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The Dynamic Connectedness of BRVM Sector Stock Indices and the International Price of Crude Oil

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Abstract

The objective of this paper is to analyze the dynamic connectivity between the stock market indices of the various sectors of the BRVM[1] financial market (finance, industry, utilities, transportation, distribution, agriculture) and the oil market (international price of Brent crude oil). The results obtained using the frequency connectivity approach based on the TVP-VAR, over the period from December 12, 2014, to December 31, 2023, show that total connectedness increases within the network and is more intense in the short term, hence the presence of contagion within the stock market. The finance sector is the main entity responsible for transmitting shocks to other sectors of activity. The oil market and agricultural sectors are the main recipients of risk at the network level. The industrial sector is both a recipient and transmitter of volatility within the network in the short term. The financial sphere of the WAEMU does not yet constitute a channel for transmitting oil shocks to the real economy of the union's member economies. Central authorities should consider potential asymmetric oil price shocks and strengthen and invigorate the regional financial market.

Keywords

Sector Indices, Oil Prices, Temporal and Frequency Connectedness

1. Introduction

In recent years, oil prices have been highly volatile, mainly due to the combined effects of the Covid-19 health crisis and the Russian-Ukrainian conflict. The pandemic caused a sharp drop in oil prices, a direct consequence of the pandemic caused a sharp drop in oil prices, a direct consequence of restrictive measures and

[1]Bourse Régionale des Valeurs Mobilières: Regional Stock Exchange.

the contraction in global demand. Conversely, the war in Ukraine has created a supply shock, causing oil prices to soar to around $100 per barrel. Fluctuations in commodity prices have a major impact on the global economic system in general and the financial system in particular. As a result, researchers and central authorities are paying particular attention to the impact of commodity price volatility, in this case fluctuations in oil prices. The connectivity between the energy market, in this case the oil market, and the stock market means that a demand or supply shock in the oil market can affect stock prices in the financial markets. Similarly, an impact on the financial market, through contagion and dependency effects, can lead to rapid propagation in the energy market and stimulate upward or downward variation in oil prices. The 2008 financial crisis is a perfect example of this.

Financial markets are platforms for mobilizing financial resources. They are crucial entities that contribute to strengthening economic activity. This is why the performance of stock markets is often seen as a lever or a measure of a country's financial and economic health. It is in this context that the link between the price of crude oil and financial markets is of major interest to researchers and policymakers, as well as investors (Caporale et al., 2015; Filis & Chatziantoniou, 2014). The West African Stock Exchange (BRVM[2]) is a common market shared by the member countries of the West African Economic and Monetary Union (WAEMU[3]), namely Benin, Burkina Faso, Côte d'Ivoire, Guinea-Bissau, Mali, Niger, Senegal and Togo. It ranks sixth[4] in terms of market capitalization in sub-Saharan Africa, behind the Johannesburg Stock Exchange (JSE) in South Africa, which ranks first, followed by the Lagos Stock Exchange (NGSE) in Nigeria, Casablanca (CSE) in Morocco, Nairobi in Kenya and Accra in Ghana.

In a context of globalization and market interconnection, the connectedness of financial markets is beginning to play a prominent role in economic and financial research, with a view to studying potential systemic risks within networks. With all the limitations and criticisms levelled at correlation analysis to explain certain economic and financial phenomena, the connectivity analysis approach based on the analysis by Diebold & Yilmaz (2009, 2012, 2014) based on Vector Autoregression (VAR) specification has made it possible to establish the degree of connection between entities within a network in the time domain. Connectivity is a widely debated concept in the literature, which focuses considerably on how the variables in a system are interconnected Diebold & Yilmaz (2014). It should be noted that Diebold and Yilmaz's analysis was based solely on the temporal dimension to understand the interconnection between variables. However, the work of Chatziantoniou et al. (2023), Barunik & Krehlik (2018), Antonakakis et al. (2020a, 2020b) and Gabauer (2021) have formulated new approaches to connectivity that take into account both the temporal aspect and the connection under the frequency scale based either on a time-varying parameter vector autoregression (TVP-VAR);

[2]The West African Stock Exchange.

[3]West African Economic and Monetary Union.

[4] According to https://investafrique.info/2022/09/30/bourses-africaines-quelles-sont-les-places-qui-comptent/.

on quantile regression (QVAR) (Chatziantoniou et al., 2021b; Chatziantoniou et al., 2022a; Deev & Lyócsa, 2020); on a quantile-to-quantile regression Gabauer & Stenfors (2024); on a copula analysis and DCC GARCH Antonakakis et al. (2020b).

Studies reveal that most US recessions have been preceded by a rise in oil prices. This suggests that oil prices are the cause of recessions Hamilton (1983). Similarly, Jones & Kaul (1996) have shown that oil prices play an important role in the formation of financial assets. Several authors have also explored the static or dynamic relationship between oil and stock markets. Most of the analysis of the links between these two markets uses aggregate indices. Few studies have explored the relationship between stock market volatility and oil price volatility in a decentralized framework, i.e., using stock market indices related to stock market sectors, in order to better measure the impact within a financial market. The degree of connectivity between financial markets or between different assets varies according to the level of integration, but also according to socio-economic shocks or disruptions that are embedded in a temporal and frequency dynamic.

