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Adaptive market hypothesis: The story of the stock markets and COVID-19 pandemic

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\textbf{ABSTRACT}

Since the level of markets’ information efficiency is key to profiteering by strategic players, shocks; such as the COVID-19 pandemic, can play a role in the nature of markets’ information efficiency. The martingale difference and conditional heteroscedasticity tests are used to evaluate the Adaptive form of market efficiency for four (4) major stock market indexes in the top four affected economies during the COVID-19 pandemic (USA, Brazil, India, and Russia). Generally, based on the martingale difference spectral test, there is no evidence of a substantial change in the levels of market efficiency for the US and Brazilian stock markets in the short, medium, and long term. However, in the long term, the Indian stock markets became more information inefficient after the coronavirus outbreak while the Russian stock markets become more information efficient. Intuitively, these affect the forecastability and predictability of these markets’ prices and/or returns. Thereby, informing the strategic and trading actions of stock investors (including arbitrageurs) towards profit optimization, portfolio asset selection, portfolio asset adjustment, etc. Similar policy implications are further discussed.

1. Motivation

The first wave of COVID-19 outbreak (early 2020) resulted in panics and temporary closure of businesses in almost all the economies simultaneously with confirmed positive coronavirus cases. Also, the second wave (early 2021) have resulted in similar actions, howbeit, at city levels. These actions are bound to affect the performance and dynamics of markets such as the stock markets. For instance, Okorie and Lin (2020b) show that the COVID-19 outbreak has a substantial fractal contagion effect on the stock markets. Other studies have also provided evidence to the substantial effect of the COVID-19 on other markets. In the same light, this article seeks to establish the impact of the outbreak of COVID-19 on the market information efficiency for four (4) stock market indexes, from the top four affected economies (based on the number of confirmed coronavirus cases\textsuperscript{1}). These economies are the United States of America (4,703,727 cases), Brazil (2,66,298 cases), India (1,697,054 cases), and Russia (839,981 cases). The informational market efficiency during a global shock is very important as it informs the trading and strategic actions of the oil market investors towards profitability outcomes given an inefficient nature of the market. For the essence of this study, it is pertinent to point out that an improved level of market efficiency (i.e. reduced market inefficiency) suggests that the prices and return of that market are less

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\textsuperscript{1} See a real time indicators of COVID-19, as at August 1, 2020, at \url{https://www.worldometers.info/coronavirus/}.

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predictable and forecastable while a reduced market efficiency level (i.e. increased inefficiency) suggests that the market is more predictable and forecastable using available information set and vice versa. Hence, investors can study the market and take strategic actions to make positive profits. The martingale process and conditional heteroscedasticity testing process are adopted to test the information efficiency of these stock markets. There are some empirical shreds of evidence about the impact of global shocks on markets. For instance, Park and Shin (2020) investigated the impact of the 2008 global financial crisis on foreign banks’ exposure at regional and national levels. Even at the local levels, the financial crisis affected financial institutions (Agosteo et al., 2020). This is also true for the stock markets at regional levels (Kenourgios & Dimitriou, 2015). The WTI (West Texas Intermediate) market became more information inefficient after the Gulf war and the financial crisis (Jiang et al., 2014). Owing to the 2008 global financial crisis, Lazár et al. (2012) investigated the effects of the crisis on the currency markets’ information efficiency level. Ghazani and Ebrahimi (2019) also used these techniques to evaluate the adaptive market hypothesis of the oil market, etc.

