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Stock Market Volatility Towards COVID-19 Drawbacks: Case of Rwanda Stock Exchange

COVİD-19 Dezavantajlarına Yönelik Hisse Senedi Oynaklıkları: Ruanda Borsası Örneği

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ÖZ

Bu çalışmanın amacı, COVID-19'un çeşitli finansal kurum ve yatırımcıların ilgisini çeken Ruanda Menkul Kıymetler Borsası üzerindeki etkisini incelemektir. Ruanda Menkul Kıymetler Borsası'nda işlem gören dört şirketin 4 Ocak 2020 ile 12 Nisan 2021 arasındaki günlük hisse senedi getirisi verilerinin ampirik bir analizini gerçekleştirdik. Çalışmada, AR, MA, ARIMA ve ARCH modelleri birbiri ardına uygulanmıştır. Serilerin durağanlığını doğrulamak için bir ARIMA modeli oluşturmadan önce zaman serisi durağanlığını kontrol ettik. ARIMA modeli tüm şirketlerin verilerine iyi uyuyor, ancak Ljung-Box testini kullanarak boş hipotezi reddetmeyi başaramadık, ARCH etkisini gösteren BOK verileri için testin p-değerinin 0.05'ten küçük olmasına rağmen, BLR, KCB ve EQRY şirketleri için ARCH etkisinin olmadığı sonucuna vardık. Sonuçlar AR modelinin yeterli olduğunu göstermektedir ve seri korelasyonlu olmadığı için BLR, KCB ve EQTY' den verileri modellemek için kullanılabilir ve verilerde ARCH etkisi tespit edilmemiştir. BOK'un tek verisi ARCH modeli kullanılarak modellenebilir ve sonuç alfa 1'in 1.000e+00 olduğunu gösteriyor ki bu çok yüksek ve bu BOK piyasasının istikrarsız olduğunu göstermektedir.

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ABSTRACT

The purpose of this study is to look into the impact of the COVID-19 on the Rwanda Stock Exchange, which is of interest to a variety of financial institutions and investors. We conducted an empirical analysis of the daily stock returns data from January 4th, 2020 to April 12th, 2021 of four Rwanda Stock Exchange-listed companies. The AR, MA, ARIMA, and ARCH models were applied one after another. To verify the series stationarity, we checked the time series stationarity before building an ARIMA model. The ARIMA model fit the data of all companies well, but using the Ljung-Box test, we failed to reject the null hypothesis and concluded that there are no ARCH effects present for BLR, KCB, and EQRY companies, despite the fact that the p-value of test was less than 0.05 for BOK data, indicating the ARCH effect. The results show that the AR model is adequate and can be used to model data from BLR, KCB, and EQTY because there is no serial correlation and no ARCH effect depicted in the data, and the only data of BOK can be modelled using the ARCH model and the result shows that alpha 1 is 1.000e+00 which is very high and this indicates that the BOK market is jumpy (unstable).

1. Introduction

Making things happen is all about money. Almost all human activities that is useful and important need financing. Financial institutions are a cornerstone of civilized society, orienting resources across space and time to their best uses, assisting and encouraging people in productive endeavors, and managing economic risks. People who provide

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investment opportunities are doing something else in real world which is risky. The way investors can use to minimize their risks and optimize their portfolio, attract many researchers and financial institutions.

It is hard to predict the nature of future financial markets, since human species is the product of a complex evolution. This evolution will depend on the involvement of young generations within the financial community. The commodity market is a volatile environment in which people prefer to be prepared for contingencies. This market is characterized by high price fluctuations and a large number of participants, including brokers, traders, portfolio managers, and investors in general, who anticipate each other's actions, particularly during times of great ambiguity, resulting in a noisy and fluctuating market (Moews and Ibikunle, 2020). Commodity prices have dropped as a result of the COVID-19 pandemic, and economic activity has suffered greatly in many countries (Sadefo Kamdem et al., 2020). However, as currency markets have become more globalized, it is now possible to gain access to financial derivatives such as futures, forwards, and options in order to hedge against price volatility risks. The securities are priced referring to the predicted price of commodity. Wrong prediction influences a huge loss to investors. Price forecasting is an integral part of commodity trading and price analysis.

The Rwanda Stock Exchange came into existence on 7th October 2005, but it officially started trading on the 31st January 2011. It just succeeded Rwanda Over the Counter Exchange that had been working since 2008 (Ngoboka and Singirankabo, 2021). The various histories related to Rwanda Stock Exchange behavior can be seen in the following studies (Innocent et al., 2018), (Mahina et al., 2014), (Kansiime, 2019), and (NOELLA, 2017). Rwanda annual report (2019) indicated that investment in Rwanda Stock Exchange has highly increased by 9.2% in terms of new investment in the year 2019. Celner, (2020) revealed that small financial institutions would generate little profitability with limited capital.

Figure 1. Market Participant 2019 in Rwanda

Investment Accounts

Source: RSE Annual Report 2019

As it is indicated in the Fig 1, active investors recorded were 83.6% as domestic investors, 13.8% were investors from Easter Africa and 2.6% of international investors.