Empirical evidence on the relationship between the oil market and financial markets has been the subject of several studies. Mensi et al. (2021) examined the asymmetric spillovers from returns on futures contracts for oil, gold, and ten sector indices on the Chinese stock market. These authors concluded that the industrial and consumer discretionary sectors are the largest contributors to and recipients of spillovers in the network. On the other hand, oil, gold, and other sector futures contracts are net recipients of spillovers in the network. Chatziantoniou et al. (2022b), drawing on the analysis of Antonakakis & Gabauer (2017) using the TVP-VAR approach, showed that the connectivity of sector indices in India, an emerging country, varies over time and is stronger between sectors during periods of crisis. They also add that the industrial, consumer spending, and finance sectors are the main net issuers of shocks at the network level. The same is true of Corbet et al. (2020), who looked at the impact of WTI crude oil prices on the financial, energy, and foreign exchange markets in the United States.

Thus, Le & Luang (2022) show a moderate interdependence between oil prices and stock market returns in different countries and conclude that investor sentiment varies over time and is strongly linked to specific events. Oil prices are a net transmitter of shocks in the United States and a net receiver in Vietnam. Similarly, Chatziantoniou et al. (2022a) stipulate that connectivity in the G7 network and the oil market is highly sensitive to events that greatly affect the financial market. The oil market is a net transmitter of volatility shocks to the network and a net receiver of volatility in periods of turbulence. The findings of Bouri et al. (2021) show that the total dynamic connectivity between five assets (gold, crude oil, global assets, currencies and bonds) was stable before the onset of the COVID-19 crisis. The US dollar and stock indices were the main drivers of shocks before the health crisis, while the bond index was the main source of shocks during the crisis. Similarly, Shahzad et al. (2021) examined the asymmetric spread of volatility among assets in Chinese stock sectors during the COVID-19 pandemic, concluding that asset volatility shocks to the network and a net receiver of volatility in periods of turbulence. The results of Bouri et al. (2021) show that the total dynamic connectivity between five assets (gold, crude oil, global assets, currencies, and bonds) was stable before the onset of asymmetry, which varies over time and is very intense during the health crisis period.

Mishra & Debasish (2022) explored the relationship between crude oil price volatility and stock market indices using wavelet analysis, concluding that there is a bidirectional causal relationship between fluctuations in international crude oil prices and the Chinese stock market. Through wavelet-GARCHSK and wavelet-GARCHSK methods, they found that the Chinese stock market using wavelet-GARCHSK and wavelet-GARCHSK.

Through a static and dynamic study of connectivity among the world's 150 largest banks over the period from 2003 to 2014, Demirer et al. (2018) show that the connectivity of global banking stocks depends on geographical areas and, dynamically, increases during periods of financial crisis.

Copula methods, Zhu et al. (2021) show that most of China's sectoral stock indices are highly dependent on SC rather than WTI in the short term. In addition, there is a strong dependence between changes in global oil prices and oil-dependent sectors of activity and a weak dependence between oil and other sectors. Badeeb & Lean (2018) add that in the long term, the relationship between oil prices and Islamic sectoral assets tends to follow a non-linear pattern and that the intensity of the reaction of stocks to oil shocks varies according to the sector of activity. Fang & Egan (2018) indicate a low degree of contagion between oil prices and Chinese stock markets, especially during periods of turbulence, which may limit investors' portfolio diversification. Also testing Granger quantile-to-quantile causality between crude oil and corporate returns, Peng et al. (2018) measured the impact of extreme risk in international crude oil on the stock returns of 529 companies listed on the Shanghai Stock Exchange, providing strong evidence of asymmetry in the relationship between corporate asset returns and extreme fluctuations in oil prices. Furthermore, the transmission of oil shocks to companies depends on the sector to which the company belongs. The long-term results of Al-Hajj et al (2017) showed that oil prices have a negative impact on Malaysian stock market returns. By examining the asymmetric propagation of yield spreads between oil prices and Islamic asset prices at the sectoral level, Adekoya et al. (2022) highlight a predominance of negative connectivity, with the exception of the onset of the COVID-19 health crisis pandemic.

The objective of this study is to analyze the effect of oil price volatility on the connectivity of the various sectors of activity on the BRVM stock market, in order to understand the effects of contagion and dependence between sector indices and oil prices, through the analysis of connectivity by Chatziantoniou et al. (2021b) and Antonakakis et al. (2020a). The connectivity analysis is based on the analysis of Diebold & Yilmaz (2009, 2012, 2014). The purpose of this study is to provide answers to the transmission of exogenous shocks, such as a crisis in the supply or demand for international oil, to the financial sphere in the African context. It will also provide answers on the behavior of stock market assets following a crisis caused by global geopolitical and financial events. Finally, it will verify the degree of connectivity between different sectors of activity when the global economy is faced with a situation of drastic increases or decreases in oil prices, as was recently the case during the Covid-19 health crisis and also with the war in Ukraine. More specifically, this will involve applying new approaches to analyzing temporal and frequency connectivity in order to quantify the degree of connection between the various stock market indices within the financial market network. Next, the effects of contagion or dependence between the oil market and the various sectors of activity on the BRVM will be analyzed.

The unique feature of this study lies in the application of a dynamic total and net connectivity approach in a time and frequency domain to measure the connectivity of sectors of activity and oil prices within an African financial market, in order to gain insight into the phenomena of contagion or dependence between assets. This study also offers a new perspective on measures of contagion connectivity of idiosyncratic and exogenous shocks that may influence the dynamics of African stock markets.

The study will be structured as follows: Section 2 provides an overview of the specification of the connectivity analysis based on the TVP-VAR specification to understand the degree of connectivity of business sectors within financial markets and the oil market. Section 3 presents the data and some descriptive analyses of the variables. Section 4 will be devoted to the analysis and discussion of the empirical results. Finally, the last section draws the main conclusions and policy implications.

