APPLICATION OF COVID-19 DATA: INVESTIGATING THE IMPACT ON WEEKLY STOCK MARKET RETURNS IN NIGERIA

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Abstract

The study applied Covid-19 data to investigate the dynamics of the pandemic with respect to stock market returns in Nigeria, using weekly Covid-19 data and weekly stock returns for eight months (March –October, 2020), a period in which the pandemic assumed a terrific wave. Employing Generalised Method of Moments (GMM) estimation techniques, the data were sourced from worldometer. The empirical results showed that economic activities indicated by stock market returns contracted significantly during the Covid-19 pandemic, with weekly stock market returns nosediving. Liquidity is positively related with stock market returns, but the impact is weak, apparently due to the weak liquidity that characterized the pandemic. Therefore, this study recommends that, policy measures and strategies to create economic resilience that will stimulate stock market activities are imperative in the form of fiscal injections into the economy; conditional cash transfer (CCT) and other welfare packages. These should be supported with strong institutional and regulatory framework to guide stock market activities in Nigeria.

Keywords: Covid-19 data, Stock returns, Market dynamics, Generalised Method Moments

Jel Classification: C22, F32, I15, O55

1. INTRODUCTION

The widespread pandemic has hampered commercial and financial operations everywhere. The global COVID-19 epidemic has presented an unprecedented challenge to public health, food systems, and global growth, with dramatic and massive implications on human life, the economy, business investment, and financial markets. Economically and socially, the epidemic has been disastrous, especially for developing economies with fragile financial, economic, and social systems. The COVID-19's economic impact has been different in different places, with the extent of that influence depending on the strength of each region's economy (Chriscaden, 2020; Ang, 2020). The primary negative economic impact of COVID-19 in developed economies has been a drop in competition, followed by diminished collaboration between enterprises and a rising difficulty in recruiting and hiring competent personnel.

Covid-19 was a time of unparalleled action, and the necessary application of data to strengthen health systems and national economies. The capital market is one viewpoint that has experienced an unusual slowdown. Various research has been conducted since the World Health Organization declared the epidemic. Many writers have focused their research on the medical aspect, examining the potential impact on healthcare systems at the virus's maximal rate of spread. In certain specialized online platforms and scholarly publications, other researchers endeavour to explicitly model the transmission mechanism among the populace. For instance, some propose simulation models that enable the instantaneous evaluation of pandemic dynamics (Harpedanne, 2020).

Some authors have made efforts to assess the effects on specific economic sectors (Ataguba, 2020). However, it is widely recognized that the uncertainty surrounding the progression and duration of the coronavirus crisis poses significant challenges in predicting declines in GDP growth or devising strategies for economic recovery. The authors of a ground breaking study on the macroeconomics of epidemics disclose a complicated macroeconomic model and simulate many scenarios of the consequences of a pandemic. Additional research has looked at the global economic effects of the 2020 coronavirus pandemic (Barro, Ursa, & Weng; Correia, Luck, & Verner; IMF; Jordà, Singh, & Taylor; Kohlscheen, Mojon, & Rees; McKibbin & Fernando; OECD; Saez & Zucman; UNCTAD). According to existing literature, it is evident that the evaluation of the macroeconomic framework and the identification of suitable economic policy measures will pose significant difficulties in the absence of estimations about the extent of the population's exposure and the duration of the pandemic's spread at the global, regional, and national scales (Albu, Preda, Lupu, Dobrata, Calin, and Boghicevici, 2020). Therefore, this research endeavours to assess its effect on the economy, particularly the stock market, using the most recent accessible statistical data. Our methodology for assessing the transmission of the Covid-19 pandemic within the population relies on the utilization of data publicly released under the title "COVID-19 (Coronavirus) Pandemic" by global authorities. Hence, this research offers empirically derived insights into the reaction of the Nigerian capital market to the pandemic, so contributing to the understanding of the pandemic's dynamics and its economic impact.

The COVID-19 global pandemic had significant negative effects on investment, liquidity, capital markets and economies all over the world. For Nigeria, the devastating effects have been huge, given the weak structures and vulnerabilities.