For most economies, the fact that curtaging the spread of COVID-19 in an economy requires the lockdown of businesses, among other things, suggests panic in the economy. Moreso, to comfortably stay at home all through the lockdown periods require financial resources to be able to afford the necessary resources that facilitate a family to stay at home. Hence, most governments have given household aids and people tend to liquidate their assets into forms (mostly cash) that would enable them to obtain the materials needed to stay at home. This includes liquidating one’s position in the stock market. Besides, this pandemic breeds bad information and by efficient market hypothesis, the markets assimilate this new information and reflect it in the prices. Investors would respond quickly to avert the losses this bad news brings, etc. Therefore, this panic makes the stock markets investors to take early actions in response to the bad news and panic. In other words, their decision to take short or long positions was not informed by the traditional alpha rule but mostly because of anticipated future price fall or to have enough resources to afford staying at home until it is necessary to resume their businesses as usual or due to the rapid fall in the asset prices. When a few investors start taking the same action, the market follows. This is likely the observed similar patterns for these sampled economies, hence, the contagion effect of the COVID-19 pandemic on the stock markets. The current coronavirus (COVID-19) pandemic emanated in a wildlife market in the city of Wuhan, China. Due to its rapid spread and threats to humans, the market was closed. Subsequently, the whole city, country, other countries of the world are locked down to strategically separate and quarantine the infected persons from the uninfected persons. This outbreak has rapidly spread from China to many, if not all, countries of the world, and a great number of deaths and confirmed positive results have been declared concurrently. In the absence of a working vaccine, an effective model for curtailing and controlling the effects of the COVID-19 in an economy involves a total lockdown and stay at home strategy. In which, the populace is subdivided overtime, into infected and uninfected persons. While the infected persons are quarantined and treated, the uninfected persons return to business as usual. This model has been very effective in salvaging economies from the consequences of the virus. This results in panic since businesses and operations would be affected, families would need resources for sustenance through the total lockdown periods, etc. In other to get these resources, most investors liquidate their positions, this includes stock market positions and thus affects the stock markets through its prices and volatility; and thereby, leading to varying natures of market information efficiency inherent in these stock markets.

The weak-form market efficient information hypothesis testing has evolved through autocorrelation testing to variance ratio tests. However, they hinge on the forecasting or predictability power of past return information over future or present returns. The information efficiency of a market is synonymous with the equilibrium spot prices for the market. The stock market is a crucial part of any economy given that it is capable of affecting most different sectors and levels in an economy through various channels. The traditional approach of testing the efficient market hypothesis has been shown to have two shortfalls. Firstly, the traditional approach is a two-sided coin approach that decides whether the whole sampled period is efficient or not and ignores relative efficiency testing (Campbell et al., 1997). Secondly, the traditional approach assumes a steady degree of market information efficiency over a predefined time (Lim & Brooks, 2011). To tackle these two challenges, Lo (2004) introduced the dynamic rolling windows Adaptive Market Hypothesis (AMH) has been employed in literature over the traditional Efficient Market Hypothesis (EMH) techniques (see Ghazani and Ebrahimi, 2019; Charles et al., 2012; Lazár et al., 2012; Lim & Brooks, 2011; Kim et al., 2011; Lo, 2005; etc.). Tabak and Cajuiero (2007) analyzed the information efficiency level of the WTI and Brent crude oil markets using fractal structures and showed that over time, both markets have become more information efficient. Based on the WTIE deregulation policy, the WTI market became less information efficient while the Brent market is weak-form efficient (Charles & Darné, 2009). Ghazani and Ebrahimi (2019) added the OPEC market to the WTI and Brent crude oil markets and showed that the OPEC market is less efficient relative to the WTI and the Brent crude oil markets over longer windows. Over short and long windows, Wang and Liu (2010) used the multi-scale rolling windows techniques to show that the WTI crude oil market is inefficient in both windows. The WTI crude oil market became more information inefficient after the Gulf war and the financial crisis (Jiang et al., 2014). Among twenty-five commodity futures markets, the heating oil is the most efficient market, followed by the WTI, cotton, wheat, coffee, etc. (Kristoufek & Vosvrda, 2014).

