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Impact of COVID-19 Pandemic and Oil Price Shock on BRVM-C Stock Market

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Abstract This paper examines the relationship between oil prices, exchange rates, and BRVM-C stock prices within the context of the COVID-19 pandemic. We identified a cointegration relationship among the variables, allowing us to estimate the long-run elasticities. Our findings indicate a statistically significant positive effect of oil prices on stock prices prior to the onset of the pandemic. However, during the COVID-19 period, this relationship lost significance, while a positive and significant effect was observed in the post-COVID resilience period. In terms of exchange rates, we found a statistically significant negative effect on stock prices before the pandemic. This relationship shifted to a positive and significant effect during the spread of the virus, followed by a return to a negative and significant effect in the resilience period. Additionally, our short-run elasticity estimates reveal that oil prices had a negative and significant impact on stock returns before the pandemic, a negligible effect during the pandemic, and a non-significant effect thereafter. Conversely, exchange rates exhibited a positive but non-significant effect before and during the pandemic, transitioning to a negative and significant effect only in the period following the pandemic.

Keywords: *COVID-19, oil price, stock market, BRVM composite*

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1. Introduction

Oil prices play a crucial role in the functioning of socioeconomic systems. Since the 1970s, fluctuations in oil prices have garnered significant attention. If oil prices influence economic activities, it stands to reason that they will also impact the stock market [1]. Theoretically, oil price shocks can affect stock market returns or prices through their impact on expected earnings, cash flows, and/or discount rates [2]. Additionally, a substantial body of research on the effects of oil is based on macroeconomic variables such as inflation, business cycles, exchange rates, and growth rates [3].

Since 2019, the global economy has been significantly impacted by the COVID-19 pandemic. Financial analysts frequently draw comparisons between the effects of COVID-19 and those of the global financial crisis of 2008. However, [4] emphasizes a distinction between these two crises, referring to the current pandemic-related challenges as the "Great Compression" [5]. Building on the foundational research by [6] and [7], a substantial body of literature has emerged demonstrating that fluctuations in oil prices have a pronounced influence on various economic indicators [7,8,9,10]. [7] discovered that any increase in oil prices tends to have a detrimental effect on economic growth in the United States, although it remains unclear if economic growth accelerates during periods of low oil prices.

While some research supports a nonlinear relationship between oil prices and macroeconomic variables [11,12,13], recent attention has primarily focused on the connection between changes in oil prices and stock market performance [14,15,16,17,18,19,20]. These diverse studies reveal that there is no consensus regarding the impact of oil price shocks on the stock market. Some research indicates a negative correlation; for instance, [14] utilized variance decomposition analysis to establish that oil price shocks adversely affect stock market returns in Greece during the initial four months. Similarly, [19] examined the relationship between oil prices and stock returns in the United States, concluding that an increase in oil prices typically leads to a decline in short-term stock returns.

Several studies have identified a positive correlation between oil price shocks and stock market returns. Notably, research by [20] and [21] highlight that oil price shocks have a favorable impact on stock returns in various markets, including China. Specifically, [21] examined the influence of oil price fluctuations and volatility on the Chinese stock market index and five sector returns, concluding that these shocks positively affect Chinese stock returns. Additionally, [20] reported significant positive effects of oil prices on stock prices in Vietnam.

Conversely, some studies have reported an insignificant response of stock markets to changes in oil prices. [22], for instance, analyzed the relationship between oil price shocks and stock market behavior in Nigeria and discovered a negligible positive response at first, which transitioned to a negative effect over time, influenced by the nature of the oil price shocks.

Furthermore, recent literature has examined the effects of oil prices on various industrial sectors within the stock market. Research by [23,24,25], and [26] has contributed to this area of study. In his 2011 research, Arouri analyzed the impact of oil prices on stock returns for 12 European sectoral stock indices using weekly data. His findings indicate that oil price variations positively influence certain sector stock returns while adversely affecting others. Specifically, indices related to oil and gas, basic materials, and consumer services sectors exhibit a positive relationship with oil price changes, whereas sectors such as financials, food and beverages, technology, telecommunications, healthcare, transportation, and manufacturing show a negative response to oil price fluctuations.

[27] and [28,29] contribute to the understanding of the relationship between changes in oil prices and their impact on the economy and financial markets by distinguishing the origins of oil price shocks. Following [29], the real oil price can be classified into three categories: crude oil supply shocks, shocks to the global demand for all industrial commodities, and demand shocks specific to the global crude oil market [30]. A growing body of literature suggests that supply-side oil price shocks no longer significantly affect the economy or financial markets [29,31,32,33,34].

While numerous studies have examined the relationship between oil price fluctuations and stock market returns, a consensus on a uniform relationship has yet to be established. Furthermore, most of these studies have focused on developed countries, with only a few addressing developing regions such as ECOWAS and WAEMU (West African Economic and Monetary Union). This paper aims to reassess the impact of oil price changes on the BRVM Composite stock returns in the context of the COVID-19 pandemic. Specifically, it seeks to analyze how fluctuations in oil prices and the ongoing pandemic have influenced BRVM Composite stock returns.

This study contributes to existing literature in two significant ways. First, it employs the [35]'s test to explore the cointegration relationship while accounting for potential endogenous structural breaks. In this research, we utilize the last three models proposed by Gregory-Hansen. The second contribution of this paper involves considering the impact of the COVID-19 pandemic in the analysis of how emerging stock markets respond to fluctuations in oil prices and exchange rates.

The structure of this paper is organized as follows: the next section will present the data and methodology employed in the study. Section 3 will discuss the estimation process, and the results obtained. Finally, Section 4 will provide concluding remarks.

2. Data and Methodology

2.1. The Data

We utilized daily data from the INVESTIN.COM database covering the period from May 1, 2000, to September 6, 2021. The data series include oil prices (BR Brent), the BRVM-C stock price index, and the nominal exchange rate. The exchange rate analyzed is the euro-to-dollar rate, as the CFA franc and euro maintain a fixed exchange rate (1€ = 655.96 CFA francs). The dataset is categorized into three distinct periods: the first period (pre-COVID-19) spans from May 1, 2000, to February 28, 2020; the second period (during COVID-19) occurs from March 2, 2020, to June 8, 2020; and the third period (post-COVID-19), which corresponds to the timeframe following the last phase of confinement in the region, starts from June 9, 2020. The BRVM serves as the stock market for member countries of the West African Economic and Monetary Union (WAEMU). Observations of data plots indicate that all series exhibit a trend (refer to Figures 1-24 in the appendix), with oil prices and exchange rate growth displaying greater volatility compared to BRVM-C stock returns. This finding is inconsistent with the results presented by [36]. Additionally, return series are easier to analyze than raw series, as returns adhere more closely to statistical properties [37].

2.2. Methodology

2.2.1. Empirical Model

We consider the following long-run model (Narayan and Narayan, 2010):

$$\ln BSPG_t = \alpha_0 + \alpha_1 \ln OP_t + \alpha_2 \ln ER_t + \varepsilon_t \quad (t = 1, \ldots, T) \tag{1}$$

Where $BSPG$ is the BRVM-C stock price returns (growth), OP is oil prices and ER is the exchange rate. There are many types of returns but those interest us is the continuous component returns because it includes all the proprieties of the others method of calculation like this:

$$G_t = \log\left(BSP_t / BSP_{t-1}\right) * 100 \tag{2}$$

2.2.2. Unit Root Tests

We will present here augmented Dickey-Fuller (ADF), ADF-GLS and Philip-perron (PP) unit root tests.

Augmented Dickey-Fuller test (ADF, 1981)

[38] unit root test supposes that the series y_t is an autoregressive process $AR(1)$. Higher-order lags of series correlation can violate the assumption of white noise in disturbances. To address this issue, the Augmented Dickey-Fuller (ADF) test is employed to adjust for higher-order correlations. This assume that the series y_t contain an $AR(p)$ process with p lagged difference terms of y_t in the right hand side.

$$\Delta y_t = \lambda y_{t-1} + \sum_{j=1}^{p} \beta_j \Delta y_{t-p} + x_t{}' \delta + \varepsilon_t \tag{3}$$

Where x_t are exogenous regressors which can be considered like optional (a constant, or a constant and trend). λ, β and δ are parameters to be estimated.