The pandemic which began to have significant negative effects on the Nigerian economy in the first three months of the year 2020, led to serious market liquidity problems, dwindling investment, both domestic and external. The capital market witnessed significant decline in investment inflows and liquidity due to economic downturn and fragilities. A number of studies have examined the effect of Covid-19 on national health and economies (see Albu et al., 2020; Harpedanne, 2020), little empirical attention has been devoted to the application of covid-19 data on capital market in developed and emerging economies. In addition, these studies have found mixed findings, due apparently to data and methodological approaches. For a developing country like Nigeria, with many unfolding dynamics and susceptibilities, it is important that the effect of covid-19 on the capital market be investigated. This is the imperative of this current study.

On this basis, the objective of this study is to investigate the impact of the Covid-19 pandemic on stock returns in Nigeria.

2. BRIEF SURVEY OF LITERATURE

On the application of Covid-19 pandemic data, the preponderance of studies has focused on its impact on health systems (see Garattin, Raffle, Aisya, Sartain, and Kozlakidis, 2019; Wu, Wang, Nicholas & Maitland, 2020; Qiu, Yuan, Wu, Zhou, Zheng and Huang, 2020; Ayyoubzadeh, Zohedi, Ahmadi, and Niakan, 2020; Guraya, 2020). A study conducted by Haleem, Javaid, Khan, and Vaishya (2020) investigated the primary applications of big data within the framework of the COVID-19 pandemic in India. Bragazzi, Dai, Damiani, Behzadifar, Martini, and Wu (2020) examined strategies for combating the COVID-19 pandemic by utilizing big data and Artificial Intelligence. Additional research examines the global economic repercussions of the coronavirus pandemic. Barro (2020); Correia et al. (2020); IMF (2020); Jordà et al. (2020); Kohlscheen et al. (2020); McKibbin and Fernando (2020); OECD (2020); Saez and Zucman (2020); and UNCTAD (2020) are among these studies. Albu et al. (2020) conducted an estimation of the Covid-19 pandemic's transmission and economic repercussions. Limited recent research has been conducted on the transmission and consequences of the Covid-19 pandemic (refer to Yang et al., 2020; Qin et al., 2020).

Each of these empirical studies does not exclusively examine the financial market repercussions of the CoVD-19 pandemic. This research is necessary because of the glaring gap that has been identified.

2.1. STATISTICAL DATA ON COVID-19

The Covid-19 pandemic started in China in August 2019, with the first incidence recorded. From initial Covid-19 tested positive cases of 52, a rise of 5 % percent was followed. This figures increased successively on daily basis to 570 active cases in that same month. By November 2019, total active cases at global level rose to 2,345. The rise continued in the succeeding months of January 2020 to an astronomical level of 54,204, with China, USA, and United Kingdom accounting for a large proportion of the growth. According to the Covid-19 outbreak, situation report by the Nigeria Centre for Disease Control (NCDC), the first active Covid-19 case was recorded in Nigeria on 27th of February, 2020, when a 44-year-old Italian citizen was diagnosed with Covid-19 in Lagos State. This was followed with 19 contacts under- follow up cases in Ogun and 5 in Lagos, making a total of 24 contacts under follow-up cases. As of February 29, 2020, there were a total of 85,403 confirmed cases recorded globally, with 95.5% of these cases occurring in China. (Albu, Preda, Lupu, Dobrata, Calin, and Boghicevici, 2020). The number of deaths reported was 2,924. A total of 49 nations were affected by the outbreak, including three countries in Africa: Egypt, Algeria, and Nigeria.

On January 8th, 2021, subsequent to the occurrence of a second wave of the Covid-19 pandemic, the Nigeria Centre for Disease Control (NCDC) confirmed a total of 1,544 newly reported cases of Covid-19 infections. Consequently, the cumulative number of infections in Nigeria reached a total of 97,478 cases (Albu, Preda, Lupu, Dobrata, Calin, and Boghicevici, 2020).