Markets are interconnected and as such, both global and specific market shocks can impact different markets (Okorie, 2020c; Okorie & Lin, 2020d). Okorie and Lin (2020a) show that the crude oil market is connected with the cryptocurrency markets through returns and volatility. Such information comes in handy when forecasting the short-term and long-term asset price as Nguyen and Nabney (2010) showed in the electricity market. Moreso, crises, such as terrorist attacks are also capable of affecting commodity markets (Ramiah et al., 2019). Okorie (2020a), Okorie (2020b) and Okorie and Lin (2020c) show that the Chinese government’s decision to ban ICOs altered the bitcoin market significantly. Ortiz-Cruz et al. (2012) adopted the informational entropy analysis to provide evidence to the evolution of information efficiency and complexity in the crude oil market. Kjerland (2010) shows that the deregulation in the energy market resulted in an undervaluation of the assets during the ex-post periods relative to the ex-ante periods. Aroui et al. (2013) test the long and short-run market efficiency of nine precious metal markets and found evidence to support the bias-ness of futures prices as predictors of the spot prices and the futures market is not risk-neutral. Therefore, this article tests the information efficiency of four (4) stock market indexes (both ex-ante and ex-post COVID-19 outbreak) using the Adaptive Market
Hypothesis (AMH) techniques that were introduced by Lo (2004). Based on the martingale difference spectral results, there is no evidence of a substantial change in the levels of market efficiency for the US and Brazilian stock markets in the short, medium, and long term. However, in the long term, the Indian stock markets became more information inefficient after the coronavirus outbreak while the Russian stock markets become more information efficient. The conditional heteroscedasticity test results often confirmed that of the martingale difference spectral test. The rest of the article is structured as; empirical strategy in Section 2, results & discussions in Section 3, and conclusion in Section 4.

2. Empirical strategy

In other to test the level of efficiency for these four stock market indexes (USA stock market, Brazil stock market, India stock markets, and Russia stock markets) we adopt two testing techniques over different (short, middle, and long) rolling windows to better grasp the evolution of the markets efficiency levels. These two techniques are the martingale difference test (Escanciano & Velasco, 2006) and the conditional heteroscedasticity test (Lobato et al., 2001; Box & Pierce, 1970). These two approaches are used to test the hypothesis that the markets return series are martingale (i.e. no forecastability or predictability). The return series is defined as Eq. (0).

\[ Z_t = 100 \log \left( \frac{P_t}{P_{t-1}} \right) \]  

(0)

2.1. Martingale difference spectral (MDS) testing techniques

The martingale difference testing techniques adopted is the Generalized Spectral test by Escanciano and Velasco (2006). The MDS test is a non-parametric dependency (linear and non-linear) test in a time series, free of any unit-root. This technique has been applied in the literature to test the market level of efficiency before and after the financial crisis (Lazar et al., 2012), Ghazani and Ebrahim (2019) also used the MDH to evaluate the adaptive market hypothesis of the stock markets, etc. The martingale difference hypothesis is expressed as

\[ H_0 : m_\theta(Z_t) = 0, \forall \theta \geq 1 \]

\[ \omega_\theta(k) = E[|Z_t - \mu| \exp(ikZ_{t-\theta})] \]  

(1)

where the martingale process is \( Z_t \) at time \( t, t, \theta \in [1, ..., T] \), i.e. unforecastable stochastic process and the pairwise function is \( m_\theta(Z_t) = E[Z_t - \mu Z_{t-\theta}] \). Given the conditional mean nonlinear dependency gauge function in Eq. (1) where \( k \in \mathbb{R} \) and the exponential weight captures non-linear dependence. Consistently, the null hypothesis becomes \( \omega_\theta(k) = 0 \forall \theta \geq 1 \). The Escanciano and Velasco (2006) generalized spectral distribution function is defined as

\[ H(k, \varphi) = \omega_\theta(k)\varphi + 2 \sum_{\vartheta=1}^{\infty} \omega_\theta(k) \frac{\sin(\vartheta \pi \varphi)}{\vartheta \pi} \]  

(2)

\[ \hat{H}(k, \varphi) = \omega_\theta(k)\varphi + 2 \sum_{\vartheta=1}^{\infty} \omega_\theta(k) \frac{\sin(\vartheta \pi \varphi)}{\vartheta \pi} \sqrt{1 - \frac{\theta}{T}} \]  

(3)

\[ \hat{\omega}_\theta(k) = \frac{1}{T} \sum_{\vartheta=1}^{T} \left( Z_{t-\theta} - \hat{Z}_{T-\theta} \right) e^{ikZ_{t-\theta}} \]

\[ \hat{H}(k, \varphi) \] is the sample estimate of the spectral density function in Eq. (2) where \( \varphi \in [0, 1] \) and the finite sample correction factor is \( \sqrt{1 - \frac{\theta}{T}} \). Under this spectral definition, the martingale difference hypothesis is consistent with \( H(k, \varphi) = \omega_\theta(k)\varphi \). The test is developed under the difference between the sample estimate \( \hat{H}(k, \varphi) \), and the hypothesized null \( H(k, \varphi) = \omega_\theta(k)\varphi \) as stated in Eq. (4).