2. Methodology

2.1. TVP-VAR Specification

The frequency connectivity analysis based on TVP-VAR summarizes the work of Barunik & Krehlik (2018) and Antonakakis et al. (2018). The latter were based on the connectivity analyses of Diebold & Yilmaz (2009, 2012, 2014), attempting an extension of the Vector Autoregressive (VAR) model with a time-varying parameter vector autoregression (TVP-VAR) by Koop & Korobilis (2014). The TVP-VAR estimator was introduced to address the limitations of the vector autoregressive (VAR) specification. The advantage of the time-varying variance (TVP-VAR) connectivity model is that it overcomes the limitations of the rolling window VAR methodology, where the size of the rolling window is chosen arbitrarily, but also, compensates for missing observations and the sensitivity of outliers. In this study, we use the connectivity model of Chatziantoniou et al. (2021a) and Antonakakis et al. (2020a), which are based on the basic connectivity analysis of Diebold & Yilmaz (2012, 2014), to measure the different forms of connectivity between variables following a temporal and frequency decomposition. The TVP-VAR analysis is as follows:

$$x_t = \phi_{1t} x_{t-1} + \phi_{2t} x_{t-2} + \cdots + \phi_{pt} x_{t-p} + \varepsilon_t \quad \text{or} \quad x_t = \sum_{i=1}^{p} \phi_i x_{t-i} + \varepsilon_t \tag{1}$$

with $x_t \to N(0, \varepsilon_t)$.

x_t and x_{t-1} represent the vectors of the dimensional variables $(N \times 1)$; ε_t is the error term vector that follows a centered normal distribution and is reduced to

Σ_t. The latter represents the matrix of the variance-covariance matrix varying over time. The latter represents the matrix of the variance-covariance matrix varying over time. ϕ_{it} *with* $i=1,\cdots,p$ of dimension $(N\times N)$ is the matrix of time-varying VAR coefficients of dimensions $(N\times N)$. This polynomial [Equation (1)] can be simplified using the identity matrix I_N. Therefore, using the polynomial shift matrix of dimension $(N\times N)$, we then obtain: $\Phi(L)=\left[I_N-\phi_{1t}-\cdots-\phi_{pt}L^p\right]$, with I_N representing the identity matrix. Thus, the model can be summarized as follows: $\Phi Lxt=\epsilon t$.

Now, since the TV P −V AR process is stable (stationary), it can be written in the form: TVP-VMA (∞).

$x_t=\psi(L)_{\varepsilon_t}$, or $\psi(L)$ represents the matrix of infinite shift polynomials that can be calculated recursively from $\phi(L)=\left[\psi(L)\right]^{-1}$. However, since $\psi(L)$ includes an infinite number of shifts, it is approximated by ψ_h, with $h=1,\cdots,H$ horizons.

2.2. Connectedness Analyses

TVP-VMA coefficients are used to calculate the generalized forecast error variance decomposition (GFEVD[5]) based on Koop et al. (1996), and Pesaran & Shin (1998). The advantage of this GFEVD model is that it allows the order of variables to be maintained according to Wiesen et al. (2018). GFEVD can be used when there is no theoretical framework that would allow the error structure to be identified. GFEVD is interpreted as the effect of a shock on variable *j* in terms of forecast error variance and can be written as follows:

$$\theta_{ij}(H)=\frac{(\Sigma_t)_{jj}^{-1}\sum_{h=0}^{H}\left((\Psi_h\Sigma_t)_{ijt}\right)^2}{\sum_{h=0}^{H}(\Psi_h\Sigma_t\Psi'_h)_{ii}} \tag{2}$$

$$\theta_{ijt}(H)=\frac{1}{(\Sigma_t)_{jj}}\frac{\sum_{h=0}^{H}\left((\Psi_h\Sigma_t)_{ijt}\right)^2}{\sum_{h=0}^{H}(\Psi_h\Sigma_t\Psi'_h)_{ii}} \tag{3}$$

$$\tilde{\theta}_{ijt}(H)=\frac{\theta_{ijt}(H)}{\sum_{k=1}^{N}\theta_{ijt}(H)} \tag{4}$$

where Equation (3), $\tilde{\theta}_{ijt}(H)$ denotes the contribution of the *j*th variable to the variance of the forecast error of the ith variable at horizon *H*. It measures the connectivity between pairs of variables at a given horizon *H*. According to Baruník & Křehlík (2018), it is a measure of causality in the time domain. Thus, since the sum of the lines of $\tilde{\theta}_{ijt}(H)$ is not equal to one, we must normalize them, which gives $\tilde{\theta}_{ijt}$. Thanks to normalization, we obtain the following identities:

$$\sum_{h=0}^{N}\tilde{\theta}_{ijt}(H)=1 \text{ et } \sum_{i=1}^{N}\tilde{\theta}_{ijt}(H)=N$$

This expression will allow us to calculate the various connectivity measures, in accordance with the basic analysis by Diebold & Yilmaz (2009, 2012, 2014).

[5]Frequency of generalised decomposition of forecast error variance.

Net connectivity per variable pair is calculated as follows:

$$NPDC_{ijt}\left(H\right)=\tilde{\theta}_{ijt}\left(H\right)-\tilde{\theta}_{jit}\left(H\right) \tag{5}$$

If $NPDC_{ijt}\left(H\right)>0$, (respectively $NPDC_{ijt}\left(H\right)<0$) this means that variable j has a strong (respectively weak) influence on variable i.