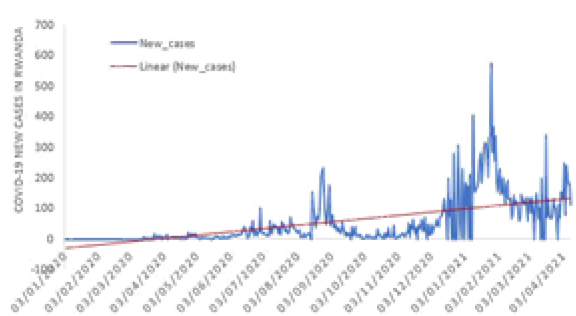
COVID-19 was first discovered in December 2019 in Wuhan, China's capital of Hubei province (Wang et al., 2020). From Wuhan city, COVID-19 rapidly spread to the whole of China and the rest of the World. Currently, over 136.9 Million confirmed cases and 2.953 Million deaths, and 110.081 Million recovered worldwide. As of the second of April 2020, only seven African countries had not reported a case of coronavirus (COVID-19) (Odhiambo et al., 2020). In Rwanda, the first COVID-19 case appeared on 21st March 2020. Like other countries in the rest of the World, Rwanda applied the same measures to fight against COVID-19, including total lockdown, banning of traveling, isolation of infected people, hand washing, and face mask use. Due to the lockdown, Rwanda has closed schools and high learning institutions, churches and mosques, markets, and other related services that require people to gather. The government encouraged citizens to work from home and implemented cashless transactions in business services. Restaurants allowed only take away, the nightclubs are closed, and so on. These precautions have been taken to slow the spread of COVID-19, especially in the exposed population. Here we presented data of COVID-19 new cases and death cases in Rwanda.

Table 1. COVID-19 in Rwanda Data description

	New Cases	New Deaths
Min.	0	0
1st Qu.	2	0
Median	13	0
Mean	50	0.6782
3rd Qu.	67	1
Max.	574	11

Source: World Health Organization

Figure 2. Covid-19 New Cases Trend in Rwanda



The Fig 2 presents the COVID-19 trend in Rwanda with a linear line that shows the slope or increase of COVID-19 new cases. We see that the increase rate of Covid -19 varies with time.

Figure 3. Covid-19 Death Cases Trend in Rwanda

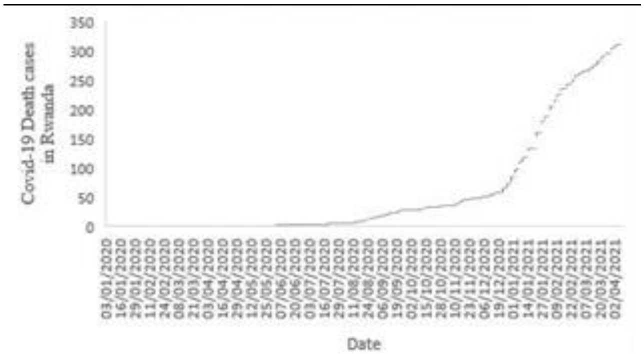
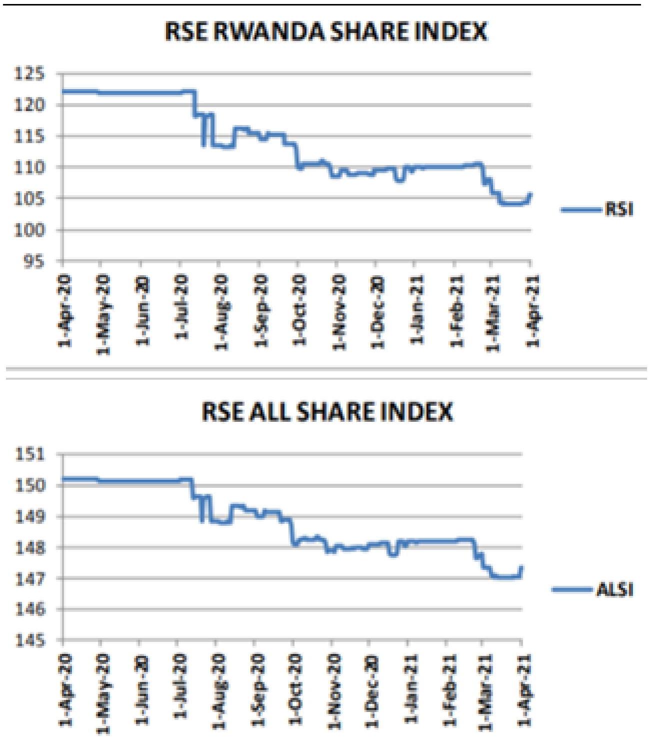


Fig 3 depicts the increase in the number of deaths over time. As many other different countries in the world also Rwanda faces the consequence of COVID-19 in different organs including financial markets. We can see the historical trend of Rwanda stock market from 1st April 2020 to 1st April 2021. Fig 4 shows how Rwanda Stock Exchange share index decreased as COVID-19 new cases increased.

Figure 4. Rwanda Stock Market Share Index and All Share Index



Source: Rwanda Stock Exchange Report

The ARCH model is applied to analyze the daily log-return of four stock markets of financial institution listed at Rwanda Stock Exchange (BOK, BLR, KCB, and EQTY), data covered the period from 4th January 2020 through 12th April 2021 recorded by Rwanda Stock Exchange. These companies were selected based on data availability and longevity of the companies on Rwanda Stock Exchange. For instance, KCB (Kenya Commercial Bank Group) listed at RSE in January 2008, BLR (Bralirwa) joined on 31/01/2011, BOK (Bank of Kigali) listed on 31/06/2011 while EQTY (Equity Group Holdings Limited) followed. These companies focus on Banking, Finance while only BLR focuses on Brewing, Bottling. The spread of the COVID-19 brought much stress and losses in different corners of the world. Some researchers argued that the COVID-19 shocks and losses that it has caused is even higher compared to the losses caused by financial crisis in 2007-2008. However, there is no study on financial markets behaviour towards covid-19 drawbacks in Rwanda. In literature, there is enough evidence that COVID-19 had a significant impact on global financial markets. This compelled us to conduct research and contribute to the existing literature. The purpose of this study was to investigate the impact of the COVID-19 on Rwanda's financial market, in order to forecast and estimate volatility of stock markets during COVID-19. The daily log-return of the stock gets employed to attain the objective of the study. We have to see how to test the ARCH effects and how to rid of the ARCH effect and serial correlation. The following is how this paper is organized: Section 2 contains Literature review, section 3 covers Methodology, Section 4 shows results and interpretations, while section 5 represents conclusion.