\[ S_T(k, \varphi) = \sqrt{T} \left( \hat{H}(k, \varphi) - \omega_\theta(k)\varphi \right) = \sum_{\vartheta=1}^{T} \sqrt{T - \theta} \hat{\omega}_\theta(k) \frac{\sqrt{2}\sin(\vartheta \pi \varphi)}{\vartheta \pi} \]  

(4)

\[ D_T = \int \left( |S_T(k, \varphi)| \right)^2 W(dk) \]  

(5)

\[ D_T = \sum_{\vartheta=1}^{T} \sum_{\vartheta=1}^{\infty} \sum_{\vartheta=1}^{T} \left( Z_{t-\theta} - \hat{Z}_{T-\theta} \right) \left( Z_{t-\theta} - \hat{Z}_{T-\theta} \right) e^{i(kZ_{t-\theta} - Z_{T-\theta})} \]  

(6)

Eq. (5) captures the distance of \( S_T(k, \varphi) \) from the origin for all the possible values of \( k \) and \( \varphi \) using the Cramer-Von Mises norm. To satisfy the conditions on the weighting matrix, \( W(.) \), the standard normal distribution function is adopted as the weighting function to develop the generalized spectral test statistic in Eq. (6) applied to test the markets return series martingale difference hypothesis.
2.2. Conditional heteroscedasticity (CH) testing technique

The conditional heteroscedasticity test adopted is the Automatic Portmanteau test by Lobato et al. (2001) that builds on the Box and Pierce (1970) testing technique. Ghazani and Ebrahim (2019) used the CH approach to evaluate the adaptive market hypothesis of the stock market. The Automatic Portmanteau test statistic is defined in Eq. (7) at a merged AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) optimal lag length.

$$Q_T = \frac{T}{T-\theta} \sum_{j=\theta+1}^{T} \hat{\gamma}_j \left( Z_t - \hat{\theta}_j Z_t - Z_t \right)^2$$

(7)

3. Results and discussions

3.1. Data

Major stock market index information from the top 4 countries that have recorded over 800,000 confirmed COVID-19 cases, are sampled from 3rd June 2019 to 31st December 2019 (the Calm Period) and from 1st January 2020 to 31st July 2020 (the COVID-19 Period). These economies are: the United States of Ameria (4,703,727 cases), Brazil (2,66,298 cases), India (1,697,054 cases), and Russia (839,981 cases). The daily closing price series from these major stock exchange indexes are sourced from Investing.com platforms for NYSE Composite (U.S.A), Bovespa (Brazil), BSE Sensex 30 (India), and MOEX (Russia). However, 2020-01-01 is pinned down as the COVID-19 pandemic point to define the ex-ante and ex-post periods following Okorie and Lin (2020b). The choice of this date, before the WHO announcement date, is because the virus was already spreading rapidly in Wuhan, China (China constitutes a substantial global emerging market) and has been recorded in many other economies by 2020-01-01, before it was pronounced a global threat. Relatively equal sample sizes are collected for these ex-ante and ex-post periods to conduct the event impact analysis of the COVID-19 pandemic on the adaptive efficiency level of the four stock markets. This article selects a relatively short periods before and after the outbreak of the COVID-19 virus to minimize the occurrences of other exogenous shocks or factors that might affect the stock markets and thus bias the findings of this study. In line with this, MacKinlay (1997) stated in his article entitled, Event studies in Economics and Finance, “thus, a measure of the event’s economic impact can be constructed using security prices observed over a relatively short-time period...”. The idea hinges on the fact that there might be other events which may have occurred after the event being studied. As such, the effect of the particular event under study is best captured using a relatively small window around the event’s announcement date. Indeed, this is often the case. For instance, after the ICO ban in China, Okorie (2020a), Okorie (2020b) and Okorie and Lin (2020c) used relatively small window information around the ICO ban event in China to investigate its effect in the Bitcoin market.

