their economy.

The sum of the differences from the baseline showed that there are different levels of impact and Lagos State (most negatively impacted) is at the worst end while Kwara State is at the best end (most positively impacted). The variations observed in the number of infections could not be attributed to the extent of cases in each State, but the number of cases, restriction compliance, and risk perception across the State could offer a better explanation. For example, Lawal and Nwegbu (2020) reported that States where infections were discovered earlier and their neighbours witnessed an increase in mobility towards transportation hubs as the year ran out. Indicating that people are beginning to either accept the risk or take their chances, with such variation in the perception of risk, there are likely to be wide variations in economic impacts as well. Thus, even States with a relatively low number of infections could experience serious negative impacts due to the risk perception of the populace and the general risk communication framework. With the network attribute capturing inter-state mobility, this study provided a different dimension of changes in spatial interaction compared to the work of Lawal and Nwegbu (2020). More so, the summed differences highlight the potential for categorisation of States based on their role within the complex network of spatial interactions within Nigeria.

4 CONCLUSIONS

The definitive extent of the impact of the COVID-19 pandemic on the socio-economic condition of the populace is still emerging as the pandemic is still ongoing. With each State adopting varying measures to combat the disease, variations also emerged in the graph analysis of the complex network (spatial network) of mobility across the States.

From the result we can deduce that the more network efficient (lower average shortest path length) and central (higher betweenness value) States have a higher economic output.

From the comparison of baseline against the crisis period network attributes, we can conclude that there are significant changes over these periods. However, the efficiency of the network interactions among the State suffered the most and witnessed a decline across all States.

States with high centrality and betweenness values had a greater decline during the lockdown compared to baseline values. The summed difference for the two attributes offered an opportunity to create an index of impact based on the complex network of interaction among the States in Nigeria. Thus, providing an insight into one of the aspects of the extent of the economic impact of the COVID-19 on each State.

It should be noted that the data captured inter-state interaction only, therefore there is a need to complement this with intra-state interactions to fully capture the extent of the economic impact of COVID-19 in the country.

The study utilised aggregated mobility data from Facebook app users who had location tracking enabled. This is a limited population, as such incomplete data, however, in the absence of other mobility data for this period this represents the only viable option. Based on the ubiquity and the increasing penetration of mobile telephony and smartphones, this represents one of the viable options to track and understand the dynamic of spatial interaction across the country.

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Compliance with Ethical Standards

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Modelovanie potenciálneho ekonomického vplyvu COVID-19 v Nigérii: dôkazy z grafickej analýzy

Súhrn

Pandémia nového koronavírusu z roku 2019 (COVID-19) vytvorila šokovú vlnu, ktorú možno pocítiť v každej sfére spoločnosti a životného prostredia. Na začiatku pandémie prijali rôzne krajiny rôzne opatrenia. „Lockdowns“ krajiny však boli na celom svete celkom bežné. Keď sa objavili prvýkrát správy o epidémii (december 2019), Svetová zdravotnícka organizácia (WHO) pôvodne vyhlásila prepuknutie choroby za ohrozenie verejného zdravia medzinárodného významu a neskôr ju povýšila na globálnu pandémiu, keďže sa šírenie zintenzívňovalo. Za prvý týždeň marca 2021 celosvetový celkový počet prípadov nakazených vírusom COVID-19 prekročil 117 miliónov, zatiaľ čo úmrtia boli výrazne nad 2,6 milióna (Worldometer, 2021). Keďže choroba prerástla z lokálnej udalosti na pandémiu postihujúcu milióny ľudí a mnoho krajín, mnohé vlády zaviedli formu „lockdown“ alebo iné modely obmedzení mobility na obmedzenie šírenia choroby. Preto boli potrebné stimuly na zmiernenie dopadov sociálneho a ekonomického poklesu vyvolaného pandémiou.

V Nigérii zaviedla federálna vláda Nigérie celoštátny „lockdown“ 29. marca 2020 (Prezidentská pracovná skupina pre COVID19, 2020). Uzamknutie bolo po piatich týždňoch uvoľnené na celoštátny nočný zákaz vychádzania, ktorý pokračoval do 1. júna (prvá fáza uvoľneného blokovania), zatiaľ čo druhá fáza sa začala od 2. júna a predĺžila sa do 3. septembra 2020. Potom sa začala sa tretia fáza, ktorá trvá už štyri týždne a krajina je v čase písania tohto príspevku stále v tejto fáze.