2. Literature Review

To deal with volatility which usually appearing in financial and economic time series, Engle (1982) introduced ARCH Model. Bollerslev (1986) and Nelson (1991) investigated the generalized version of ARCH model. Later on GJR-GARCH and EGARCH were developed. To see the historical progression of GARCH family (GARCH, GJR-GARCH, EGARCH and APARCH Models) one can look at (Abdalla and Winker, 2012; Dana 2016; Murenzi et al., 2015) among others.

There is a huge literature on forecasting and modelling stock market volatility from different authors around the world. In the last four decades, researchers all over the world used the ARCH/GARCH models to model the stock volatility. For example, using daily All-share stock data, Ekong and Onye (2017) estimated the optimal forecasting model of stock returns and the nature of stock return volatility in Nigeria. The study adopted to GARCH-Family models of stock returns volatility. Over the sample period, the results show evidence of high volatility in making a negative return on investment in the Nigerian stock market. Bahamonde et al., (2018) investigated the extension of the ARCH model in order to capture intraday price fluctuations and market liquidity. Cheong (2009) looked into the volatility of two major crude oil markets over time. The ARCH model was used to account for the stylized volatility facts. The results show that generalized ARCH provides the best forecasted evaluation for Brent Crude oil data.

Volatility models are becoming more important as they play a crucial role in asset pricing and risk management. It is, however, not directly observed and must thus be estimated.

Wei (2012) predicted and captured the distributive characteristics of conditional variance about the empirical financial data mainly taking several volatility models. The results show that by comparing the Root Mean Square Error values of different models, one can find the best model to predict the conditional variance of the stock return. Bollerslev et al., (1992) provided an overview of some recent developments in the formulation of ARCH models, as well as a survey of numerous empirical applications based on financial data. Mathur et al., (2016) investigated the impact of Global Financial crisis on the Indian stock market. They used the GARCH family to conduct empirical analysis on the daily stock returns of the top 20 companies listed on the Bombay Stock Exchange from 2001 to 2012. The findings show the high volatility of all 20 companies stock returns. Dana (2016) used ARCH/GARCH models to model and estimate the volatility in Jordan's stock Market. Abdalla and Winker, (2012) modelled stock market volatility using univariate GARCH models while Brooks (2007) studied the power ARCH modelling of the volatility of emerging equity markets, and many studies have been conducted like Bollerslev et al., 1994; Che 2017; Ahmed and Suliman, 2011).

There is enough evidence in the literature to suggest that covid-19 had a direct impact on global financial markets. Demir ve Esen, (2021) studied the effects of COVID-19 and transformation needed in Turkish Economy. Arturo et al., (2020) studied the impact of COVID-19 pandemic on economic and financial markets. They developed an analytical framework to comprehend the spatiotemporal patterns of epidemic disease occurrence, as well as the implications for financial market activity. The analysis of major stock markets shows the effects of COVID-19, which can cause similar damage to the 1929 crisis, and concludes that it will require at least a 12-month recovery period. Sattar et al. (2020) presented the financial market indices' response to the COVID-19 pandemic, and the study used a log-log simple regression model. The results show that COVID-19 has a negative impact on market indices because financial market indices fall as COVID-19 cases rise. El-basuony, (2020) looked into the effect of the COVID-19 on Arab financial markets. The simple regression model was used in the study to investigate the impact of the COVID-19 on the Arab Financial Markets. The findings revealed a negative significant relationship between confirmed cases and death cases. This indicates the significant impact of COVID-19 on the financial markets. Haldar, (2021) looked into the impact of media coverage of covid-19 data on global financial market volatility. The EGARCH model was applied to analyse data from the 10 worst hit countries. The results show negative stock returns and high stock market volatility. The study also used bivariate time-series regression and panel regression, and the results show that COVID-19 has a significant effect on stock market media coverage. Sansa, (2020) investigated the impact of COVID-19 on financial markets. The findings indicate that there is a significant positive relationship between the COVID-19 confirmed cases and all financial markets.

3. Methodology

3.1. Data description

The daily stock returns data of BOK, BLR, KCB, and EQTY recorded by Rwanda Stock Exchange (RSE) from 4th January 2020 to 12th April 2021 was applied in the study.

3.2. Model Structure

A volatility analytical solution measures the dispersion of data points that has become a critical issue in many business and finance applications. Time series data usually suffer from heteroscedasticity. Because conventional time series and econometric models are based on the assumptions of constant variance and error term independence, alternative time series heteroskedastic models should be used. A time series is said to be stationary if the mean value of the time series remains constant over time, the variance does not increase with time, and the seasonality effect is minimized. Various methods are used to test the time series stationarity like Augmented Dickey-Fuller (ADF) t-statistic test for unit root, Autocorrelation Function (ACF), Ljung-Box Test for independence among others. In this study the last two were applied.