Dickey-Fuller test with GLS detrending (DFGLS)

In the above test, one can include a constant, or a constant and a time trend in the ADF test. These situations lead [39] to propose a modification of the ADF tests. It consists to remove (detrended data) explanatory variables before running the test regression like this:

$$d\left(y_t \mid a\right)=\begin{cases} y_t & if\ t=1 \\ y_t-ay_{t-1} & f\ t>1 \end{cases} \quad (4)$$

Where the quasi-difference of y_t depends on the value of the specific point alternative a against which on wish to test the null. Finally, the DFGLS test involves estimating the standard ADF test (3) after substituting the GLS detrend the GLS detrended y_t^d for the original y_t as follows:

$$\Delta y_t^d=\lambda y_{t-1}^d+\sum_{j=1}^{p}\beta_j\Delta y_{t-1}^d+\varepsilon_t \quad (5)$$

The DFGLS t-ratio follows a Dickey-Fuller distribution only in the case of constant, but the asymptotic distribution differs when including a constant and a time trend ([39] ERS, 1996).

Phillips-Perron (1988) unit root test

A nonparametric method that allows to control for the serial correlation when we test for unit root is proposed by [40]. This test is based on the statistics:

$$\tau_\alpha=t_\alpha\left(\frac{\gamma_0}{f_0}\right)^{1/2}-\frac{T\left(f_0-\gamma_0\right)\left(se(\hat{\alpha})\right)}{2f_0^{1/2}s} \quad (6)$$

Where $\left(se\left(\hat{\alpha}\right)\right)$ is the coefficient standard error, $\hat{\alpha}$ the estimated, s the standard error of the test regression, γ_0 the consistent estimate of the error variance and f_0 is an estimator of the residual spectrum at frequency zero.

2.2.3. Cointegration Tests

The following sub-section presents Johansen and Gregory-Hansen tests of cointegration.

Johansen test

Pour qu'une relation de cointégration existe entre des variables, deux conditions doivent être réunies. D'abord, les variables doivent être non stationnaires et intégrées du même ordre. Ensuite, leurs tendances stochastiques doivent être liées. Il existe donc une relation de long terme entre les variables. L'approche initiale de Johansen repose sur l'estimation d'un VAR

$$X_t=\Pi_1X_{t-1}+\ldots+\Pi_kX_{t-k}+\mu+\Psi D_t+\varepsilon_t \quad (7)$$

Où X_t est un vecteur de k variables, D_t un vecteur des variables exogènes incluant une tendance et des variables indicatrices, et ε_t le vecteur des perturbations suivant une loi normale.

Cependant puisque certaines variables économiques sont I (1), l'estimation du VAR en différence peut conduire à une perte d'information si les séries sont effectivement cointégrées. Pour tenir compte de cette dimension potentiellement cointégrée des variables économiques, Johansen (1988) réécrit (10) sous la forme Vectorielle à Correction d'Erreurs (VECM)

$$\Delta X_t=\mu+\Pi X_{t-k}+\sum_{i=1}^{k-1}\Gamma_i\Delta X_{t-i}+\Psi D_t+\varepsilon_t \quad (8)$$

Selon l'auteur, si on étudie N variables avec $N>2$, on peut avoir jusqu'à ($N-1$) relations de cointégration. Ainsi, ce test repose sur l'hypothèse nulle qu'il existe au plus r relations de cointégration. Les statistiques du test sont la suivante

$$TR\left(H_0\left(r\right)/H_1\left(p\right)\right)=-T\sum_{i=r+1}^{N}\log(1-\hat{\lambda}_i) \quad (9)$$

$$\lambda_{\max}\left(H_0\left(r\right)/H_1\left(r+1\right)\right)=-T\ln\left(1-\hat{\lambda}_{r+1}\right) \quad (10)$$

$\hat{\lambda}_i$ est la $i^{\text{鏋}e}$ valeur propre maximale estimée.

La première statistique teste l'hypothèse nulle de cointégration de rang r $\left(H_0\left(r\right):rang\left(\Pi\right)=r\right)$ contre l'alternative de la stationnarité $\left(H_1\left(p\right):rang\left(\Pi\right)=p\right)$. Cette statistique est appelée statistique de la trace. La seconde statistique teste $\left(H_0\left(r\right):rang\left(\Pi\right)=r\right)$ contre $\left(H_1\left(r\right):rang\left(\Pi\right)=r+1\right)$. Elle porte le nom de statistique de la valeur propre maximale.

Structural break cointegration test (Gregory-Hansen, 1996)

Following the Johansen test, we proceeded with additional cointegration tests that account for structural breaks: the [35] and its extension by [41], which incorporates two endogenous structural breaks. The first test addresses one endogenous structural break, while the second accommodates two. The [35]'s methodology offers several models that facilitate the analysis of cointegration with structural changes, including standard cointegration, level shift, level shift with trend, and regime shift.

Model 1: Standard cointegration

$$y_{1t}=\mu+\alpha^{\tau}y_{2t}+e_t$$
$$t=1,\ldots,n \quad (11)$$

Where y_{2t} is $I\left(1\right)$ and e_t is $I\left(0\right)$. In this model, μ and α describe the m-dimensional hyperplane towards which the vector process y_t tends over time (see [35]. If model 1 is to capture a long-run relationship, one will want to consider μ and α as time invariant.

Model 2: $y_{1t}=\mu_1+\mu_2\varphi_{1t}+\alpha^{\tau}y_{2t}+e_t$

$$t=1,\ldots,n \quad (12)$$

where $\varphi_{t\tau} = \begin{cases} 0\, if\ t \le [n\tau] \\ 1\, if\ t > [n\tau] \end{cases}$ $\tau \in (0,1)$ and μ_1 represents the intercept before the shift, and μ_2 represents the change in the intercept at the time of the shift. Adding a time trend into the level shift model we obtain model 3.

Model 3: $y_{1t} = \mu_1 + \mu_2\varphi_{1t} + \beta t + \alpha^{\tau} y_{2t} + e_t$

$$t = 1, \ldots, n \tag{13}$$

Another possible structural change allows the slope vector to shift as well. This permits the equilibrium relation to rotate as well as shift parallel. It is called the regime shift model.

Model 4: $y_{1t} = \mu_1 + \mu_2\varphi_{t\tau} + \alpha_1^{\tau} y_{2t} + \alpha_2^{\tau} y_{2t}\varphi_{t\tau} + e_t$

$$t = 1, \ldots, n \tag{14}$$

Whith μ and μ_2 are as in the level shift model, α_1 denotes the cointegrating slope coefficient before the regime the regime shift, and α_2 denotes the change in the slope coefficients. [35] propose a suite of tests to analyze the cointegration between y_t and x_t with structural change. One will be interested in the smallest values of the test statistics. These statistics are commonly used ADF statistics and extensions of the Z_t and Z_α test statistics of [43]. These statistics are:

$$Z_\alpha^* = \inf_{\tau \in T} Z_\alpha(\tau) \tag{15}$$

$$Z_t^* = \inf_{\tau \in T} Z_t(\tau) \tag{16}$$

$$ADF^* = \inf_{\tau \in T} ADF(\tau) \tag{17}$$

All these tests have the same null hypothesis of no cointegration.

2.2.4. Error Correction Model

[42] and [35]'s tests confirm the presence of long-run relationship between the set of variables. In this case we should use a dynamic error correction model in order to catch the short-run dynamic as shown by [44]. The short-run regression model dynamic is the following:

$$BSPG_t = \beta_1 + \sum_{q=0}^{m} \eta_q OPG_{t-q} + \sum_{q=0}^{m} \theta_q ERG_{t-q} + \lambda\varepsilon_{t-1} + \mu_t \tag{18}$$

All variables in equation (9) are defined in section 3.1 and 3.2, m is the lag length and ε_{t-1} is the lagged error correction term.

2.2.5. Parameter Stability Test

We apply the parameter stability test proposed by [45] accounting for one or more unknown structural breakpoints.

Test de stabilité des paramètres de Quandt-Andrews (1993)

The Quandt-Andrews test (1993) ([45]) investigates one or more unknow structural breakpoints in the sample. This test is based on the Sup or Maximum statistic (or Likelihood Ratio F-statistic, Wald F-statistic) the Exp statistic and the Ave statistic with null hypothesis of "no breakpoints". In this test, the trimming of 15% is used. The Maximum statistic is simply the maximum of the individual Chow F-statistics like follow:

$$MaxF = \max_{\tau_1 \le \tau \le \tau_2} (F(\tau)) \tag{19}$$

The "Exp statistics" takes this form:

$$ExpF = \ln\left(\frac{1}{k}\sum_{\tau=\tau_1}^{\tau_2} \exp\left(\frac{1}{2}F(\tau)\right)\right) \tag{20}$$

Finally, the "Ave statistics" is the simple average of the individual F-statistics:

$$AveF = \frac{1}{k}\sum_{\tau=\tau_1}^{\tau_2} F(\tau) \tag{21}$$

3. Results and Discussion

3.1. Unit Root Test

The initial phase of our empirical analysis involves conducting unit root tests. We implement three specific tests: the Augmented Dickey-Fuller (ADF) test, the Dickey-Fuller generalized least squares (DF-GLS) test, and the Phillips-Perron (PP) test. These tests are applied to the BRVM-C Stock Price (BSP), the BRVM-C Growth Rate of Stock Price (BGSP), Crude Oil Price (OP), the Growth Rate of Crude Oil Price (OPG), the Nominal Exchange Rate (ER), and the Nominal Exchange Growth Rate. The results are summarized in Table 1. All tests share a common null hypothesis, which posits the presence of a unit root. Our findings indicate that the variables BSP, OP, and ER display a unit root. Conversely, we successfully reject the null hypothesis at the 1% level of significance for the variables BGSP, OPG, and ERG. These results facilitate our exploration of potential long-term relationships among these variables.