Fig. 1 shows the trend of the stock market index returns from the top coronavirus affected economies within the sample periods. The verticle line, in red, marks the coronavirus outbreak. One basic fact that’s clearly shown in Fig. 1 is that the return volatility increased in the ex-post periods relative to the ex-ante periods. This suggests substantial differences between both periods. The results in Table 1 are the basic statistical properties of the return series from the four stock market indexes. The total number of the observed return series are recorded for both the full and subsamples (before and after the COVID-19 outbreak). Based on the full sample, on average, the US, Brazil, and Russia stock markets have positive returns except for the Indian stock market, which has a negative return within the sample period. However, all the stock markets show a positive average return before the outbreak of the COVID-19 pandemic and are all negative, on average, after the outbreak for all the markets. This invariably suggests that the pandemic impacted the returns (and prices) of these stock market indexes. For both the full and subsamples, there are negative minimum returns and a positive maximum returns within all samples and markets. While all the market returns are negatively skewed in the full and subsamples sample, the Indian stock market is positively skewed for the ex-ante subsample. The normality test of Jarque Bera rejects the null hypothesis that the return series are normally distributed both for the full and sub-samples. The return series are also statistically stationary based on the Augmented Dickey-Fuller test results. Both the first and higher-order Ljung-Box portmanteau tests imply that the return series contain some information that could be elicited through statistical methods. On these bases, we employ the martingale and portmanteau testing methods for the adaptive market information hypothesis on both the full sample and the subsamples as follows.

3.2. Analysis of the full sample

The Martingale Difference Spectral and the Conditional Heteroscedasticity tests are conducted on the full samples of the four (4) stock markets to tests for the adaptive efficient market information hypothesis inherent in these markets over time, ignoring the coronavirus outbreak. These tests are conducted for three rolling windows, i.e. 5 (short-term), 10 (medium-term), and 50 (long-term) rolling windows. The results are summarized in Table 2 and the graphical representations of the results in Table 2 are shown in Fig. 2. Table 2 presents the proportion of times, the efficient market information hypothesis is rejected at different levels of test sizes (1%, 5%, 2)

See a real time indicators of COVID-19, as at August 1, 2020, at https://www.worldometers.info/coronavirus/.

3 See https://www.investing.com/indices/shanghai-composite-historical-data.
and 10%) for each rolling window length. For each of the four markets, the results are reported based on the MDS and CH testing techniques. For instance, in the 5 rolling windows column and using the MDS test for the USA stock market, about 8.2% of all the possible rolling windows rejected the null hypothesis at a 10% test size while none is rejected at both 1% and 5% levels of significance using the Martingale difference test. Similarly, 0.3% and 4.1% of times for all short term rolling windows rejected the information efficiency hypothesis at the 5% and 10% level of significance using the Conditional Heteroscedasticity test. The interpretations are the same for other values in Table 2.

Fig. 2 shows the p-values for the MDS and CH tests for all rolling window lengths in the four stock markets. Each row represents the scenario for each of the four markets while the columns show the rolling window lengths and testing techniques. The red, green, and blue lines are the 1%, 5%, and 10% critical values respectively, below which the efficient market information hypothesis is rejected for each rolling window at a given test size. Based on these cutoff points, the number (and proportion) of times the efficient market