Let r_t be the log return of an asset at time t, which is serially correlated but dependent series. Consider the conditional mean and variance of r_t given by the information set Γ_{t-1} available at previous time $t-1$. The Γ_{t-1} contains functions of the past returns. It is assumed that r_t follows a stationary ARMA(p,q) model with possible explanatory variables. Thus

$$r_t = \mu_t + a_t \tag{1}$$

$$\mu_t = \omega_0 + \sum_{i=1}^{k} \beta_i X_{it} + \sum_{i=1}^{p} \omega_i r_{t-i} - \sum_{i=1}^{q} \theta_i a_{i-1} \tag{2}$$

with k, p, q are non-negative integers and X_it are explanatory variables. By calling AR(1) model

$$r_t = \omega_0 + \omega_1 r_{t-1} + a_t \tag{3}$$

With $E(r_t) = \mu$ and $Var(r_t) = \gamma_0$, both μ and γ_0 are constant. Taking expectation of equation (3) using $E(a_t) = 0$ yields $E(r_t) = \omega_0 + \omega_1 E(r_{t-1})$, by stationarity $E(r_t) = E(r_{t-1}) = \mu$

Hence

$$E(r_t) = \mu = \frac{\omega_0}{1-\omega_1} \tag{4}$$

the mean of r_t is zero if and only if ω_0 is zero. From equation (4), $\omega_0 = (1-\omega_1)\mu$ using it in AR(1) model yields

$$r_t - \mu = \omega_1(r_{t-1} - \mu) + a_t = a_t + \omega_1 e_{t-1} + \omega_1^2 e_{t-2} + \cdots = \sum_{i=0}^{\infty} \omega_1^i a_{t-i} \quad (5)$$

The MA model is defined as:

$$X_t = \mu + A_t - \theta_1 A_{t-1} - \cdots - \theta_q A_{t-q} \quad (6)$$

Where μ is the mean of the series, A_{t-i} with $i = 1,2,..,q$ are white noise and $\theta_1, \ldots, \theta_q$ are model parameters. The ARMA model is defined as:

$$X_t = \sigma + \omega_1 X_{t-1} + \cdots + \omega_p X_{t-p} + e_t + A_t - \theta_1 A_{t-1} - \cdots - \theta_q A_{t-q} \quad (7)$$

Where σ is defined as in the AR(p) model.

The conditional heteroskedastic model (volatility model) is concerned with the evolution of σ_t^2. The way which σ_t^2 changes over time differentiates one volatility model from another.

3.3. The ARCH Model

The idea of ARCH model is to describe the dependence of volatility on recent returns r_t. As it described by Engle (1982), ARCH model has mean and variance equations as its specifications.

The shock a_t of an asset return is serially uncorrelated but dependent. The dependence of a_t can be described by a simple quadratic function of its lagged values. The ARCH(m) is defined as follows

$$\begin{cases} a_t = \sigma_t e_t \\ \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \cdots + \alpha_m a_{t-m}^2 + e_t^2 \end{cases} \quad (8)$$

Where e_t is a sequence of i.i.d random variables with mean 0 and variance 1, $\alpha_0 > 0$ and $\alpha_i \geq 0$. To make sure that the unconditional variance of a_t is finite, the coefficients α_i should satisfy some regularity conditions. The error term e_t is assumed to follow the normal or t-student distribution.

3.4. Properties of ARCH Model

By considering a stationary r_t which can be expressed as an AR(p) in the equation (3), with its random error term's time series $a_t = \sigma_t e_t$, where a_t are (0,1) Gaussian or Student i.i.d random variables with zero mean and unit variance. The expectation of the square error term is the variance of the random error term.

$$Var(a_t) = E(a_t^2) - (E[a_t])^2 = E(a_t^2) \quad (9)$$

The white noise series a_t follows the m-order ARCH process, then we can use this model to estimate the variance of r_t. Since, the unconditional mean of a_t is given by

$$E(a_t^2) = E[E(a_t|\Gamma_{t-1})] = E[E(\sigma_t e_t)] = E[\sigma_t E(a_t)] = 0 \quad (10)$$

and the unconditional Variance become

$$Var(a_t) = E(a_t^2) = E[E(a_t^2|\Gamma_{t-1})] = E[\alpha_0 + \alpha_1 a_t^2] = \alpha_0 + \alpha_1 E(a_{t-1}^2) \quad (11)$$

Hence, a_t is a stationary process with $E(a_t) = 0$, $Var(a_t) = Var(a_{t-1})$ implies that $\sigma_t^2 = Var(a_t) = Var(a_{t-1}) = \alpha_0 + \alpha_1 Var(a_t) = \frac{\alpha_0}{1-\alpha_1}$ Since $Var(a_t) > 0$ then $0 \leq \alpha_1 < 1$ and $\alpha_0 > 0$. The volatility is modelled using ARCH model by specifying the series of σ_t^2 given in equation (8). By using ordinary least square (OLS) an ARCH(m) model can be estimated. An ARCH process is stationary. If the returns are not centered, then we have equation (1). To test for the presence of the ARCH effect, we must determine whether or not the coefficient of the ARCH term α_i is statistically significant. The discovery of the ARCH effect suggests that GARCH family models should be used.

3.5. ARCH Effect Hypothesis-Testing

It is necessary to test whether the ARCH effect exists in the error term of the mean equation. The null hypothesis considers squared residuals series to be uncorrelated and there is no ARCH effect when using the ARCH-LM test, whereas the alternative hypothesis considers variance of error term to be non-constant and there is an ARCH effect.

$H_0: \alpha_1 = \alpha_2 = \cdots = \alpha_m = 0$

$H_a: \alpha_1, \alpha_2, \ldots, \alpha_m \neq 0 \ (all\ not\ zero)$

Under H_0, the OLS estimators are efficient, while the OLS estimators become inefficient in the case of the alternative hypothesis.

4. Results and Discussion

This section presents the statistical findings from the analysis. Table 2 below shows the descriptive measures for the daily stock data for four financial markets (BOK, BLR, KCB, and EQTY).