2.2. APPLICATIONS OF BIG DATA TECHNOLOGY FOR COVID-19

The implementation of big data technology for the treatment of COVID-19 encompasses a wide range of information, including medical and health data, media and social data, data collected by intelligent apparatus, data on content related to epidemic prevention, online consumer data, and deep learning data (Kohlscheen et al., 2020)

2.3. MEDICAL AND HEALTH DATA

Big data in health care can improve the efficiency of hospital management under pressure, increase the likelihood of swiftly discovering diagnosis and treatment methods, and promote the timely detection and reporting of cases, all of which are important for the prevention and control of epidemics. At first, the EMRS disease reporting system had trouble properly detecting and reporting COVID-19 instances. Frontline physicians were inefficient in the earliest phases of the epidemic in gathering patient data, diagnosing illnesses, and reporting infectious disorders. For instance, the Chinese Center for Disease Control and Prevention (CDC), a government public welfare organization, has integrated EMRS data into its technological management of disease control and public health (Kohlscheen et al., 2020).

Connecting the CDC's early warning system with hospital EMRS allowed for the rapid application of big data technology to the collection and analysis of medical big data. To get started, the CDC's AI knowledge base used automatic matching to look for EMRS entries including terms like "pneumonia." When probable hospital cases were detected, the EMRS would alert front-end physician computers, prompting doctors to verify the EMRS data was complete and accurate before issuing an infectious disease report. Using a surveillance system reduces the risk of infectious diseases going undetected or underreported. Second, the successful transmission of health data and the avoidance of late or underreporting were made possible by CDC monitoring, which enhanced the finding and testing of EMRS large data. The CDC surveillance system, for instance, cut down on the 5-8 minute average time it took for clinicians to report a COVID-19 case to within 40 seconds, and the 2-3 minute average time it took for online reporting via the CDC's web-based infectious disease reporting system to a few seconds (Jordà et al., 2020)

COVID-19 diagnoses in China and elsewhere were backed up by CDC surveillance. The COVID-19 virus was first discovered in China; and subsequent studies, electron micrographs, and adapted primers and probes were published for use elsewhere across the world. The delay in releasing information on COVID-19 in China contributed to its rapid spread in the country and beyond. Chinese and worldwide researchers were given access to COVID-19 genes and gene sets, as well as big data information for COVID-19 research platforms, at the disease's intermediate phases thanks to the prompt release of scientific resources and data (Wu et al., 2020).

Hospital administration was bolstered by data gathered by the Centre for Disease Control. In order to better manage things like protective supplies, health status reports, epidemic developments, and telecommuting, the CDC advocated for the integration of data from electronic medical record systems, hospital information systems, and library information systems. Hospital management made judgments and decisions based on the combined data through analytical and visual processing (Wu et al.,2020), When medical facilities were overrun with patients, big data technology was used to create a hierarchical system for diagnosis and treatment that made the most efficient use of available resources. Predicting how an outbreak will affect available healthcare resources was the primary use case for big data predictive analytics in the context of epidemic control and prevention. Predictive analytics has been used to forecast the peaks and inflection points of epidemics by using big data models such as communication dynamics and risk level distribution of the incidence rate and close connections. This approach enables the strategic allocation of resources to regional hospitals based on varying needs. According to Wu et al. (2020), the use of internet platform big data searches and susceptible-exposed-infectious-removed (SEIR) transmission modeling has shown the potential to forecast COVID-19 transmission patterns (Qin et al., 2020).

Health departments prepared for the epidemic in advance by deploying preventative resources in high-risk areas based on expected epidemic trends and risk level information. Big data prediction analytics were also used by the relevant government agencies to pinpoint the epidemic's peak and inflection point and so estimate when normal operations could resume. Last but not least, HIS medical expenditures and insurance information were integrated using big data predictive analytics to forecast the spread of disease, the percentage of patients with certain histological types, the cost of diagnosis and treatment, and the distribution of healthcare resources (Wu et al., 2020). Treatment for patients infected with COVID-

19 can be aided by using big data diagnostic analytics to screen currently used clinical pneumonia medications. The effectiveness and composition of Chinese medicinal ingredients for treating COVID-19, for instance, were investigated using big data on patients' prescription traditional Chinese medicine. Thirteen of the natural substances utilized in Chinese medicine were discovered to have potential anti-COVID-19 effects, including regulation of viral replication, modulation of immunological and inflammatory pathways, and inhibition of the hypoxic cascade, according to a thorough screening (Zhang *et al.*, 2020).