| Statistic | Obs. | Mean | St.Dev. | Min | Max | Skew. | Kurt. | JB | ADF | Q(10) | Q^2(10) |
|-----------|------|------|---------|-----|-----|-------|-------|----|-----|------|--------|
| **Full Sample** |      |      |         |     |     |       |       |    |     |      |        |
| USA       | 295  | 0.00 | 2.01    | −12.60 | 9.56 | −1.21 | 11.09 | 0.00*** | 0.00*** | 0.00*** | 0.00*** |
| Brazil    | 291  | 0.02 | 2.59    | −15.99 | 13.02 | −1.60 | 13.26 | 0.00*** | 0.00*** | 0.00*** | 0.07*** |
| India     | 287  | −0.03| 1.89    | −14.10 | 8.59 | −1.57 | 14.32 | 0.00*** | 0.00*** | 0.00*** | 0.00*** |
| Russia    | 292  | 0.02 | 1.47    | −8.65 | 7.43 | −1.00 | 11.28 | 0.00*** | 0.00*** | 0.012*** | 0.00*** |
| **Ex-Ante COVID-19 Periods** |      |      |         |     |     |       |       |    |     |      |        |
| USA       | 148  | 0.08 | 0.69    | −2.84 | 1.76 | −1.15 | 3.54  | 0.00*** | 0.00*** | 0.127*** | 0.00*** |
| Brazil    | 145  | 0.12 | 1.00    | −299  | 2.35 | −0.60 | 0.51  | 0.004*** | 0.00*** | 0.816*** | 0.007*** |
| India     | 141  | 0.02 | 0.91    | −2.08 | 5.19 | 1.3   | 6.54  | 0.00*** | 0.00*** | 0.3598*** | 0.4899*** |
| Russia    | 149  | 0.07 | 0.69    | −2.02 | 1.95 | −0.08 | 0.03  | 0.089*** | 0.001*** | 0.485    | 0.6514*** |
| **Ex-Post COVID-19 Periods** |      |      |         |     |     |       |       |    |     |      |        |
| USA       | 147  | −0.07| 2.76    | −12.60 | 9.56 | −0.84 | 4.77  | 0.00*** | 0.00*** | 0.00*** | 0.00*** |
| Brazil    | 146  | −0.08| 3.55    | −15.99 | 13.02 | −1.17 | 6.22  | 0.00*** | 0.00*** | 0.00*** | 0.00*** |
| India     | 146  | −0.06| 2.54    | −14.10 | 8.59 | −1.34 | 7.6   | 0.00*** | 0.00*** | 0.00*** | 0.00*** |
| Russia    | 143  | −0.03| 1.99    | −8.65 | 7.43 | −0.76 | 5.62  | 0.00*** | 0.001*** | 0.231    | 0.00*** |

Notes: Jarque-Bera (JB) statistic tests for the null hypothesis of a normally distributed return series. Q (10) and Q^2 (10) are Ljung-Box test statistics of returns and squared returns, up to lag order of 10 serial autocorrelations, respectively. Ljung Box is a portmanteau univariate statistic test of conditional heteroscedasticity. The Augmented Dicky Fuller (ADF) test confirms a stationary return series. The p-values are reported for these tests. 
*** p-value < 0.01; ** p-value < 0.05; * p-value < 0.1.
information hypothesis are dictated and represented in Table 2. Examining the information in Table 2 and Fig. 1, in the short term, the USA stock market is the most inefficient using the MDS test at 10% test size, followed by the stock market of Russia. Similarly, in the long term, the Russian stock market is relatively the most efficient, followed by that of Brazil using the MD spectral test at 10%.

Table 2
Proportion of times Efficient Market Hypothesis is rejected.

| Market | Statistic | Rolling Windows |
|--------|-----------|-----------------|
|        |           | 5               | 10              | 50               |
| USA    | MDS Test  | 0.00.082        | 0.00.003        | 0.00.003         |
|        | CH Test   | 0.00.041        | 0.013          | 0.013           |
|        |           | 0.000.017       | 0.092          | 0.011           |
| Brazil | MDS Test  | 0.00.076        | 0.00.003        | 0.00.003         |
|        | CH Test   | 0.00.027        | 0.039          | 0.039           |
|        |           | 0.000.0248      | 0.057          | 0.057           |
| India  | MDS Test  | 0.00.060        | 0.00.035        | 0.00.012         |
|        | CH Test   | 0.00.031        | 0.010          | 0.000           |
|        |           | 0.000.042       | 0.008          | 0.021           |
| Russia | MDS Test  | 0.00.079        | 0.00.003        | 0.00.003         |
|        | CH Test   | 0.00.020        | 0.00.028        | 0.00.028         |
|        |           | 0.00.098        | 0.007          | 0.007           |

The proportions represent the proportion of times the efficient market hypothesis is rejected at 1%[5%]10% test sizes.

Fig. 2. Full sample (5, 10, & 50 Rolling Window).