4.1. Data Description

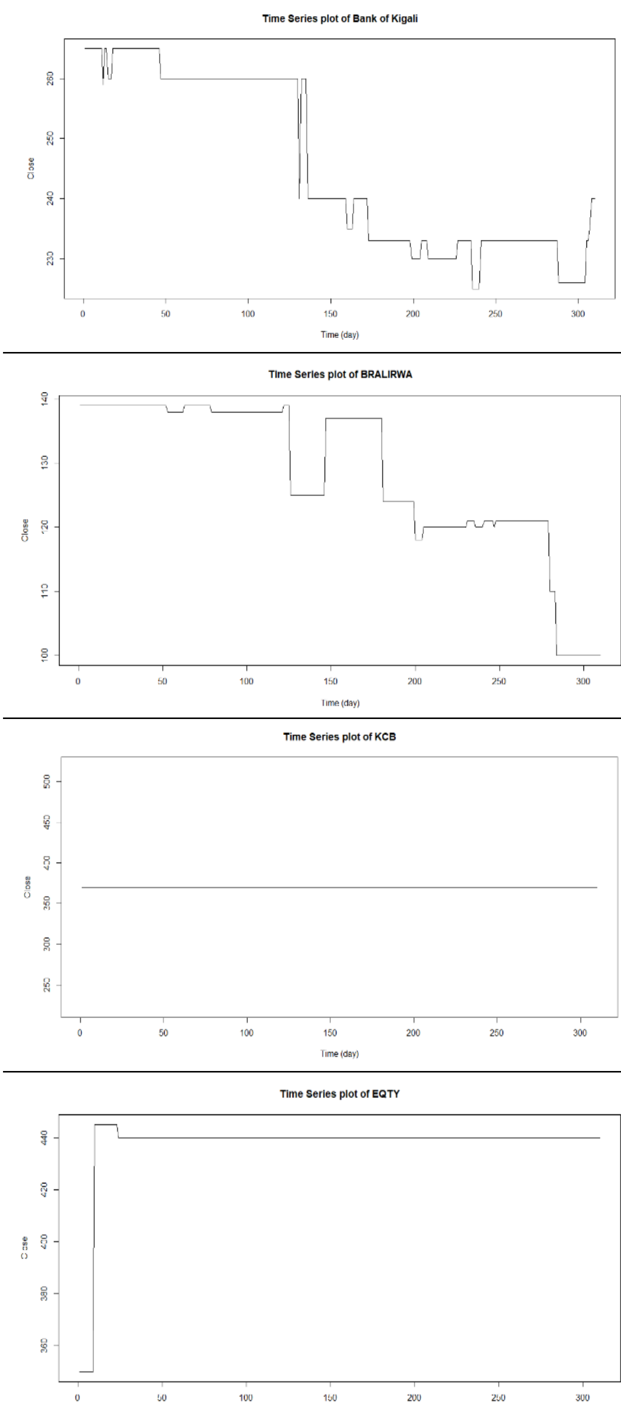
Table 2. Descriptive Statistics for daily return index

Descriptive Statistics	BOK	BLR	KCB	EQTY
Min.	225.0	100.0	370	350.0
1st Qu.	233.0	121.0	370	440.0
Median	240.0	137.0	370	440.0
Mean	245.5	128.2	370	437.6
3rd Qu.	260.0	138.0	370	440.0
Max.	265.0	139.0	370	445.0

Both the mean of 245.5, 128.2, 370, 437.6 and median of 240.0, 137.0, 370, 440.0 for BOK, BLR, KCB and EQTY respectively, indicate where the center of the data is located, and what the typical daily stock is sold.

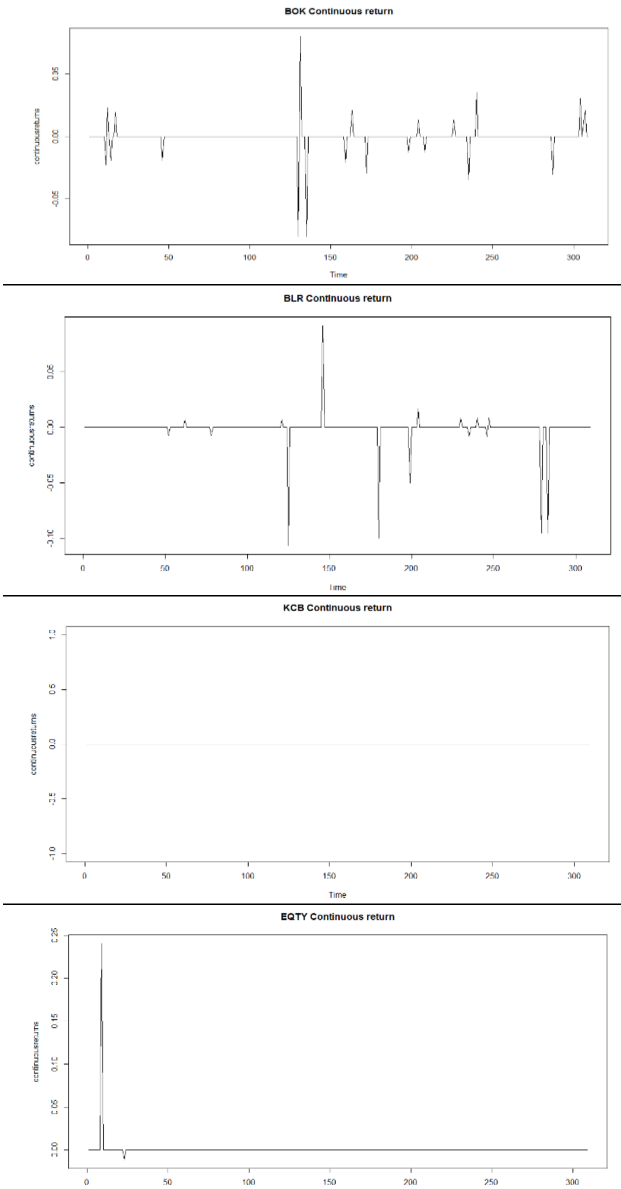
Time series trend among the companies namely BOK, BLR, KCB and EQTY show the stock behavior during COVID-19 outbreak.