2.4. NEWS MEDIA AND SOCIAL DATA

During the outbreak, there were false claims and misleading information spread on the internet, including that children could not be infected with COVID-19, that drinking Banlangen and smoked vinegar could prevent COVID-19, and that gargling with salt water could make you immune. As a result of hearing such untruths, people became less vigilant and took ineffective efforts to limit the spread of the COVID-19 outbreak. Following the discovery of incorrect material regarding COVID-19, internet service providers notified national authority epidemic prevention organizations and specialists. China responded to the spread of misleading information by using state-run media, documentaries, and live broadcasts (Zhou & Chen, 2020; Qin et al., 2020)

The negative effects of viral illnesses may be outweighed by the negative effects of uncertainty and panic on social activity during a big epidemic. The geographic dispersion of public opinion can be tracked and evaluated with the help of social media data. A user semantic behaviour evolution model was created to measure and analyze shifts in public opinion (Zhou & Chen, 2020; Qin et al., 2020) by monitoring topics and attitudes that arose in microblog users' timelines in response to COVID-19. The findings showed that between January 9 and February 10, 2020, over 60% of posts about the government's COVID-19 announcements and the popularization of scientific research on illness prevention were upbeat and consistent. For instance, "help-seeking" messages were highly concentrated in Wuhan, the epicenter of the pandemic, but "donation information" posts were dispersed extensively around the country (Zhou & Chen, 2020).

The number of possible or confirmed new cases of COVID-19 was predicted, for instance, by Qin et al. (2020) using big data. The authors discovered that COVID-19 outbreaks might be detected 6-9 days in advance by using a number of lagging "social media search indexes" for various terms including clinical symptoms of the virus (such as dry cough, fever, chest pain, and pneumonia).

2.5. ONLINE CONSUMER DATA

Businesses can improve their production, marketing, logistics, and safe resumption of work with the use of big data. During an epidemic, businesses that manufacture medicines and other essentials can gauge public demand with the use of big data, allowing them to schedule optimal production and efficient distribution.

With the help of big data, businesses were able to focus on producing and distributing electric pressure cookers, which were among the most discussed goods during the outbreak (Wu et al., 2020).

2.6. DEEP LEARNING DATA

Deep learning is a machine learning analytical method widely used to probe massive data, completing tasks that are challenging for standard analysis methods (Bs, Janowczyk & Madabhushi, 2020). It finds use in a wide range of disciplines. Using deep learning and large data, we can more accurately predict the future course of diseases like COVID-19. According to Xu, Gel, Ramirez, Nezafati, Zhang, and Tsui (2017), deep learning outperformed the generalized linear model, the least absolute shrinkage and selection operator model, and the autoregressive integrated moving average (ARIMA) model in predicting the prevalence of influenza-like illnesses in Hong Kong. Medical resource optimization and early prevention before patients develop severe COVID-19 symptoms may benefit from the rapid screening tool that deep learning provides, as found by Wang et al. (2020).

Large volumes of data, such as meteorological factors and internet big data, have been shown to improve the accuracy of predictions of infectious diseases in a number of research conducted outside of China. Three viral diseases in Korea were predicted one week into the future using deep learning by Chae, Kwon, & Lee (2020), who found that deep neural network and long-short term memory learning models beat ARIMA techniques. Ayyoubzadeh et al. (2020) used data mining algorithms to predict COVID-19 outbreak trends and found that the frequency with which people searched for information about handwashing, hand sanitizers, and antiseptics was the most accurate predictor. According to Togacar, Ergen, and Comert (2020), a deep learning model trained on data relating to COVID-19, pneumonia, and baseline x-ray imaging was able to effectively detect COVID-19.

3. METHODOLOGY

It comprises model specification, sources of data and estimation technique used in this study.

3.1. SOURCES OF DATA

There are currently numerous data banks that document the spread of the Coronavirus pandemic. Worldometer is the go-to source for information since it publishes official data for eleven variables tracking the spread of the epidemic, both globally and nationally, in near real time. To better understand how the Covid-19 epidemic would affect Nigeria's stock market, we compared the average weekly reporting of cases to stock returns from March 2020 to October 2020. The period was the peak of the Covid-19 Pandemic, when symptoms were at their most severe. The degree to which equities react to information increases at weekly frequency relative to monthly ones. Also, the possibility for greater estimating error increases with lower frequencies. The robustness of the data may be tested every week.