Table 1. Unit root tests

Variables	ADF	DF-GLS	PP
	Before-COVID-19		
BRVM-C stock price (BSP)	-1.191	-0.372	-1.121
BRVM-C stock price (BSPG) growth	-27.793***	-23.569***	-70.222***
Oil price (OP)	-1.762	-1.479	-1.794
Oil price growth (OPG)	-73.654***	-72.461***	-73.613***
Exchange rate (ER)	-1.468	-1.422	-1.443
Exchange rate growth (ERG)	-70.760***	-70.338***	-70.764***
	During-COVID-19		
BRVM-C stock price (BSP)	-1.335	-0.862	-1.421
BRVM-C stock price (BSPG) growth	-8.209***	-8.103***	-8.214***
Oil price (OP)	-2.008	-1.073	-2.051
Oil price growth (OPG)	-7.151***	-7.121***	-7.127***
Exchange rate (ER)	-2.932	-2.994	-2.037
Exchange rate growth (ERG)	-6.867***	-6.707***	-6.857***
	After-COVID-19		
BRVM-C stock price (BSP)	-2.151	-0.908	-2.294
BRVM-C stock price (BSPG) growth	-12.775***	-12.801***	-12.844***
Oil price (OP)	-1.306	-1.113	-1.063
Oil price growth (OPG)	-14.055***	-13.045***	-14.559***
Exchange rate (ER)	-1.480	-1.529	-1.524
Exchange rate growth (ERG)	-13.592***	-13.166***	-13.618***

Note: The 1% critical value for the DF-GLS test is -3.460. *** denotes statistical significance at 1% level.

Table 2. Cointegration test

H_0	H_A	λ_{tr} test	P-values
	Before COVID-19		
$r=0$	$r=1$	613.921**	0.000
$r\leq 1$	$r=2$	16.187	0.477
H_0	H_A	λ_{max} test	P-values
$r=0$	$r=1$	597.733**	0.000
$r=1$	$r=2$	13.807	0.267
	During COVID-19		
$r=0$	$r=1$	49.616**	0.009
$r\leq 1$	$r=2$	22.631	0.120
H_0	H_A	λ_{max} test	P-values
$r=0$	$r=1$	26.984**	0.035
$r=1$	$r=2$	14.226	0.239
	After COVID-19		
$r=0$	$r=1$	70.335**	0.000
$r\leq 1$	$r=2$	4.628	0.846
H_0	H_A	λ_{max} test	P-values
$r=0$	$r=1$	65.707**	0.000
$r=1$	$r=2$	4.623	0.788

Note: * denotes rejection of the null hypothesis at the 5% level and ** denotes the p-values using MacKinnon and al approach (1999).

3.2. Cointegration Tests

3.2.1. Johansen Test

We examine the long-run relationship between BSPG, LOP, and LER (exchange rate). The methodology outlined by [42] and [46] presents a multivariate long-run equilibrium framework based on vector autoregression (VAR), which enables us to identify statistically significant long-run relationships. The Johansen cointegration test allows for the possibility of multiple long-run equilibrium relationships. Prior to conducting this test, it is essential to determine the optimal lag length of the VAR model. The optimal lag lengths identified are 4, 1, and 1, corresponding to the periods before, during, and after the COVID-19 pandemic. This methodology involves two key statistics: trace statistics and the maximum eigenvalue statistics. Both the trace and maximum eigenvalue statistics indicate one (1) long-run relationship across all specified periods (refer to Table 2).

3.2.2. Structural Break Cointegration Test

Table 3 reports the results of the three tests: the one-break, two-break and the three-break tests. When using [35] Gregory-Hansen (1996) critical values at 5% level (see [35] p.11 Table 1) the null of no cointegration is rejected for almost all these tests in presence of structural breaks and then the Johansen test above is consistent. There is a long-run relationship between the BRVM-C stock returns, crude oil price and exchange rate.

Table 3. Gregory and Hansen test

BGSP=(LOP,LER)	ADF	T_b	Z_t^*	T_b	Z_α^*	T_b
		Before COVID-19				
One-break	-22.161**	9/28/2006	-68.310**	4/28/08	-4744.300**	4/28/08
Two-break	-22.152**	9/28/2006	-68.374**	4/28/08	-4748.785**	4/28/08
Three-break	-22.179**	1/18/2006	-68.340**	4/28/08	-4746.377**	4/28/08
		During COVID-19				
One-break	-9.340**	4/01/2020	-9.414**	4/01/2020	-75.472**	4/01/20
Two-break	-9.716**	4/27/2020	-9.793**	4/27/2020	-78.508**	4/27/20
Three-break	-9.682**	4/01/2020	-9.759**	4/01/2020	-77.999	4/01/20
		After COVID-19				
One-break	-13.535**	12/30/20	-13.570**	12/30/20	-190.386**	12/30/20
Two-break	-13.899**	12/30/20	-13.934**	12/30/20	-195.541**	12/30/20
Three-break	-13.693**	12/30/20	-13.728**	12/30/20	-192.672**	12/30/20

Note: The one-break 5% critical values are -5.50 and -58.33 respectively for the ADF / Z_t^* tests and Z_α^* tests. The corresponding two-break 5% critical values are -6.00 and -68.94 and the corresponding three-break 5% critical values are -6.41 and -78.52. The null hypothesis is no cointegration.

3.3. Long-run Elasticities

In Table 4, we report the long-run elasticities obtained from Ordinary Least Squares (OLS). All variables are statistically significant. Before the COVID-19 pandemic, an increase of 1% of oil prices increased the BRVM-C stock prices around 0.69% while an increase of 1% exchange rate led to a decrease of 0.24% of BRVM-C stock prices. This result is conformed to those of [47] and [20].

During the COVID-19 pandemic period, the effect of the exchange rate became positive on BSP. Thus, an increase in the exchange rate increases BSP of 1.25%. COVID-19 influenced BSP via the exchange rate comparatively to others sub periods (before and after). An increase in exchange corresponds to a depreciation of national current. This situation can lead to a surplus on balance of trade. But the oil prices are statistically not significant corresponding Babatunde and al. 2012 study in Nigeria.

After COVID-19, the rise of 1% of oil prices and exchange rates led respectively to an increase of 0.19% and a fall of 0.41% of BRVM-C stock prices. We note that before and after Covid-19 period response in the same way in contrast to the middle period which is during COVID-19. Following Narayan and Narayan, (2010), the relationship exist between exchanges rates and stock returns could be negative or positive. It depends on the type of country (import or export dominant country). According to [48] the competitiveness of firms can be affected by reducing their earnings.

Table 4. Long-run elasticities

	OLS	
	Coefficient	t-Statistic
	Before COVID-19	
LOP	0.692*** (0.016)	42.717
LER	-0.241*** (0.056)	-4.244
const	2.227*** (0.0576)	38.635
	During COVID-19	
LOP	0.018 (0.016)	1.120
LER	1.253*** (0.261)	4.794
const	4.745*** (0.049)	96.333
	After COVID-19	
LOP	0.190*** (0.018)	10.259
LER	-0.412*** (0.118)	-3.469
const	4.216***(0.060)	70.267

Note: *** denotes statistical significance at 1% level. Values in brackets are the standard deviation.

3.4. Error Correction Model

The long-run relationship is captured by the lagged value of error correction term reflecting the convergence of the long-run equilibrium system. The above equation considers the short and long-run relationship between BRVM-C stock returns, the oil price and exchange rate returns.

Table 5 reports the short-run dynamic results. As shown for all sub-periods, in the first there is a short-run relationship between OPG and BRVM-C stock returns. An increase of 1% of OPG led to a decrease in BSPG by around 0.01%. The adjustment rate of 0.7% is low. During and after COVID-19 pandemic periods, only the constant and the adjustment rate are statistically significant. The adjustment rate during pandemic period 13.1% is the largest of all but those after pandemic 4.3%. The insignificant short run during and after could be explained by time latency before seeing pandemic effect on the stock market returns. Finally, the residual diagnostic (Table 6) reveals that over the three periods, only those during pandemic have homoscedasticity and no serial correlation of residuals. This can also be explained by the fact that during this period most of the world economic and financial activities have slowed down.