Table 3
Proportion of times Efficient Market Hypothesis is rejected (Ex-Ante).

| Market | Statistic | Rolling Windows |
|--------|-----------|-----------------|
|        |           | 5               | 10              | 50               |
| USA    | MDS Test  | 0.00.104        | 0.00.007        | 0.00.020         |
|        | CH Test   | 0.00.020        | 0.028          | 0.020           |
|        |           | 0.00.151        | 0.020          | 0.020           |
| Brazil | MDS Test  | 0.00.070        | 0.00.014        | 0.00.010         |
|        | CH Test   | 0.00.021        | 0.044          | 0.044           |
|        |           | 0.00.235        | 0.010          | 0.010           |
| India  | MDS Test  | 0.00.058        | 0.00.037        | 0.00.004         |
|        | CH Test   | 0.00.029        | 0.015          | 0.015           |
|        |           | 0.00.098        | 0.010          | 0.010           |
| Russia | MDS Test  | 0.00.096        | 0.00.007        | 0.00.090         |
|        | CH Test   | 0.00.020        | 0.00.014        | 0.00.090         |
|        |           | 0.00.085        | 0.010          | 0.010           |

The proportions represent the proportion of times the efficient market hypothesis is rejected at 1%[5%]10% test sizes.
3.3. Analysis of the ex-ante COVID-19 pandemic subsample

This paper repeats the MDS and CH testing techniques on two subsamples for periods before (ex-ante) and after (ex-post) the COVID-19 outbreak. The data properties and distributions are reported in Table 1 for these subsamples. The ex-ante COVID-19 sample is used to conduct efficient market information hypothesis testing for the same three window lengths (i.e., 5, 10, and 50). The MDS and CH test results for the stock markets and each of the rolling windows are presented in Table 3 while Fig. 3 presents the same results graphically.

Just as explained in Table 2, the interpretation of the results in Table 3 is the same as that of Table 2. The only difference being that Table 2 is for the market’s full sample while Table 3 is for the ex-ante COVID-19 subsample. At least, either the MDS or CH tests reject the efficient information hypothesis for each of the four stock markets at different levels of significance. This confirms that these markets are not perfect form but weak form efficiency for the periods right before the outbreak of COVID-19. More so, the level of market inefficiency for the stock markets is relatively higher in the medium term relative to the short and long term. This suggests that these markets are more predictable (forecastable) for the next 10 days relative to 5 and 50 days ahead. Fig. 3 follows a similar order like Fig. 2.

3.4. Analysis of the COVID-19 pandemic ex-post subsample

The same analyses performed on the full and ex-ante subsamples, presented in Tables 2 and 4 respectively, are conducted in the ex-post subsamples and presented in Table 4. The interpretation of the results presented in Table 4 follows (or is the same with) that of Table 2 (for the full sample) and Table 3 (for the ex-ante subsample). Based on the results in Table 4, the proportion of times the efficient market information hypothesis is rejected is relatively higher than the case using the ex-ante subsample. This suggests some levels of substantial differences in the level of efficient market information hypothesis inherent in these stock markets for both periods. Besides, this also confirms that these markets are not perfect form but weak form efficiency for the periods right after the outbreak of COVID-19. This confirms the ex-ante subsample and full sample results. Fig. 4 presents the graphical representation of the p-values for all markets for the short-term, medium-term, and long-term. Their interpretations are the same as that of Figs. 2 and 3. In subsection 3.5, the efficient information hypothesis test results for the ex-ante and ex-post subsamples are compared statistically to ascertain the impact of the COVID-19 pandemic on the market information efficiency level in these four stock markets.

3.5. COVID-19 pandemic impact assessment on stock markets’ efficiency

At this point, the results for the ex-ante and ex-post market information efficiency for the four stock markets are compared to ascertain the COVID-19 pandemic impact on the market information efficiency on these markets. The results of this statistical procedure are presented in Table 5. The tested null hypothesis is there is no substantial change or difference in the level of market information efficiency for each of the markets for both periods (ex-ante and ex-post). For instance, considering the martingal spectral test results, there is no evidence of a substantial difference in the levels of market information efficiency between both periods for USA and Fig. 3.
Brazil stock markets for short, medium, and long term analysis. This is also the case for India and Russia for short and medium-term analysis except for the long-term analysis at 5% and 10% test size respectively. The Indian stock markets became more information inefficient after the coronavirus outbreak while the Russian stock markets become more information efficient. The conditional heteroscedasticity results are interpreted accordingly. The CH and MDS have similar conclusions most of the time under the short, medium, and long-term analyses.