Weekly returns are often sufficient for identifying delayed impacts given that attention is focused on equities with the greatest severe delay (information asymmetry), whose lagged response often takes several weeks. The definition of weekly returns is the sum of the daily returns from one Friday to the next.

To this end, we study a stock returns model that looks at the short-term and immediate effects of information delay on weekly stock price data in order to discover how stock prices react to the Covid-19 data resulting from average weekly information.

3.2. MODEL SPECIFICATION

In empirical specification, the systematic relationship between weekly Covid-19 data and weekly stock returns in Nigeria is captured in this form:

$$SR_t = f(COVID - 19_t, X_t) \quad (1)$$

Where:

SR= is the dependent variable, here, stock returns is used as a measure of capital market performance;

COVID-19= is Covid-19 data,

$t = is$ time/period t, and

X= is a vector of additional variables, in line with the literature, that influence stock returns. These variables include: growth rate of the economy, measured by the growth of real GDP (GRGDP) and market liquidity (LIQ). The inclusion of growth rate of the economy is particularly instructive given that it captures the level of economic activities, particularly during the period in focus, and given that, Covid-19 affects the capital market through the channel of economic activities, its inclusion is in line with theory.

On the inclusion of these variables, the empirical model to be estimated is:

$$SR = \alpha_0 + \alpha_0 SR_{t-1} + \alpha_2 COVID - 19_{,t} + \alpha_3 GRGDP_t + \alpha_4 LIQ_t + \varepsilon_{i,t}, \quad (2)$$

where the variables are as earlier defined, and 'ε' is the unobserved error term.

Apriori, $\alpha_1, \alpha_3, \alpha_4 > 0; \alpha_2 < 0$.

3.3. ESTIMATION TECHNIQUE

In measuring the responsiveness of stock returns to a Covid-19 pandemic data and a host of control variables, it is important to note that stock returns can be endogenously correlated (see Lee & Sung, 2005). It is therefore important to use an appropriate estimation technique capable of addressing potential endogeneity bias, simultaneous or reverse causation, and omission variable problem. Following this, the study adopts the Generalised Method of Moments (GMM) estimation, which is capable of addressing reverse causality, potential endogeneity and downward bias that could likely result when Ordinary Least Square (OLS) is used. As an appropriate instrumental variable (lagged estimation method), the GMM is best suited for this study since it uses the moments of endogenous variables as instruments (see Holtz-Eakin, Newey & Rosen, 1988).

In using the GMM, the moment condition is used in generating the lag instruments, which are microstructure constituent variables. The GMM is an instrumental variable dynamic technique that uses appropriate instruments in providing reliable estimates. The Generalised Method of Moments selects instruments based on the moment conditions of the probability distribution and thus produces more consistent, error-free, heteroscedasticity free estimators than other instrumental variable technique (IV) like the Two Stage Least Squares technique (2SLS). The GMM estimator is computed by minimizing the quadratic form

$$q = m'W - 1\, m \tag{3}$$

Where:

$m = T - 1 \sum Z't \otimes U_t + 1$ (4), and

W= asymptotic variance/covariance matrix associated with the m-th weighting element under orthogonality.

If one chooses 'W' so that it converges to the inverse of the long-run covariance matrix, as shown by Hansen (1982), then one obtains an optimal or asymptotically efficient GMM estimator of the parameter. 'q' and 'T' denote the full time period used to calculate the average moments, whereas 'Z_t' represents a subset of the present information set's variables used to represent the instruments in the model. As the lags in the equity market's return cycle, instruments play a key role in the GMM framework. In its quadratic form, the objective function 'JT,' given as, is minimized via the GMM as follows:

$$J_T = g_T(\theta)^{'}\, W g_T(\theta) \tag{5}$$

Where:

$g_T(\theta)$= is a set of *moment conditions*, and

W= is a matrix of arbitrary weight for the instruments.