Table 5. Short-run elasticities

	Coefficient	t-statistics
Panel A: OLS	Before COVID-19	
Constant	4.102***(0.145	28.237
OPG	-0.011**(0.005)	-2.108
ERG	0.022(0.019)	1.176
ε_{t-1}	-0.007**(0.003)	-2.174
	During COVID-19	
Constant	4.410***(1.135)	3.885
OPG	0.004(0.015)	0.279
ERG	0.022(0.183)	0.120
ε_{t-1}	-0.127***(0.044)	-2.835
	After COVID-19	
Constant	5.419***(0.987)	5.485
OPG	-0.002(0.027)	-0.090
ERG	-0.180***(0.148)	-1.216
ε_{t-1}	-0.043(0.0184)	-2.363
Panel B: Garch (1,1)		
	Before COVID-19	z-Statistic
Constant	4.065***(0.124)	32.615
OPG	-0.001(0.004)	-0.029
ERG	0.023(0.014)	1.593
ε_{t-1}	-0.004***(0002)	-1.402
	After COVID-19	
Constant	5.704***(0.585)	9.750
OPG	0.018(0.025)	0.733
ERG	-0.225**(0.097)	-2.302
ε_{t-1}	-0.028*(0.015)	-1.809

Note: *** is the significant at 1% level

Table 6. Residuals dignostic tests

Hypothèse du test	Tests	Values (Prob)
	Before COVID-19	
Autocorrelation	Breusch-Godfrey	6.723 (0.001)
Heteroscedascticity	Arch	16.766 (0.000)
Normality	Jarque-Bera	77040.08 (0.000)
	During COVID-19	
Autocorrelation	Breusch-Godfrey	0.460(0.633)
Heteroscedascticity	Glejser/Arch	0.304(0.932)/0.079(0.779)
Normality	Jarque-Bera	330.99(0.000)
	After COVID-19	
Autocorrelation	Breusch-Godfrey	2.288(0.104)
Heteroscedascticity	Arch	4.326 (0.000)
Normality	Jarque-Bera	41.721 (0.000)

Note: (Jarque-Bera) is the normality test, H_0 : no serial correlation (Breusch-Godfrey), H_0 : homoscedasticity (Arch). P-values are in brackets.

The short-run diagnostic for before and after the COVID-19 exhibit ARCH effects. This situation could lead to bias in using the short-run OLS estimation. Hence, we estimate the short-run model using a GARCH (1, 1) specification. Before-COVID-19, we apply a GARCH (1, 1) model and thus the ARCH LM (1, 4816) test statistic 0.880 with 0.348 of probability value does not exhibit an ARCH effect.

3.5. Parameter Stability Tests

The results are reported in Table 7. Before the pandemic, with 3374 breakpoints considered, the null hypothesis is not rejected for some tests. The during-COVID-19 period considered 45 breakpoints and the null hypothesis of no breakpoints cannot be rejected. After the pandemic, Quandt-Andrews unknown breakpoint test cannot also reject the null hypothesis with 175 number of breaks compared. These results are confirmed by CUSUM test below. This means that parameters are stable.

Table 7. Quandt-Andrews unknown breakpoint test

Statistic	Value	p-value
	Before COVID-19	
Max. LR F-stat. (7/18/2007)	4.377	0.419
Max. Wald F-stat. (7/18/2007)	51.640	0.419
Exp LR F-stat.	1.856	0.006
Exp Wald F-stat.	21.166	0.031
Ave LR F-stat.	2.631	0.627
Ave Wald F-stat.	18.422	0.627
	During COVID-19	
Max. LR F-stat. (5/18/2020)	3.930	0.685
Max. Wald F-stat. (5/18/2020)	27.513	0.685
Exp LR F-stat.	0.672	0.382
Exp Wald F-stat.	10.118	0.007
Ave LR F-stat.	1.080	0.351
Ave Wald F-stat.	7.563	0.351
	After COVID-19	
Max. LR F-stat. (10/28/2020)	3.335	0.461
Max. Wald F-stat. (10/28/2020)	23.349	0.461
Exp LR F-stat.	0.843	0.328
Exp Wald F-stat.	8.221	0.047
Ave LR F-stat.	1.570	0.131
Ave Wald F-stat.	10.992	0.131

Notes: probabilities calculated using Hansen's (1997) method.

4. Concluding Remarks

This paper aims to analyze the relationship between oil prices, exchange rates, and BRVM-C stock prices within the context of the COVID-19 pandemic. The pandemic has been identified as a source of systematic risk, as noted by [49], and warrants an examination of its financial implications. In response to the pandemic, many governments implemented stringent measures such as shutdowns, lockdowns, and restrictions on mobility, which have led to a decline in economic activity and financial instability. Our analysis utilizes daily data from three distinct periods: prior to the pandemic (from January 5, 2000, to February 28, 2020), during the pandemic (from the declaration of the first case on March 2, 2020, to the conclusion of restrictions on June 8, 2020), and post-pandemic (from June 9, 2020, to March 18, 2021, corresponding to the resilience period).

Our analysis indicates that stock prices on the BRVM-C, along with oil prices and nominal exchange rates, exhibit a cointegrated relationship, as confirmed by the Johansen test. Additionally, the Gregory-Hansen structural break cointegration test validates these findings, suggesting a long-term relationship among these variables. We proceeded to estimate the long-run elasticities and discovered a statistically significant positive impact of oil prices on stock prices prior to the COVID-19 pandemic. This relationship became statistically insignificant during the COVID-19 period, while re-establishing a significant positive correlation post-COVID, referred to as the resilience period.

Regarding exchange rates, we found that their impact on stock prices was statistically significant and negative before the onset of the pandemic. During the spread of the virus, this relationship shifted to a positive and significant correlation, followed by a negative and significant association during the resilience period. We have estimated the short-run elasticities and found that oil prices exert a negative and statistically significant effect on stock returns prior to the COVID-19 pandemic. During and after the pandemic, however, this effect was not significant. In contrast, exchange rates demonstrated a positive but non-significant effect on stock returns before and during the pandemic, transitioning to a negative and statistically significant impact only after the pandemic period. The lack of significant effects of oil prices and exchange rates on stock returns during the COVID-19 period may be attributed to the general slowdown in global economic and financial activities during this time.