Total directional connectivity to other sectors, as expressed in Equation (6), quantifies the magnitude of a shock to variable i that is transmitted to other variables.

$$TO_{it}\left(H\right)=\sum\nolimits_{j=1,i\neq j}^{N}\tilde{\theta}_{ijt}\left(H\right) \tag{6}$$

The total directional connectivity from others on variable i is given by:

$$FROM_{it}\left(H\right)=\sum\nolimits_{j=1,i\neq j}^{N}\tilde{\theta}_{ijjt}\left(H\right) \tag{7}$$

Total net directional connectedness it represents the difference between total connectivity relative to other variables and connectivity originating from other variables, which can be explained as the variable of influence i on the analyzed network.

$$NET_{it}\left(H\right)=TO_{it}\left(H\right)-FROM_{it}\left(H\right) \tag{8}$$

If the value of the net directional connectivity index is positive $NET_{it}\left(H\right)>0$ (respectively $NET_{it}\left(H\right)<0$) then variable i has a strong (or weak) influence on the other variables j, and the other variables have a weak influence on it. Thus, variable i is considered a net shock transmitter (or receiver) within the network.

The Total Connectedness Index (TCI): It measures the degree of network interconnection. It can be calculated as follows:

$$TCI_{t}\left(H\right)=N^{-1}\sum\nolimits_{i=1}^{N}TO_{it}\left(H\right)=N^{-1}\sum\nolimits_{i=1}^{N}FROM_{it}\left(H\right) \tag{9}$$

In other words, this measure shows the average impact of a shock to one variable on all other variables. The higher this value, the higher the market risk, and vice versa. $\Psi\left(\mathrm{e}^{-i\omega}\right)=\sum\nolimits_{h=0}^{\infty}\mathrm{e}^{-i\omega h}\Psi_{h}$, it's where $i^{8}=\sqrt{-1}$ and ω where i[6] = $\sqrt{-1}$ and ω denotes frequency. Thus, we can continue with spectral density x_t with frequency ω, which can be characterized by the Fourier transform of the time-varying parameter vector moving average [TVP-VAR (∞)].

$$S_{x}\left(\omega\right)=\sum\nolimits_{h=-\infty}^{\infty}E\left(x_{t}x_{t}'\right)\mathrm{e}^{-i\omega h}=\Psi\left(\mathrm{e}^{-i\omega h}\right)\Sigma_{t}\Psi\left(\mathrm{e}^{-i\omega h}\right) \tag{10}$$

As in the time domain, the frequency of the generalized decomposition of forecast error variance must be normalized and formulated as follows:

$$\theta_{ijt}\left(\omega\right)=\frac{\left(\Sigma_{t}\right)_{ij}^{-1}\left|\sum\nolimits_{h=0}^{\infty}\left(\Psi\left(\mathrm{e}^{-i\omega t}\right)\Sigma_{t}\right)_{ijt}\right|^{2}}{\sum\nolimits_{h=0}^{\infty}\left(\Psi\left(\mathrm{e}^{-i\omega t}\right)\Sigma_{t}\Psi\left(\mathrm{e}^{-i\omega t}\right)\right)_{ii}} \tag{11}$$

$$\tilde{\theta}_{ijt}\left(\omega\right)=\frac{\theta_{ijt}\left(\omega\right)}{\sum\nolimits_{k=1}^{N}\theta_{ijt}\left(\omega\right)} \tag{12}$$

With $\tilde{\theta}_{ijt}\left(\omega\right)$, the part of the spectrum associated with the ith variable at a given

[6] i is an imaginary unit defined as the square root of −1.

frequency ω that can be attributed to the *j*th variable. According to Křehlík & Baruník (2017), $\tilde{\theta}_{ijt}(\omega)$ is interpreted as an indicator of intra-frequency causality.

Using this equation, we will evaluate short-term and long-term connectivity. This will involve aggregating all frequencies within a specific range, such as: *d*, which is equal to the pair (a,b) such that $a<b$ and a and $b\in[-\pi;\pi]$. So, we have:

$$\tilde{\theta}_{ijt}(d)=\int_a^b \theta_{ijt}\mathrm{d}\omega$$

$\tilde{\theta}_{ijt}(d)$ is a cumulative frequency band. Thus, all connectivity's will be calculated in accordance with the analysis by Diebold & Yilmaz (2014).

Total connectivity by frequency is as follows:

$$TO_{it}(d)=\sum_{i=1,i\neq j}^{N}\tilde{\theta}_{jit}(d) \tag{13}$$

Total directional connectedness:

$$FROM_{it}(d)=\sum_{i=1,i\neq j}^{N}\tilde{\theta}_{ijt}(d) \tag{14}$$

Net directional connectedness:

$$NET_{it}=TO_{it}(d)-FROM_{it}(d) \tag{15}$$

The total connectedness index will be:

$$TCI_t(d)=\frac{1}{N}\sum_{i=1}^{N}TO_{it}(d)=\frac{1}{N}\sum_{i=1}^{N}FROM_{it}(d) \tag{16}$$

Network connectedness is such that:

$$NPDC_{ijt}(d)=\tilde{\theta}_{ijt}(d)-\tilde{\theta}_{jit}(d) \tag{17}$$

However, all these connectivity measures are based on the specific portion of the spectrum and not on the overall impact. Thus, the analysis by Barunik & Krehlik (2018) suggests weighting all measures of contribution to frequency bands, to a set of systems $\Gamma(d)=\frac{1}{N}\sum_{i,j=1}^{N}\tilde{\theta}_{ijt}(d)$. Thus, this system will be weighted for each connectivity measurement.