The GMM estimator $\hat{\theta}$ is given by:

$$\hat{\theta} = arg \min_{\theta} J_T = arg \min_{\theta} g_T\,(\theta)' W g_T(\theta) \tag{6}$$

For the system to be identified, it should be noted that there must be at least as many moment conditions $[g_T(\theta)]$ as parameters (θ). Following Hansen (1982), the estimator in equation (6) is not only consistent but also asymptotically efficient, if the weighting matrix W^{-1} is chosen. W^{-1} is the inverse of a covariance matrix with asymptotic variation. It is considered optimal because it produces θ with the least amount of asymptotic variance.

4. EMPIRICAL RESULTS AND ANALYSIS

The empirical result of regressing stock returns on Covid-19 data and other variables is presented in table 1. The adjusted R^2 value of 0.93 shows that the regressors explain 93 percent of the systematic variations in stock returns during the Covid-19 pandemic period. The model thus, has good accuracy and predictability. A DW statistic of 1.88 indicates that autocorrelation is absent from the model, making it suitable for policy formulation and implementation.

Table 1. *COVID-19 Stock Return Model -GMM Estimates*

Variable	Coefficient	t-Stat.	Prob.
SR (-1)	-1.0251	1.1171	0.27
COVID-19	-0.1196	-2.2237	0.03
GRGDP	0.2870	1.7866	0.08
LIQ	0.1053	1.1029	0.28
Adjusted R-squared	0.93		
DW Stat	1.88		
J-Stat	5.23 (0.29)	0.125	

*Source**:** Author's computation 2021*

The coefficient of the first lag of stock returns is positively signed but not significant. Thus, the performance of stock during the heat of the pandemic had some level of persistence, given that it was a global phenomenon. The coefficient of Covid-19 data is negatively signed in line with the presumptive signs and is significant at the 5 percent level. Thus, without doubt, the Covid-19 pandemic has had a deteriorating effect on stock performance, given that investment both local and foreign declined considerably. With decelerating business and investment activities, stock returns witnessed a sharp deceleration. The finding is consistent with the findings of Ataguba, et al. (2020), IMF (2020), OECD (2020) and Albu et al. (2020).

The coefficient of growth rate of the economy- a measure of economic activities is positively signed with stock returns but passes the significance test only at the 10 percent level. Invariably, increased economic activities tend to induce stock market transactions. The effect is nonetheless mild given the fact that the Covid-19 has occasioned economic downturns in national and global perspective that significantly slowed economic activities, such that stock performance plummeted. This finding supports the findings of Correia et al. (2020) and UNCTAD (2020).

Finally, the coefficient of liquidity is positive but not significant. Without doubt, increased market liquidity stimulates stock returns but the effect is found to be weak in this current Covid-19 pandemic. Apparently, the significant decline in economic activities, business, investment and financial liquidity precipitated by the Covid-19 pandemic has negatively and significantly affected stock market performance.

Considering key diagnostic tests for robustness and validity of results obtained, the Hansen-J over-identification test of 0.125 fails the significance test at the 5 percent level, indicating that non-rejection of the null hypothesis that the over-identifying restrictions are equal to zero. Apparently, the models along with the selected instruments actually pass the identification tests. The specification of the model can therefore not be rejected as it is appropriate and the instruments are robust and valid. The model is therefore fit for structural and policy analysis.

5. CONCLUSION AND RECOMMENDATION

The study applied Covid-19 data to investigate the dynamics of the pandemic with respect to stock market returns in Nigeria, using weekly Covid-19 data and weekly stock returns for eight months (March –October, 2020) in which the pandemic assumed a terrific wave. Based on our simulations, the pandemic evolution can be classified into four distinct phases. Employing GMM estimation techniques, the empirical results show that economic activities and stock market significantly contracted during the Covid-19 pandemic (although, still in the pandemic, but with less terrific wave and consequences).

The study recommends the necessity for stringent global and national economic, budgetary, medical, and technology safeguards. There is need for Governments to inject enormous amounts of fiscal stimulus to help the population and businesses hit by Covid-19. It is also crucial that Nigeria establish a robust institutional and regulatory framework to direct stock market activity.

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