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APPENDIX

Before-COVID-19 series graphs

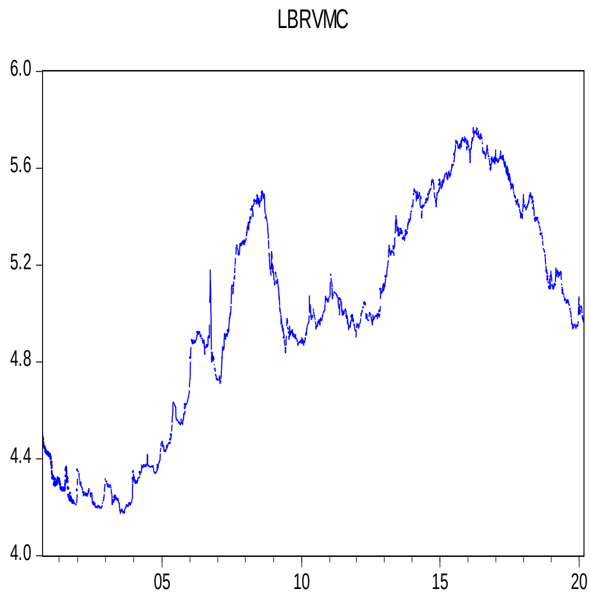

Figure 1: BRVM-C stock price index

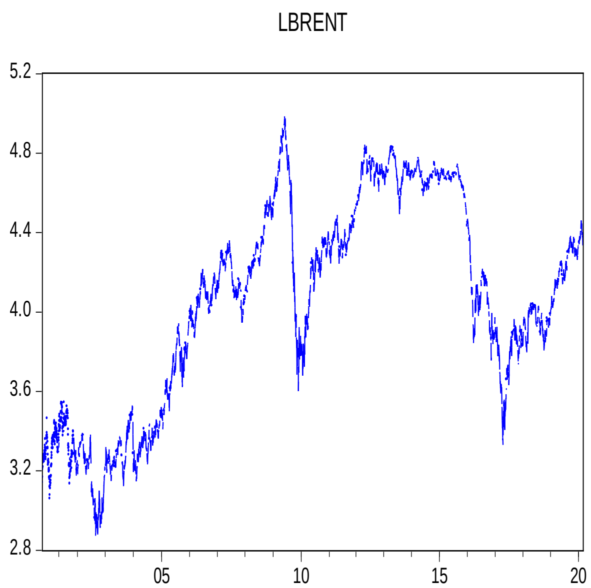

figure 2: Oil price series

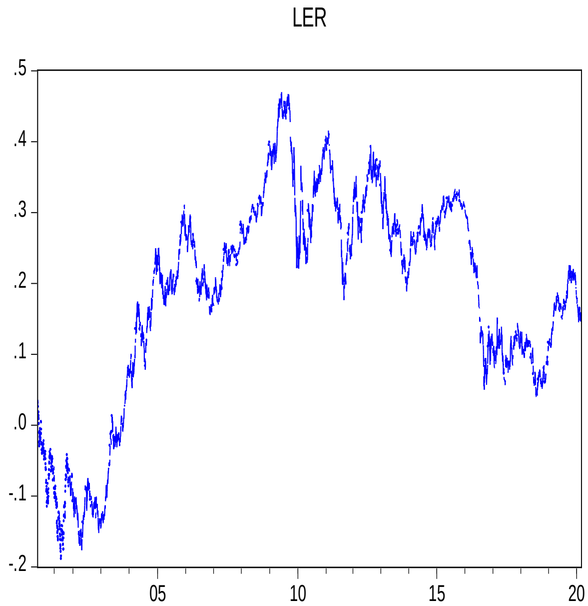

Figure 3: Exchange rate series

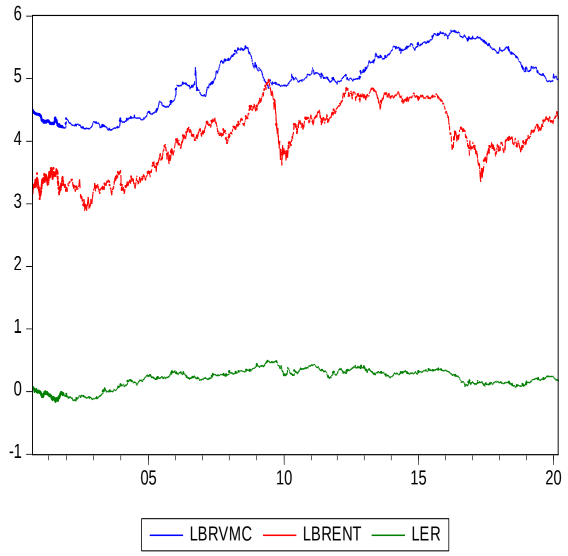

Figure 4: All series

Before-COVID-19 returns graphs

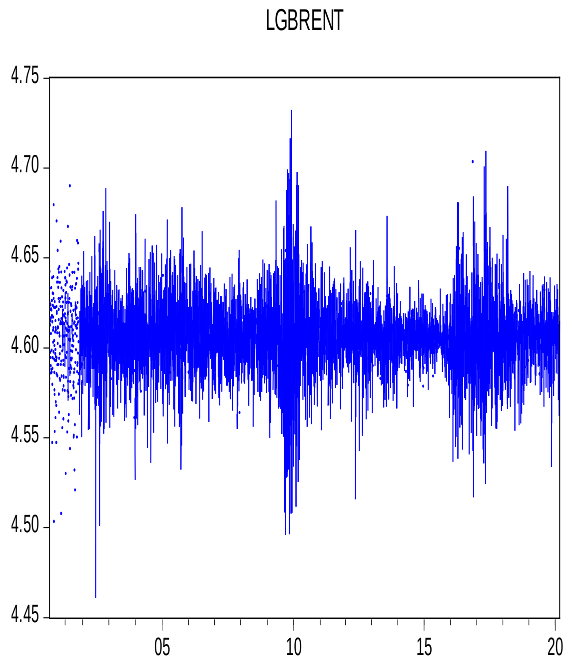

Figure 5: Crude oil price growth rate

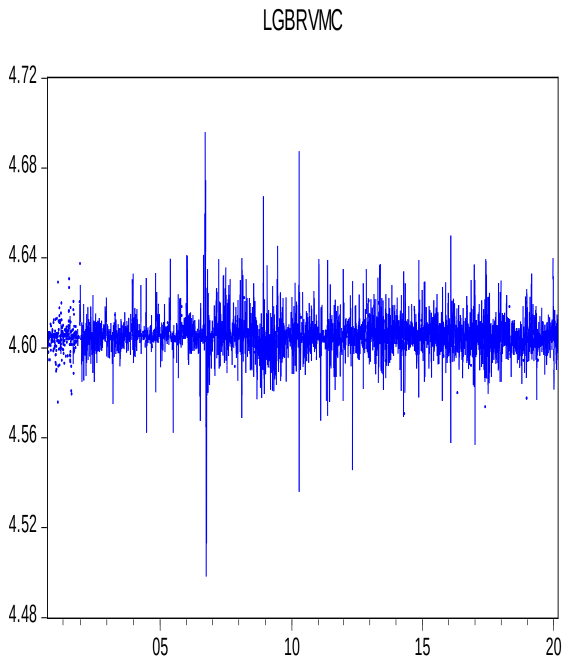

Figure 6: BRVM-C stock price growth rate

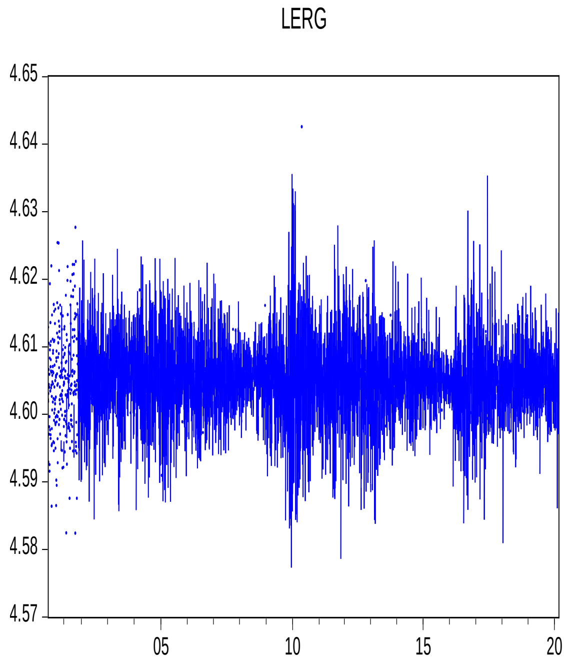

Figure 7: Nominal exchange rate growth

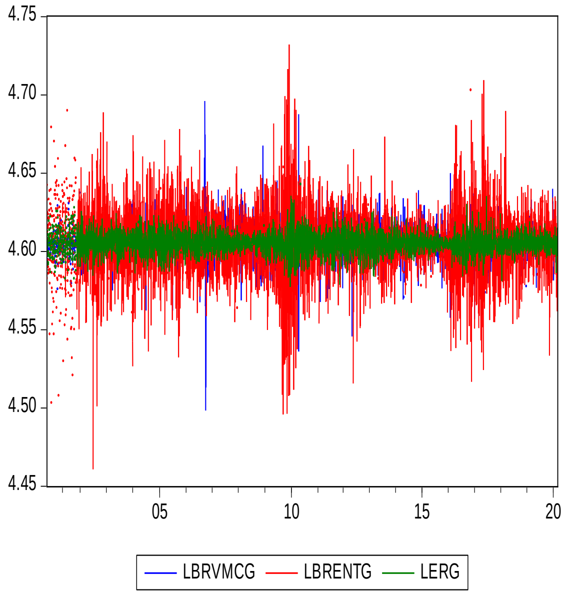

Figure 8: Growth rate of all series

During-COVID-19 series graphs

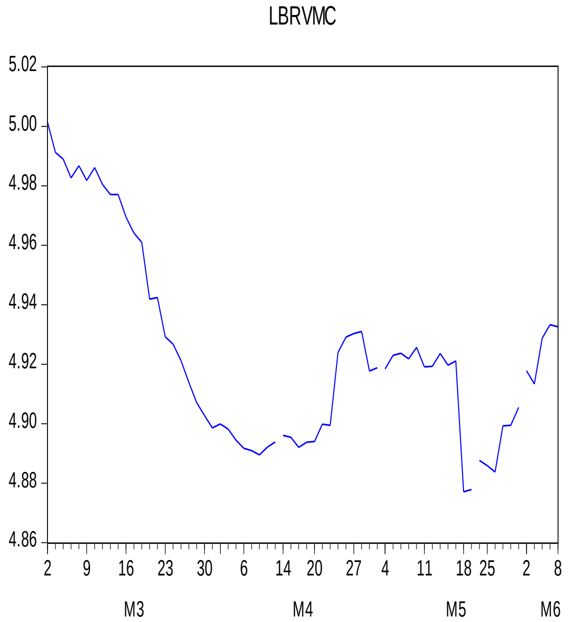

Figure 9: BRVM-C stock price index

Figure 10: Oil price series

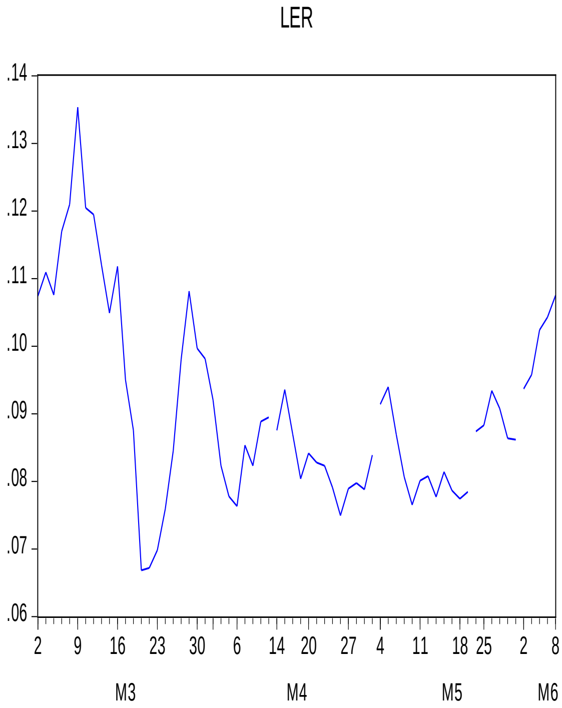

Figure 11: Exchange rate series

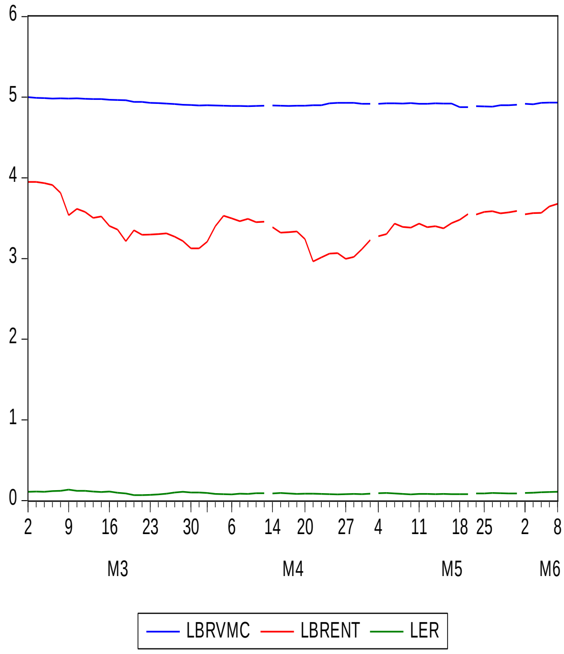

Figure 12: All series

During-COVID-19: returns graphs

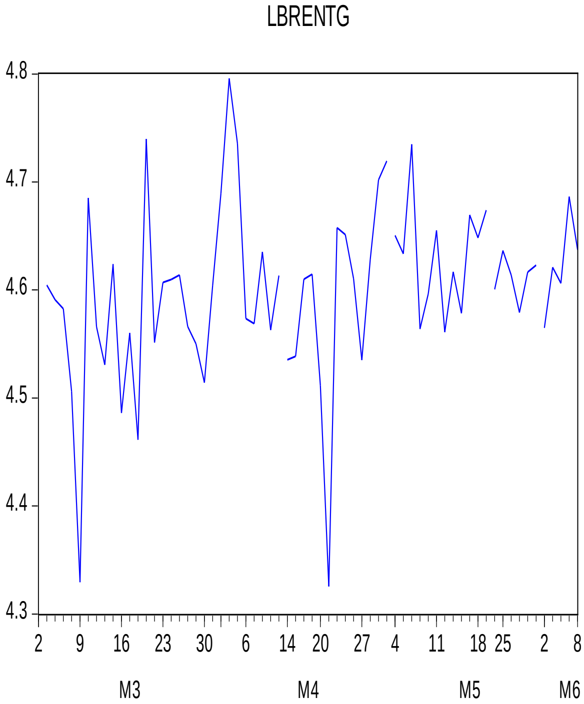