$$\widetilde{NPDC}_{ijt}(d)=\Gamma(d)\cdot NPDC_{ijt}(d)$$

$$\widetilde{TO}_{it}(d)=\Gamma(d)\cdot TO_{it}(d)$$

$$\widetilde{FROM}_{it}=\Gamma(d)\cdot FROM_{it}$$

$$\widetilde{NET}_{it}=\Gamma(d)\cdot NET_{it}$$

$$\widetilde{TCI}_t(d)=\Gamma(d)\cdot TCI_t(d)$$

We then have a relationship between the connectivity analysis in the temporal domain by (Diebold & Yilmaz, 2014) and the frequency connectivity analysis by Barunik & Krehlik (2018), which can be summarized as follows:

$$NPDC_{ijt}(H)=NPDC_{ijt}(d) \tag{18}$$

Equation (18) means that the directional connectivity per variable pair in the time domain is equal to the directional connectivity per pair in the frequency domain following a frequency band. The analysis by Diebold & Yilmaz (2012) did not take into account the levels of connectivity decomposition in the short and long term, and for economic and financial reasons, it is therefore important to have an overview of the relationships between entities or assets on different time and frequency scales. As a result, the analysis by Chatziantoniou et al. (2021a) is an extension of the connectivity analyses of (Diebold & Yilmaz, 2012, 2014; Baruník & Krehlik (2018); and the work of Antonakakis et al. (2020a). The results were estimated using R software, based on the work of Gabauer & Gabauer (2022).

3. Data

All data used in this study are daily data relating to the BRVM stock market and fluctuations in the price of crude oil (**Table 1**). Sector indices represent the market capitalization of the various companies listed on the stock exchange and belonging to different sectors of activity. They reflect the performance of each type of sector of activity. Unlike aggregate stock market indices, sector indices make it easier to locate the impact or fallout of a shock within a network, to verify the existence of a contagion or dependence relationship between two or more variables, and to measure the degree of interconnection between different variables. Changes in Brent crude oil prices were collected from EIA[7]. The Brent price is the European benchmark, which comes from the five major oil fields in the North Sea (Broom, Rannock, Etive, Ness and Tarbert). The value of sector stock market assets and the price of oil are established in logarithmic yield form and are calculated as follows: $r_t = \ln\left(P_t/P_{t-1}\right)$.

Table 1. Presentation of variables.

Market BRVM	Presentation and sources of variables			
	Sectors index	Periods	Encodings	Sources
	Finance	15/12/2014-31/07/2023	BRVM-Fin	Investng database
	Industrie	15/12/2014-31/07/2023	BRVM-Ind	Investng database
	Public services	15/12/2014-31/07/2023	BRVM-Spu	Investng database
	Transport	15/12/2014-31/07/2023	BRVM-Trans	Investng database
	Distribution	15/12/2014-31/07/2023	BRVM-Dis	Investng database
	Agriculture	15/12/2014-31/07/2023	BRVM-Agr	Investng database
	Crude oil	15/12/2014-31/07/2023	RBRENT	E.I.A

Table 2 presents descriptive statistics and Kendall's correlation analysis of the returns of the BRVM indices and the price of Brent crude oil over the period from 2014 to 2023. The average returns of the BRVM market sector indices are relatively low, with values close to 0. This indicates low volatility in index returns over time. Low variance values are also observed, with the highest volatility of the indices associated with the transport, finance, and distribution sectors. Meanwhile, the indices for the industry, utilities, and agriculture sectors show the lowest var-

[7]Energy Information Administration is a US agency attached to the US Department of Energy, responsible for collecting statistical information and organising supply measures for member countries.

iances and are therefore less volatile than the price of Brent crude oil. Similarly, all index volatilities are significantly skewed to the right. The various distributions are leptokurtic. These results are confirmed by normality tests, with statistics indicating that none of the series are normally distributed. The flatness and skewness tests are confirmed by the results of the JB[8] normality tests, where we note highly significant probabilities at the 1% threshold for all sector returns in the business sectors and the Brent market. The normality assumption is therefore rejected. The stationarity test also reveals that all series are stationary, autocorrelated, and exhibit at least ARCH/GARCH errors at the 1% significance level (according to Fisher & Gallagher, 2012). The normality test and the skewness and kurtosis statistics reinforce our decision to model the interdependencies of the BRVM financial market and the oil market using a TVP-VAR with variance-covariance heteroscedasticity as the base model to specify the connectivity between the different sectors of activity in the WAEMU financial market. For rank correlation expressed by Kendall's coefficients. The strongest correlations are found with the pairs of indices (Finance and Industry) and (Finance and Public Services). The price of Brent crude oil is weakly correlated with all sector indices on the stock market, and particularly with the transport, industry, and public services sector index. The high values of the kurtosis coefficients show that the returns on sector indices are leptokurtic. The positive skewness coefficients for the returns of the utilities (BRVM-Spu), finance (BRVM-Fin), agriculture (BRVM-Agr), and oil market indices show that investors are faced with an asymmetry of gains, suffer fewer losses, and are more likely to make gains. The indices for the distribution (BRVM-Dis), industry (BRVM-Ind), and transportation sectors (BRVM-Trans) show negative skewness coefficients. This reflects asymmetric gains. In other words, investors are more likely to suffer losses and less likely to make excessive gains on their investment strategies. The kurtosis coefficients are all high, reflecting significant flattening on both sides of the series and a high investment risk. The distribution is leptokurtic, indicating a high probability of returns that may be subject to extreme values on both sides of the series.

Table 2. Descriptive statistics and Kendall's correlation tests.

	BRVM-Fin	BRVM-Ind	BRVM-Spu	BRVM-Trans	BRVM-Dis	BRVM-Agr	RBRENT
Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.962)	(0.520)	(0.713)	(0.759)	(0.888)	(0.786)	(0.785)
Std-dev	0.0495	0.0134	0.0170	0.0556	0.0490	0.0155	0.0249
Variance	0.002	0	0	0.003	0.002	0	0.001
Skewness	0.134***	−0.097*	0.909***	−0.245***	−0.029	0.061	0.620***
	(0.010)	(0.061)	(0.000)	(0.000)	(0.568)	(0.237)	(0.000)
Ex.Kurtosis	1039.984***	103.811***	320.665***	661.254***	953.214***	1.239***	31.019***

[8]Jarque and Bera (1984), normality tests.