To understand the implications of these findings, it is pertinent to point out that an improved level of market efficiency (i.e. reduced market inefficiency) suggests that the prices and return of that market are less predictable and forecastable while a reduced market efficiency level (i.e. improved inefficiency) suggests that the market is more predictable and forecastable using available information set and vice versa. Therefore, Its impacts on the markets are unique and market-specific, and thus, while it increases the forecastability and predictability of a market over a certain period, it decreases that of another market. For instance, using the MDS test at 10%, the implications of the findings include that the COVID-19 pandemic altered the long-term level of information efficiency in Indian and Russian stock markets unlike that of USA and Brazil. Similar inference can as well be deduced for the short and medium-term periods and using the CH test results.

4. Conclusions

This article investigates the impact of the COVID-19 pandemic outbreak on the level of market information efficiency for four (4) stock markets (in the USA, Brazil, India, and Russia). For each of these markets, their level and dynamic evolution of market information efficiency were tested using the rolling window approach on the full sample and two (ex-ante and ex-post) subsamples. The
Martingale Difference Spectral and Conditional Heteroscedasticity test statistics were employed in this analysis. The empirical implications of the COVID-19 pandemic on the level of information efficiency for the four (4) stock markets are summarized thus, based on the martingale difference spectral test, there is no evidence of a substantial change in the levels of market efficiency for the US and Brazilian stock markets in the short, medium, and long term. However, in the long term, the Indian stock markets became more information inefficient after the coronavirus outbreak while the Russian stock markets become more information efficient.

These findings confirm that external and global shocks can significantly affect different markets just like Okorie and Lin (2020b), Park and Shin (2020). Agosto et al. (2020), Kenourgios and Dimitriou (2015), Jiang et al. (2014), and Lazár et al. (2012) showed. Moreover, this article unveils that the COVID-19 pandemic has a substantial effect on the stock markets’ level of information efficiency of the top four most affected economies (U.S., Brazil, India, and Russia). The practical significance is on investment portfolio adjustments by taking strategic long and short positions in these markets. For instance, given that a market is inefficient, it implies that the return can very well be predicted and/or forecasted. This prediction informs an investor about the sign of the market price change.

Table 5
Stock Market Efficiency Impact of COVID-19 Pandemic.

| Market     | Statistic  | Rolling Windows |
|------------|------------|-----------------|
|            |            | 5               | 10             | 50             |
| USA        | MDS Test   | 0.0[0.042]     | 0.0[0.021]     | 0.0[0.031]     |
|            | CH Test    | 0.0[0.006]     | 0.0[0.042]     | 0.0[0.439]     |
| Brazil     | MDS Test   | 0.0[0.014]     | 0.0[0.007]     | 0.0[0.01]      |
|            | CH Test    | 0.0[0.014]     | 0.0[0.123]     | 0.0[0.144]     |
| India      | MDS Test   | 0.0[0.005]     | 0.0[0.001]     | 0.0[0.03]      |
|            | CH Test    | 0.0[0.007]     | 0.0[0.018]     | 0.0[0.113]     |
| Russia     | MDS Test   | 0.0[0.032]     | 0.0[0.013]     | 0.0[0.012]     |
|            | CH Test    | 0.0[0.006]     | 0.0[0.013]     | 0.0[0.1]       |

The proportions represent the proportion of times the efficient market hypothesis is rejected at 1%[5%]10% test sizes.

* p-value < 0.05;
** p-value < 0.10.

CRediT authorship contribution statement

David Iheke Okorie: Conceptualization, Data curation, Formal analysis, Methodology, Software, Writing - original draft, Writing - review & editing. Boqiang Lin: Conceptualization, Software, Writing - original draft, Writing - review & editing.

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