Figure 13: Crude oil price growth rate

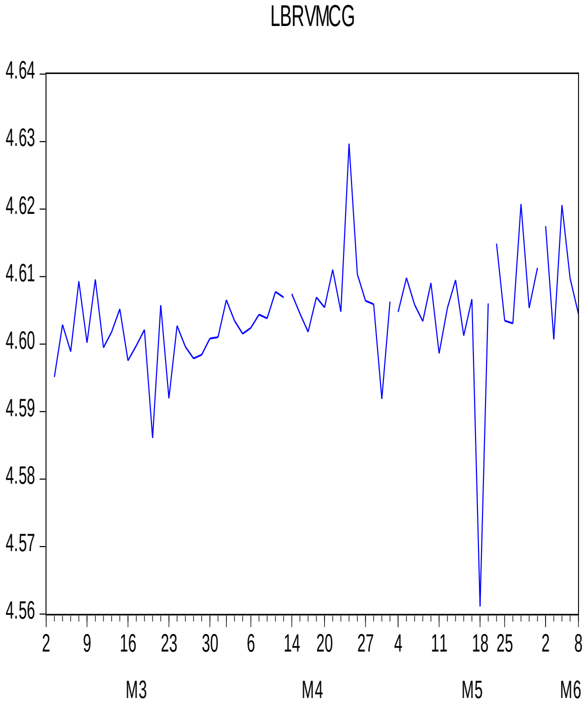

Figure 14: BRVM-C stock price growth rate

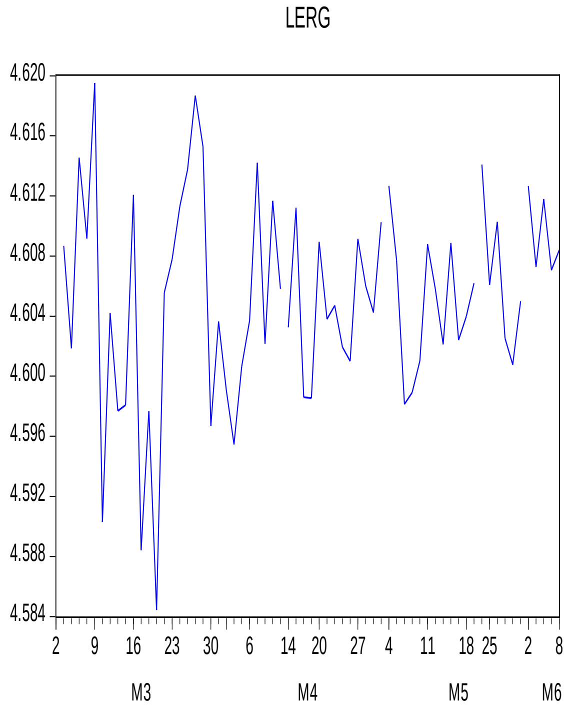

Figure 15: Nominal exchange rate growth

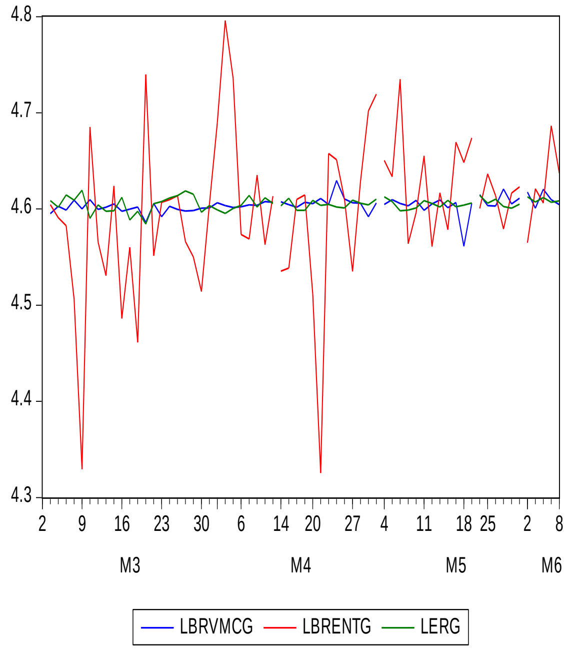

Figure 16: Growth rate of all series

After-COVID-19 series graphs

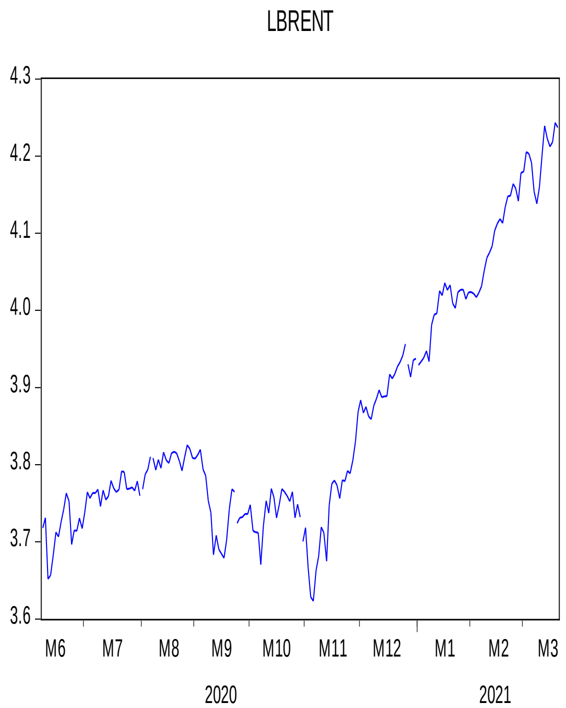

Figure 17: Oil price series

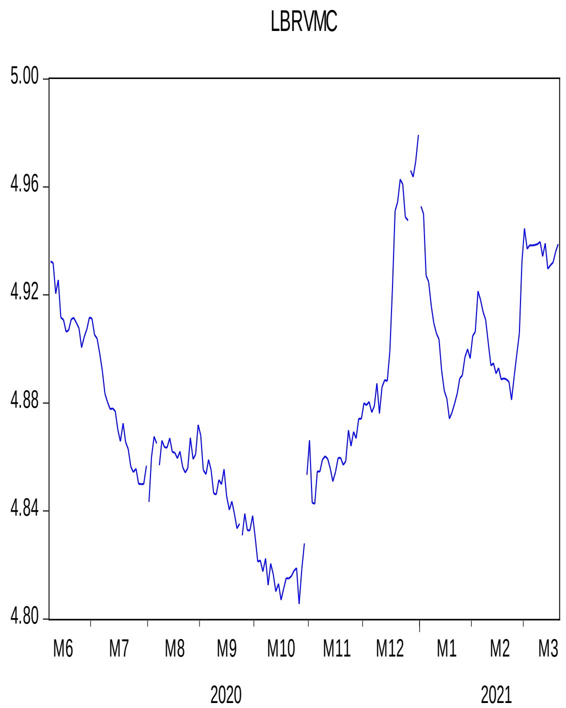

Figure 18: BRVM-C stock price index

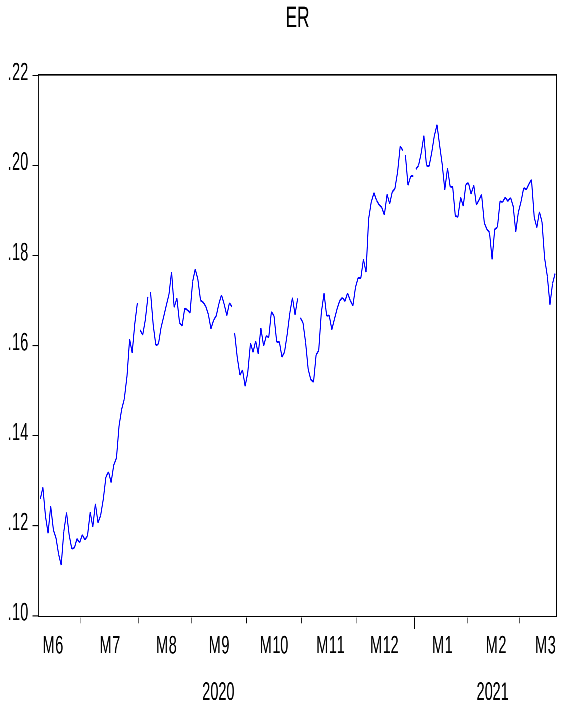

Figure 19: Exchange rate series

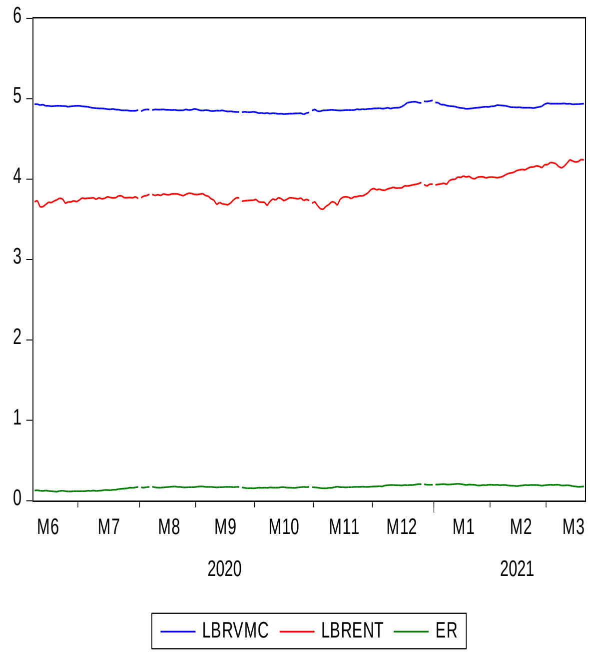

Figure 20: All series

After-COVID-19 returns graphs

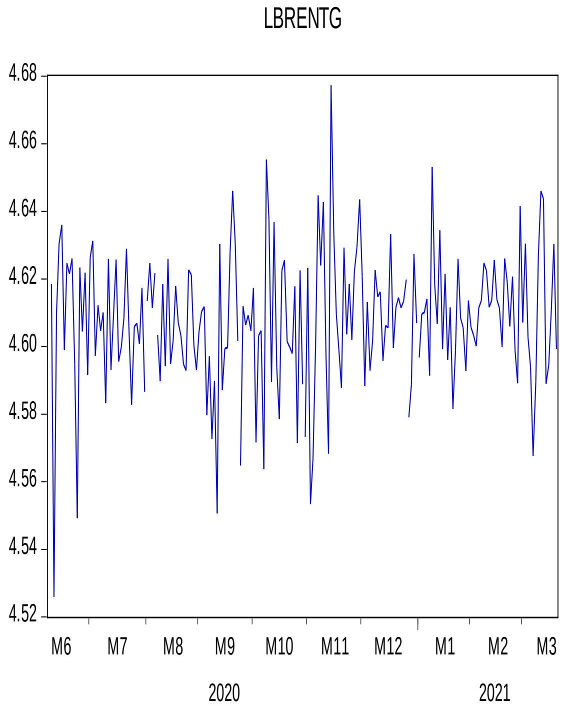

Figure 21: Crude oil price growth rate

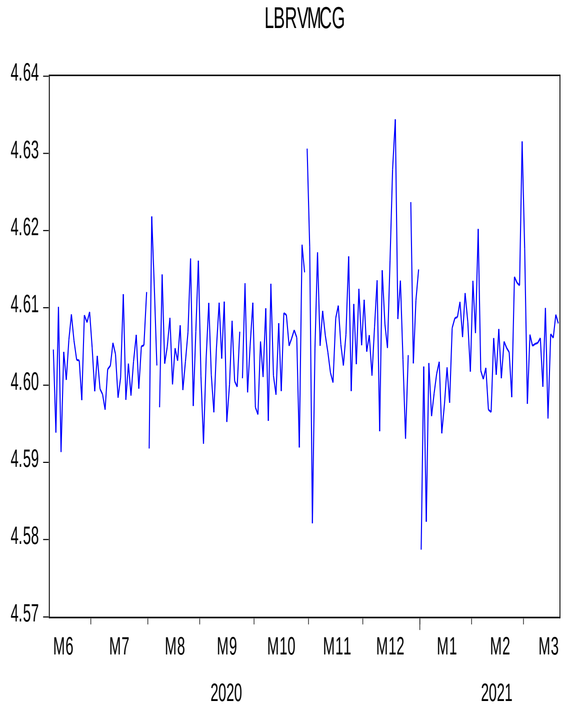

Figure 22: BRVM-C stock price growth rate

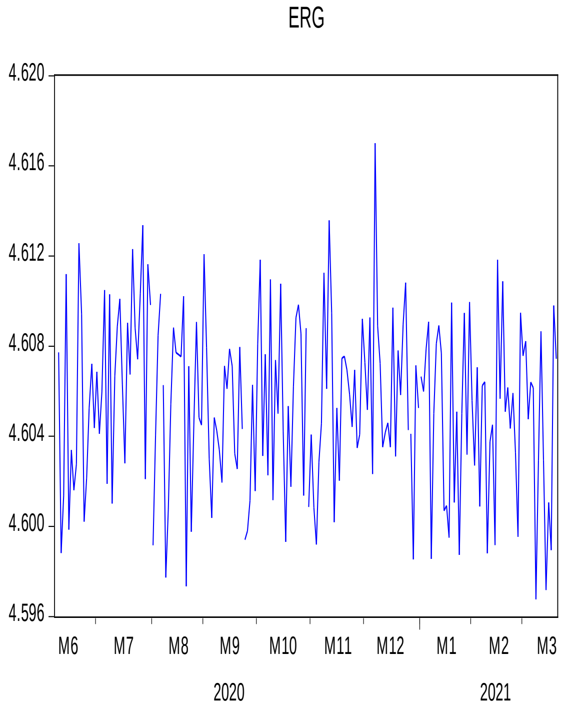

Figure 23: Nominal exchange rate growth

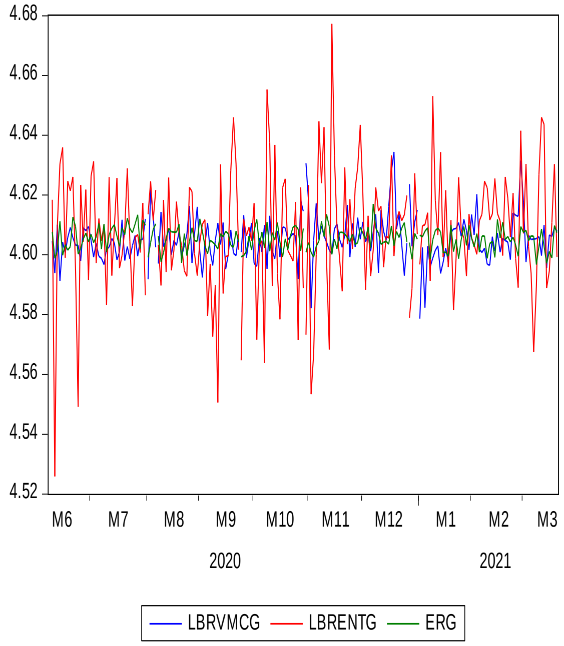

Figure 24: Growth rate of all series

CUSUM tests

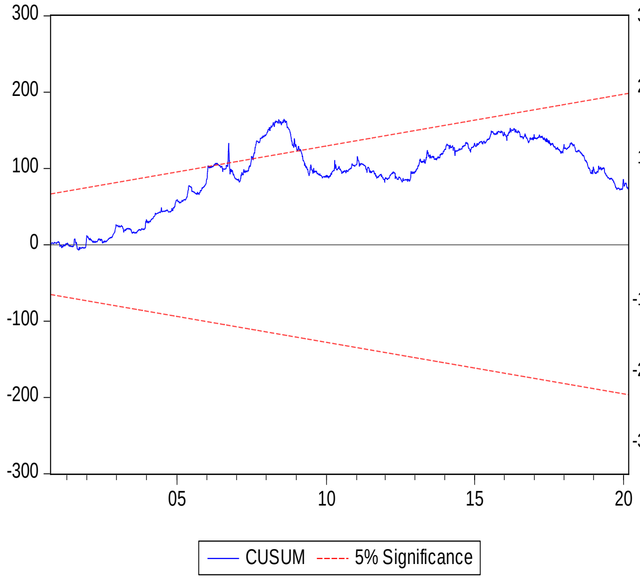

Figure 25a: CUSUM test before COVID-19