Continued

	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	100901200.7***	1005387.0***	9593123.9***	40792447.2***	84766349.8***	144.5***	89909.1***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	−29.276***	−10.294***	−18.935***	−26.438***	−9.919***	−18.235***	−17.380***
Kendall	BRVM-Fin	BRVM-Ind	BRVM-Spu	BRVM-Trans	BRVM-Dis	BRVM-Agr	RBRENT
BRVM_Fin	1.000***						
BRVM_Ind	0.115***	1.000***					
BRVM_Spu	0.098***	0.076***	1.000***				
BRVM_Trans	0.059***	0.076***	0.083***	1.000***			
BRVM_Dis	0.076***	0.083***	0.065***	0.095***	1.000***		
BRVM_Agr	0.061***	0.084***	0.053***	0.051***	0.074***	1.000***	
RBRENT	0.003	−0.008	0.002	−0.026	−0.012	0.018	1.000***

The standard deviations are all positive, with the highest coefficient observed on the return on assets in the transport sector, reflecting a certain volatility in assets in this sector. The return on the transport sector indices has the riskiest assets, followed by the distribution, finance, and oil sectors, with the highest standard deviations. The least risky assets are those in the utilities sector, which offer a certain guarantee in terms of investment. The returns of sector indices relating to different stock markets show positive or negative skewness coefficients. This means that the distribution of returns for the series is asymmetrical.

The particularity of this distribution is that it is not limited solely to the mean, but includes all extreme data points. Investors must therefore take the problem of asymmetry into account before making a choice regarding asset returns. Investors must therefore take the issue of asymmetry into account before making a choice about asset returns. A positive skewness coefficient indicates a positive asymmetric distribution of returns, meaning that investors should expect small losses and significant gains in their investment portfolios. Thus, the gains realized may cover the potential investment losses. Consequently, when the Skewness coefficient is negative, we then have a negative asymmetric distribution of asset returns, which means a possibility of huge losses and small gains for investors.

For investors, it would be prudent to consider the average returns on assets if they hold long-term positions. However, if they hold short-term positions, they should carefully examine the extreme data before making an investment choice. Figure 1 shows the Pearson correlation between sector index returns and Brent crude oil, as well as scatter plots and density functions for each series. We can see that all indices are weakly correlated with the price of oil. All assets are negatively correlated with the price of oil except for assets in the agriculture and finance sectors, which are positively correlated. The latter are therefore likely to have a positive influence on oil prices. The correlation between sectors of activity is relatively weak, with coefficients not exceeding the conventional average (0.7), except for the pairs BRVM-Dis and BRVM-Fin; BRVM-Spu and BRVM-Fin; BRVM-Dis and

BRVM-Trans, which have very high coefficients (see **Figure 1**). The low correlation coefficients between the indices of the various sectors of activity and the price of oil show that fluctuations in international oil prices have little influence on the assets of the BRVM stock market.

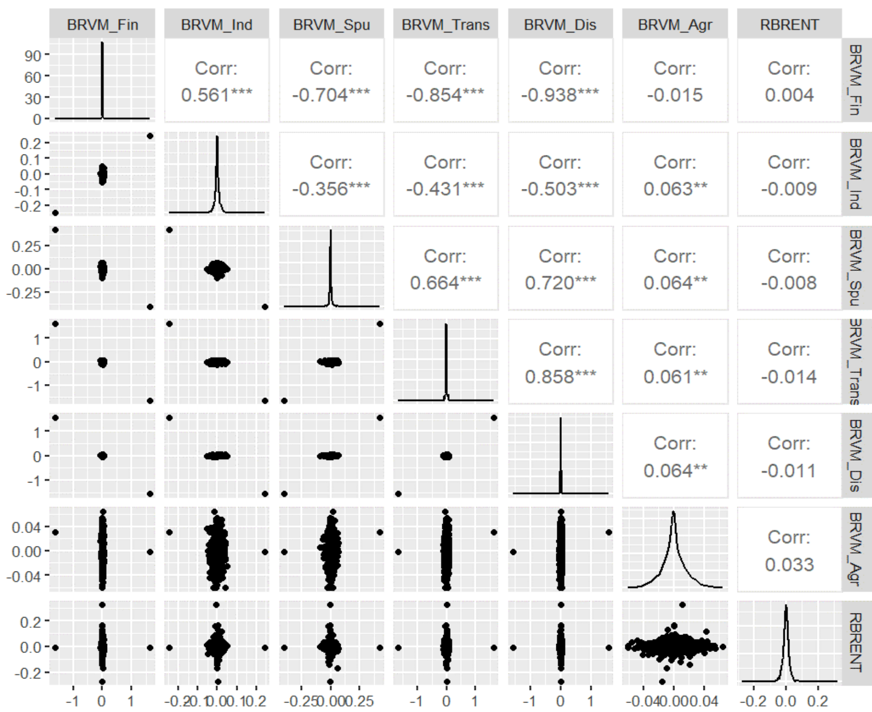


Figure 1. Scatter plots and Pearson correlation of sector indices and Brent crude oil prices.