Figure 5. Stock Market trend of BOK, BLR, KCB and EQTY



By seeing the companies with continuous returns yield.

Figure 6. Stock Market continuous return of BOK, BLR, KCB and EQTY



4.2. Autoregressive Model (AR Model)

Fitting an AR model of order 2 of the companies (BOK, BLR, KCB and EQTY) yield

Table 3. Fitting an AR model of order 2

	BOK	BLR	KCB	EQTY
Intercept	-3e-04	-0.0011	-0.0011	7e-04
ar1	-0.2525	-0.0083	-0.0083	-0.0029
ar2	-0.0670	-0.0070	-0.0070	-0.0029
s.e, Intercept	4e-04	0.0007	0.0007	8e-04
s.e, ar1	0.0567	0.0568	0.0567	0.0568
s.e, ar2	0.0566	0.0567	0.0568	0.0567
σ_t^2	8.688e-05	0.0001641	0.0001641	0.0001865
Log likelihood	1006.24	907.98	907.98	888.26
AIC	-2004.47	-1807.97	-1809.97	-1768.52

In the first approach, the partial autocorrelation function (PACF) is used to identify AR models, while in the second, some information criteria are used. The PACF of a stationary time series is a function of its ACF and can be used to calculate the order p of an AR model. The sample PACF for an AR(p) series stops at lag p.

If the sample acf plot indicates that an AR is required, the sample PACF is examined to help determine the order. We look for the point on the plot where the PACF's essentially becomes zero, at 95 percent C.I.

4.3. Moving Average (MA) model

Because ACF for an MA(q) series terminates at lag q, it can be used to specify the order for MA models; an MA series is always stationary, whereas an AR series must have all of its characteristic roots be less than one in modulus.

MA models are commonly estimated using maximum likelihood estimation. There are two methods for evaluating an MA model's likelihood function. The first method is presumptively based on the assumption that the initial shocks are zero. The second method treats the initial shocks as additional model parameters that are estimated in conjunction with other parameters. When the sample size is large, the two types of maximum likelihood estimates are very close.

Table 4. Fitting a MA model of order 2

	BOK	BLR	KCB	EQTY
Intercept	-3e-04	-0.0011	-3e-04	7e-04
ma1	-0.2623	-0.0084	-0.2623	-0.0030
ma2	-0.0454	-0.0053	-0.0454	-0.0030
s.e, Intercept	4e-04	0.0007	4e-04	8e-04
s.e, ma1	0.0567	0.0568	0.0567	0.0568
s.e, ma2	0.0646	0.0495	0.0646	0.0569
σ_t^2	8.661e-05	0.0001641	8.661e-05	0.0001865
Log likelihood	1006.71	907.98	1006.71	888.26
AIC	-2005.43	-1807.96	-2005.43	-1768.52

Table 5. Box-Ljung test

	BOK	BLR	KCB	EQTY
X-squared	0.16018	0.00022122	6.0304e-10	6.0304e-10
df	2	2	2	2
p-value	0.923	0.9999	1	1

By considering the null hypothesis of independence in a determined time series, the Ljung-Box test determines whether there is sufficient evidence for non-zero correlations at given lags. The low p-value indicates a non-stationary signal. Hence, Table 5 shows that data from mentioned companies are stationary. From Table 3 and Table 4, By comparing two models AR(2) and MA(2) using σ_{t2} and AIC, it is clear that both models fit the data well. But it should not be possible for all data of various companies to have partial autocorrelation function at the same lags hence it is important to plot ACF and PACF plots for each company to investigate the appropriate lag.

The Figure 7-9 shows ACF and PACF for BOK, BLR and EQTY respectively. There is a significant spike for BOK at lag 5 and much lower spikes for subsequent lags. Thus, an AR (5) model would likely be feasible for this data set. For BLR company the data shows a lag of 4 while ACF of residuals for EQTY shows that there is no significant autocorrelations. As a result, the standardized residuals show no residual trend, no outliers, and no changing variance over time. ACF and PACF plots for KCB are not appropriate since the minimum and maximum stock returns are zero. To validate the time series, we first checked for stationarity, and then we built an ARIMA model to see if the series is stationary.