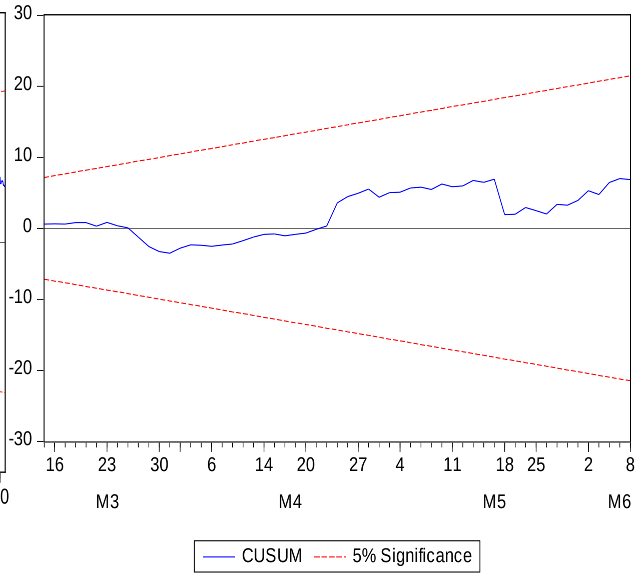

Figure 25b: CUSUM test during COVID-19

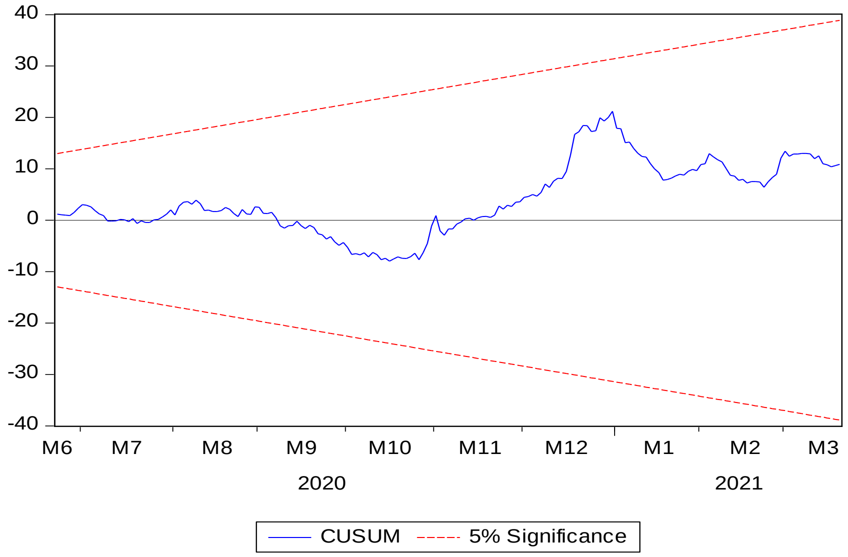

Figure 25c: CUSUM test after COVID-19

Descriptive statistics

Table 8. descriptive statistics

	LBSP	LOP	LER	LBSPG	LOPG	LERG
			Before COVID-19			
Mean	4.991	4.054	0.185	4.605	4.605	4.605
Median	5.007	4.113	0.216	4.605	4.606	4.605
Std. Dev.	0.470	0.518	0.147	0.008	0.0216	0.006
Skewness	-0.264	-0.306	-0.678	-0.083	-0.144	0.049
Kurtosis	1.905	1.973	2.730	22.610	5.981	4.590
J.B	297.064	287.339	384.311	77291.250	1803.450	510.609
Probability	0.000	0.000	0.000	0.000	0.000	0.000
Observations	4823	4823	4823	4823	4823	4823
			During COVID-19			
Mean	4.922	3.407	0.090	4.604	4.600	4.605
Median	4.919	3.400	0.087	4.629	4.609	4.605
Std. Dev.	0.031	0.215	0.014	0.008	0.080	0.006
Skewness	0.825	0.191	0.925	-1.469	-0.850	-0.476
Kurtosis	2.691	3.257	3.464	12.104	5.720	3.630
J.B	7.644	0.576	9.863	247.901	27.877	3.537
Probability	0.021	0.749	0.007	0.000	0.000	0.170
Observations	65	65	65	65	65	65
			After COVID-19			
Mean	4.880	3.861	0.168	4.605	4.607	4.605
Median	4.876	3.793	0.169	4.604	4.607	4.605
Std. Dev.	0.038	0.158	0.024	0.007	0.020	0.003
Skewness	0.277	0.873	-0.687	0.410	-0.399	-0.045
Kurtosis	2.482	2.618	2.783	5.400	4.610	2.537
J.B	4.705	26.102	15.804	52.544	26.408	1.811
Probability	0.095	0.000	0.000	0.000	0.000	0.404
Observations	196	196	196	196	196	196

Notes: JB is the statistic of Jarque and Bera test for normality, ***, **, * indicates respectively a rejection of the null hypothesis of normality at the 1%, 5% and 10% level.

Before COVID-19 pandemic, the growth rate of all series pointed of smallest standard deviation comparing to crude (gross) series. This result is similar to during and after COVID-19 pandemic periods. The growth rate series have also a mean which is approximately equal to median value. When the skewness is negative and different to zero, the returns profitability responds more to a negative chock than a positive chock. During pandemic situation, oil prices series and the nominal exchange growth rate are normally distributed. It also the case of the nominal exchange growth rate after COVID-19 period.