Hodnota HDP sa v Nigérii v rámci federácie značne líši, pričom najvyššia hodnota je zaznamenaná v Lagose a najnižšia v štáte Yobe. Štátny priemer na jeden federálny štát za rok bol tesne nad 8 miliárd USD so štandardnou odchýlkou výrazne nad 6,6 miliardy USD. Distribúcia HDP je pozitívne skreslená (tabuľka 1), čo naznačuje, že existuje viac štátov s HDP nižším ako je priemer s hodnotou vyššou ako 1 miliarda USD, čo ukazuje, že rozdelenie HDP v Nigérii je veľmi nerovnomerné.

Hodnoty HDP na úrovni štátu sa porovnali so súhrnmi údajov zo sčítania ľudu za štáty pomocou korelácie momentu produkcie medzi jednotlivcami. Výsledky ukázali, že počet ľudí s prívlastkom HQ0403 (hlavný konštrukčný materiál použitý na podlahy obydlia – cement/betón) a HQ0504 (hlavný konštrukčný materiál použitý na steny obydlia – cementové/blokové tehly) je najvýznamnejší a štatisticky vý-

znamný s koreluje HDP v jednotlivých štátoch (tabuľka 2). Hodnoty centrality ukázali, že bežné základné a krízové obdobia sa od seba štatisticky nelíšia, avšak účinnosť uzlov pre tieto dve obdobia bola štatisticky odlišná. Intenzita interakcie medzi priestorovými jednotkami (štátmi) bola pandémiou jasne negatívne ovplyvnená. Je to v súlade s očakávaním, keďže mobilita bola obmedzená, ľudia sa obávali nakazenia, čím sa šírenie vírusu síce obmedzilo, ale negatívne sa to prejavilo v ekonomike. Toto sa pozorovalo na ročnej a mesačnej úrovni agregácie. To bolo v súlade so zisteniami Lawala a Nwegbu (2020), ktoré ukázali, že počas pandémie došlo k obrovskému zníženiu mobility z vidieka do miest za službami ako sú maloobchod, rekreácia, nákup potravín, návšteva lekární, pobyt v parkoch a aj vyhľadávaním dopravných služieb.

Definitívny rozsah vplyvu pandémie COVID-19 na sociálno-ekonomickú situáciu obyvateľstva sa stále mení, keďže pandémia stále prebieha. V čase keď každý štát prijal rôzne opatrenia na boj proti tejto chorobe, rozdiely sa objavili aj v grafovej analýze komplexnej siete (priestorovej siete) mobility v rámci štátov. Z výsledku môžeme odvodiť, že sieťovo efektívnejšie (nižšia priemerná dĺžka najkratšej cesty) a centrálne lepšie (vyššia hodnota medziľahlosti) štáty majú vyšší ekonomický výstup. Z porovnania základnej línie pred pandémiou s atribútmi siete krízového obdobia môžeme konštatovať, že v týchto obdobiach pandémie dochádza k významným zmenám. Efektívnosť sieťových interakcií medzi štátmi však utrpela najviac a bola svedkom poklesu vo všetkých štátoch.

Štáty s vysokou centralitou a medziľahlými hodnotami mali počas „lockdownu" väčší pokles v porovnaní so základnými hodnotami pred pandémiou. Súhrnný rozdiel pre tieto dva atribúty ponúkal príležitosť vytvoriť index vplyvu založený na komplexnej sieti interakcií medzi štátmi v Nigérii. Poskytuje tak pohľad na jeden z aspektov rozsahu ekonomického dopadu COVID-19 na každý štát. Je potrebné poznamenať, že údaje zachytávali iba medzištátne interakcie, preto je potrebné ich doplniť vnútroštátnymi interakciami, aby sa plne zachytil rozsah ekonomického dopadu COVID-19 v krajine.

Definitívny rozsah vplyvu pandémie COVID-19 na sociálno-ekonomický život obyvateľstva sa stále skúma, lebo pandémia stále prebieha. Keďže každý štát prijal rôzne opatrenia na boj proti tejto chorobe, grafová analýza pochopiteľne odhalila rozdiely medzi jednotlivými štátmi v dopade pandémie na sociálno-ekonomický život obyvateľov jednotlivých štátov.