Figure 2 shows the evolution of sectoral stock market indices for the various sectors of activity on the BRVM financial market and the price of Brent crude oil over the period from 2014 to 2023. There was a sharp decline in sectoral market indices over the period from 2019 to 2020, followed by a recovery the following year. The same observation was made for oil price fluctuations throughout virtually the entire period covered by our study. These declines were mainly due to the health crisis, as a result of the numerous restrictions and response measures adopted by most economies. On the other hand, the upward movements or recovery in the period from late 2021 to 2023 could be attributed to the crisis in Ukraine, with a supply shock due to the geopolitical conflicts experienced during this phase. All sectors of activity on the BRVM market recorded these changes, except for the finance sector (BRVM-Fin), where there were a slight decline and a fairly linear trend.

Figure 3 shows the dynamics of sector index returns and the price of Brent crude oil. There is some volatility in sector assets around 0, except for certain extreme values. There is also low volatility in asset returns, which confirms the results of **Figure 2**. Brent crude oil returns experienced high volatility in 2019, explained by the decline in oil demand due to the consequences of the health crisis.

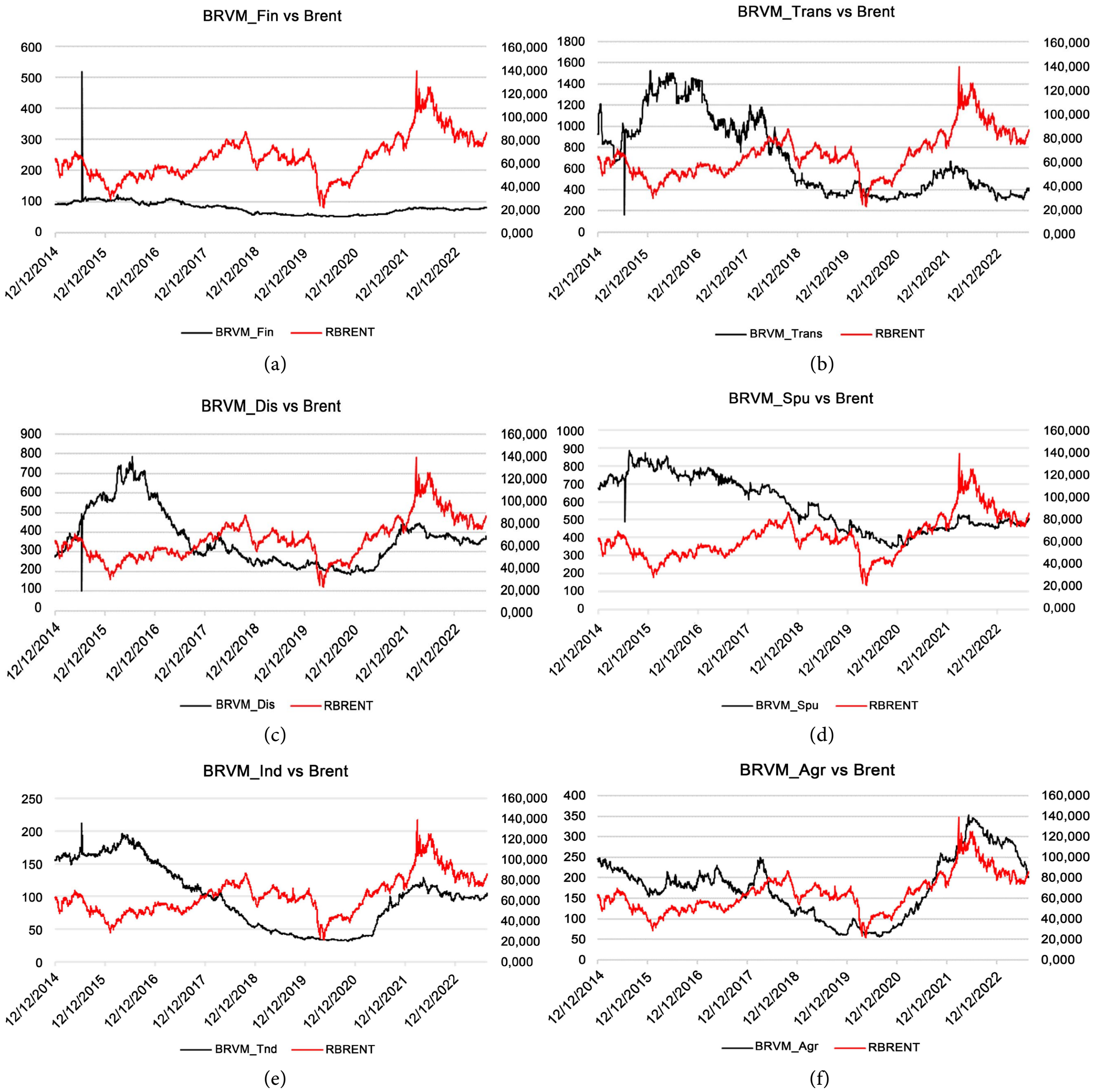


Figure 2. Changes in sector indices and the price of Brent crude oil.

However, this high volatility during this period is not observed in the various BRVM sector indices. Thus, there is a certain degree of unpredictability in the variation of the BRVM financial market sector indices. This reinforces the idea that stock market index returns fluctuate randomly around the average, but with a certain degree of volatility.