Figure 7. Model identification for BOK log returns

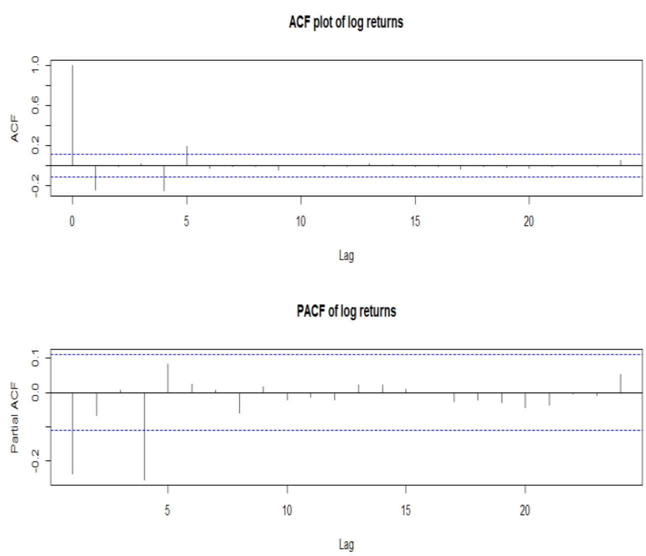


Figure 8. Model identification for BLR log returns

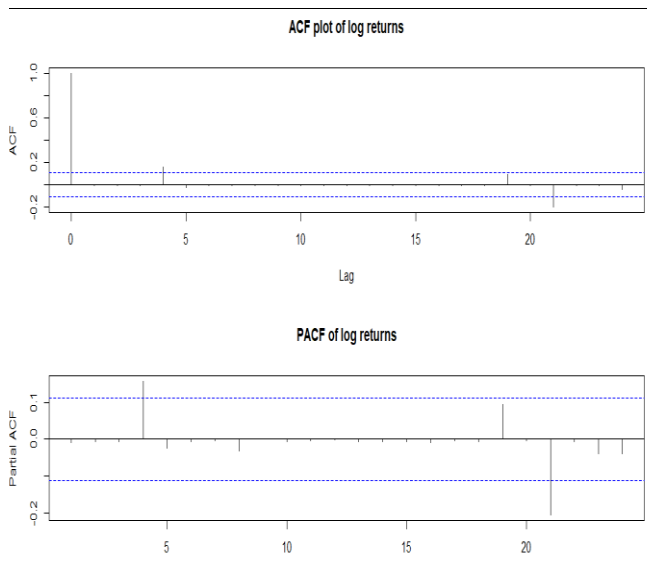
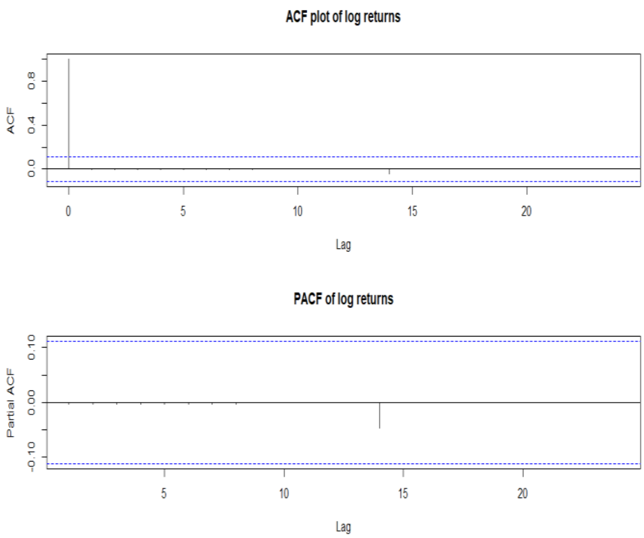


Figure 9. Model identification for EQTY log returns



4.4. Autoregressive Integrated Moving Average (ARIMA) models

Due to the high order model with many parameters required to adequately describe the dynamic structure of the data, the use of AR or MA can become cumbersome at times. An ARIMA model, in essence, combines the ideas of the AR and MA models into a compact form in order to keep the number of parameters used as low as possible, achieving parameterization parsimony. The likelihood of using ARIMA models for return series in finance is low. The concept of ARIMA models, on the other hand, is extremely important in volatility modeling. Tsay and Tiao (1984) proposed a novel method for specifying the order of an ARIMA process using the extended autocorrelation function (EACF).

Table 6. ARIMA model for BOK continuous returns

Coef.	ar1	ar2	ar3	ar4	ar5	Intercept
	-0.2298	-0.0784	-0.0552	-0.2369	0.0813	-3e-04
s.e	0.0566	0.0565	0.0571	0.0571	0.057	3e-04
σ^2		log likelihood			AIC	
8.052e-05		1017.83			-2021.66	

Table 7. Box-Ljung test

X-squared	df	p-value
0.17564	5	0.9994

Table 8. ARIMA model for BLR continuous returns

Coef.	ar1	ar2	ar3	ar4	Intercept
	-0.0073	-0.0059	-0.0057	0.1548	-0.0011
s.e	0.0561	0.0559	0.0559	0.0558	0.0008
σ^2		log likelihood		AIC	
0.0001601		911.79		-1811.58	

Table 9. Box-Ljung test

X-squared	df	p-value
0.019314	4	1

Table 10. ARIMA model for EQTY continuous returns

Coeff.	ar1	intercept
	-0.0029	7e-04
s.e	0.0568	8e-04
σ^2	log likelihood	AIC
0.0001865	888.26	-1770.52

Table 11. Box-Ljung test

X-squared	df	p-value
1.0363e-07	1	0.9997

Box-Ljung test in Table 7, 9 and 11 indicate that the p-value is significant and implies that the ARIMA model can fit well the data. For further investigation, we can see the behavior of AIC and BIC in the model as follows

Figure 10. ARIMA for BOK Continuous returns

```
> auto.arima(continuousreturns)
Series: continuousreturns
ARIMA(0,0,1) with zero mean

Coefficients:
          ma1
      -0.2626
s.e.   0.0583

sigma^2 estimated as 8.723e-05:  log likelihood=1006.12
AIC=-2008.24   AICc=-2008.21   BIC=-2000.78
```

Figure 11. ARIMA for BLR Continuous returns

```
> auto.arima(continuousreturns)
Series: continuousreturns
ARIMA(0,0,0) with non-zero mean

Coefficients:
         mean
      -0.0011
s.e.   0.0007

sigma^2 estimated as 0.0001647:  log likelihood=907.97
AIC=-1811.93   AICc=-1811.89   BIC=-1804.46
```

Figure 12. ARIMA for EQTY Continuous return

```
> #Getting the optimal model
> auto.arima(continuousreturns)
Series: continuousreturns
ARIMA(0,0,0) with zero mean

sigma^2 estimated as 0.000187:  log likelihood=887.8
AIC=-1773.61   AICc=-1773.6   BIC=-1769.88
```

Figure 13. ARIMA for KCB Continuous returns

```
> auto.arima(continuousreturns)
Series: continuousreturns
ARIMA(0,0,0) with non-zero mean

Coefficients:
intercept
        0

sigma^2 estimated as 0:  log likelihood=Inf
AIC=-Inf   AICc=-Inf   BIC=-Inf
```

From the R output in Fig 10 -12 above we can deduce that the model fit well the data for BOK, BLR, and EQTY since AIC values are less than BIC values. Fig 13 shows that ARIMA model for KCB data is not applicable since the maximum return is the same as the minimum return throughout the period. Let see the Test for ARCH Effects in Table 12.

Table 12. The Ljung-Box statistics

	BOK	BLR	KCB	EQTY
X-squared	19.511	0.10709	NA	0.0033635
df	1	1	0	1
p-value	1e-05	0.7435	NA	0.9538

The Ljung-Box statistic gives the conclusion that since the p-value of test is greater than $\alpha = 0.05$ for BLR, and EQTY but not applicable for KCB. We fail to reject the null hypothesis and conclude that there are no ARCH effects present, so we cannot proceed and model volatility. In other words, because the p-value in Table 12 is greater than 0.05, we cannot reject the null hypothesis and must conclude that an AR model of order 4 for BLR and order 1 for EQTY fits the data well but not an AR model of order 5 for BOK. Therefore, there is ARCH effect for BOK data hence we can proceed and make rid of that ARCH effect.

garchFit (formula = ~1 + garch (5, 0), data = Close, trace = F)

Coefficient(s):

mu	omega	alpha1	alpha2	alpha3	alpha4	alpha5
2.3271e+02	1.4733e+00	1.0000e+00	5.1297e-02	1.0000e-08	1.0000e-08	1.0000e-08

Std. Errors:

based on Hessian Error Analysis:

	Estimate	Std. Error	t value	Pr(>|t|)
mu	2.327e+02	1.401e-01	1660.460	< 2e-16 ***
omega	1.473e+00	2.441e-01	6.037	1.57e-09 ***
alpha1	1.000e+00	1.354e-01	7.383	1.54e-13 ***
alpha2	5.130e-02	7.788e-02	0.659	0.51
alpha3	1.000e-08	NA	NA	NA
alpha4	1.000e-08	NA	NA	NA
alpha5	1.000e-08	NA	NA	NA

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Log Likelihood:

-1064.57 normalized: -3.434095

Standardised Residuals Tests:

			Statistic	p-Value
Jarque-Bera Test	R	Chi^2	3142.84	0
Shapiro-Wilk Test	R	W	0.7155395	0
Ljung-Box Test	R	Q(10)	882.783	0
Ljung-Box Test	R	Q(15)	1200.586	0
Ljung-Box Test	R	Q(20)	1413.117	0
Ljung-Box Test	R^2	Q(10)	0.6879248	0.9999698
Ljung-Box Test	R^2	Q(15)	0.8869485	0.9999999
Ljung-Box Test	R^2	Q(20)	2.790847	0.9999978
LM Arch Test	R	TR^2	0.7721134	0.9999967

Information Criterion Statistics:

AIC	BIC	SIC	HQIC
6.913352	6.997726	6.912362	6.947081

From the Output above the Lagrange Multiplier has a p-value of 0.9999967 which is greater than 0.05 and AIC is less than BIC then, we conclude that the mean equation fitted for the data is significant. The results show that alpha 1 is 1.000e+00 which is very high and indicates that the market is jumpy (unstable). In addition, Shapiro-Wilk test shows that W=0.7155395 and p-value = 0; Since the p-value is less than α=0.05, then we should reject the null hypothesis and conclude that residuals are not normally distributed.

By exploring LM test;

Chi-squared = 290.97, df = 12, p-value < 2.2e-16

It shows that there are no ARCH effects present after fitting ARCH (5) model since p-value is less than 0.05. Therefore, from ARCH Effect hypothesis, it is clear that there is no enough evidence to reject null hypothesis.

5. Conclusion

The COVID-19 has become a big challenge on financial markets and economic growth. Many researches have been done in various part of the world to evaluate its impact on financial sector. Because of previous errors, the ARCH model allows the conditional variance to change over time while keeping the unconditional variance constant. According to the study, COVID-19 has had no significant impact on some Rwandan financial markets, such as KCB and EQTY, as evidenced by the constant stock returns of these two companies since the pandemic outbreak until April 12th, 2021. The stock returns changed a little bit for BLR Ltd while high volatility appears in BOK company. This mean that both BLR and BOK made a high profit during this pandemic but also accounted some losses.

The results show that AR and MA at lag of 2 for all data behave almost the same and both fit well the data, but because it is impossible for all data of various companies to have partial autocorrelation function at the same lags hence to plot ACF and PACF plots for each company was needed in order to investigate the appropriate lag and we found lag of 5 for BOK, lag of 4 for BLR and lag of 1 for EQTY. we have checked the time series stationarity before building an ARIMA model. The model fit well the data as it is emphasized by Box-Ljung test in Table 7, 9, and 11. The Test for ARCH Effects in Table 12 showed that there are no ARCH effects present for KCB, BLR, and EQTY but it found for BOK data. The results show that the volatility is very high which implies the market instability.

The COVID-19 destroys and delays many economic activities and affect badly financial markets. Financial markets in Rwanda also faced the same challenges but some of them are still doing well as it observed in the results. We recommend investors around the world to invest in Rwanda Stock Exchange (RSE), it is young in East Africa but it is promising. For further study one can investigate the stock volatility of all companies listed at Rwanda Stock Exchange considering a long period of time, maybe from the beginning of RSE up to date.

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