4. Empirical Results

This section presents the results of estimating the connectivity measures of the returns of sector indices on an African stock market, namely the BRVM, and the

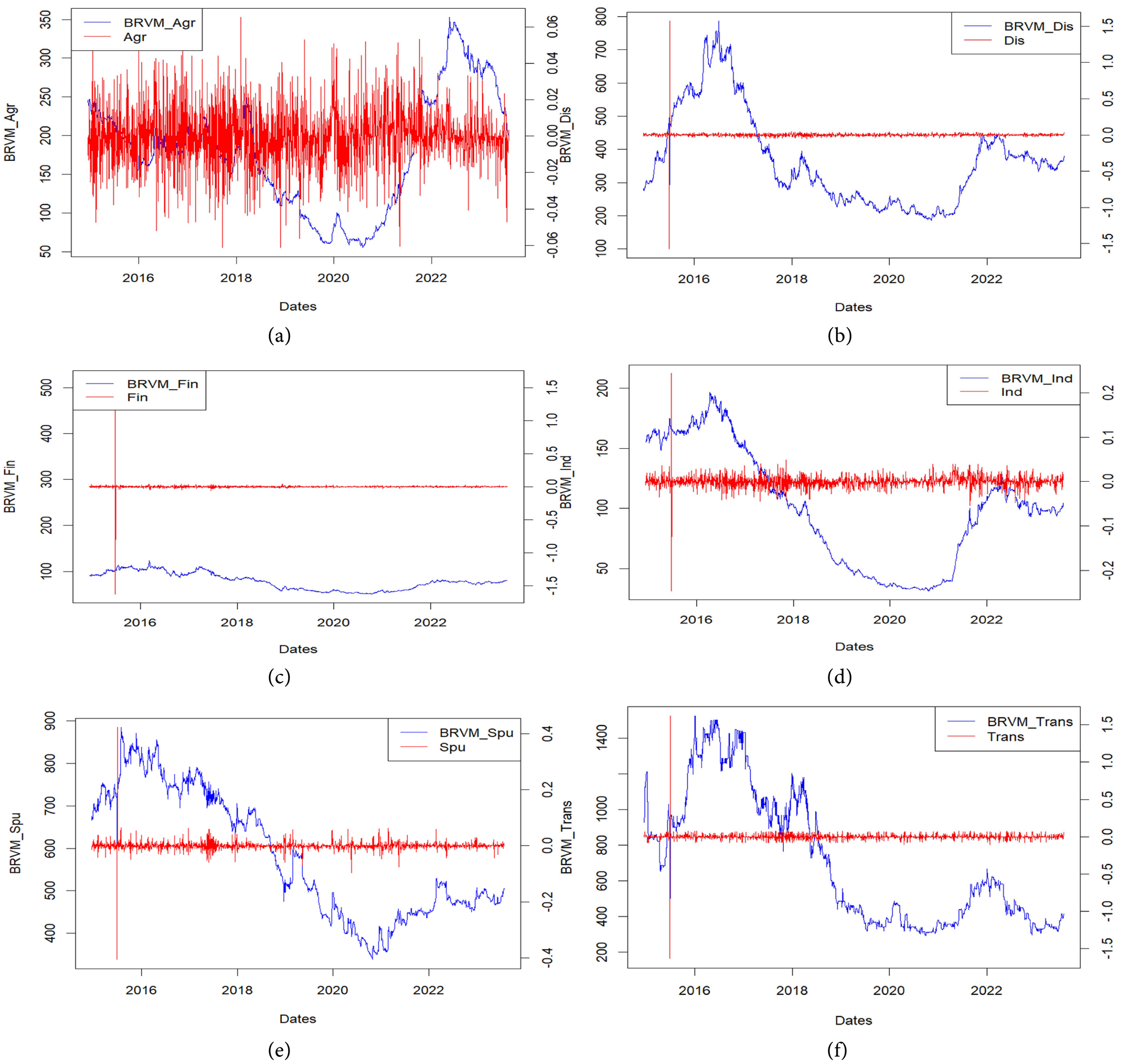


Figure 3. Changes and returns over time in oil prices and sector indices on the BRVM market.

international price of crude oil, based on a time-frequency dynamic inspired by the work of Baruník & Krehlik (2018) and Chatziantoniou et al. (2021b). The results are recorded in **Table A1** in **Appendix**. Connectivity indices are calculated in this study according to two different frequency bands. The first spectral band corresponds to movements of up to five days (corresponding to one trading week), while the second refers to movements ranging from 6 to 200 days. These frequency bands capture the short- and long-term dynamic connectivity, respectively, between Brent oil prices and the returns of the financial market sector indices of the WAEMU countries. Thus, the time-frequency dynamic connectivity measures are estimated using a 200-day sliding window and a 100-day forecast horizon. Based on a time-varying parameter autoregressive (TVP-VAR) model specification as the base model, for each sliding window, the optimal lag length of the networks is chosen according to Schwarz's information criterion. The TVP-VAR model will be decomposed according to a generalized decomposition of the variance of the forecast error, which is essential for connectivity analysis. Thus, in line with the approach of Diebold & Yilmaz (2012, 2014); Chatziantoniou et al. (2021b), various connectivity measures are calculated to gauge the degree of contagion and dynamic interdependence between the BRVM financial market and the crude oil market, deepening the analysis at the level of the stock exchange's sectors of activity.

The results of the traditional approach in a time frame by Diebold & Yilmaz (2012) were introduced in order to better visualize the total connectivity and transmissions of the forecast error variance from one variable to the other variables. However, the latter provides an overview of the frequency dynamics of system connectivity, hence the importance of the analysis by Chatziantoniou et al. (2021b).

4.1. Average Total Dynamic Connectedness

Table A1 presents the results of the average dynamic connectivity of sector stock market index returns and crude oil prices. These results include total connectivity, which is broken down into short-term and long-term connectivity. The first part of the table corresponds to connectivity over the entire observation period. The second part (in the middle) corresponds to high-frequency dynamics (describing the short term with a trading week of 1 - 5 days). And the last part of the table shows connectivity over low-frequency dynamics (long term, i.e. over a horizon of 5 days to a relatively long period).

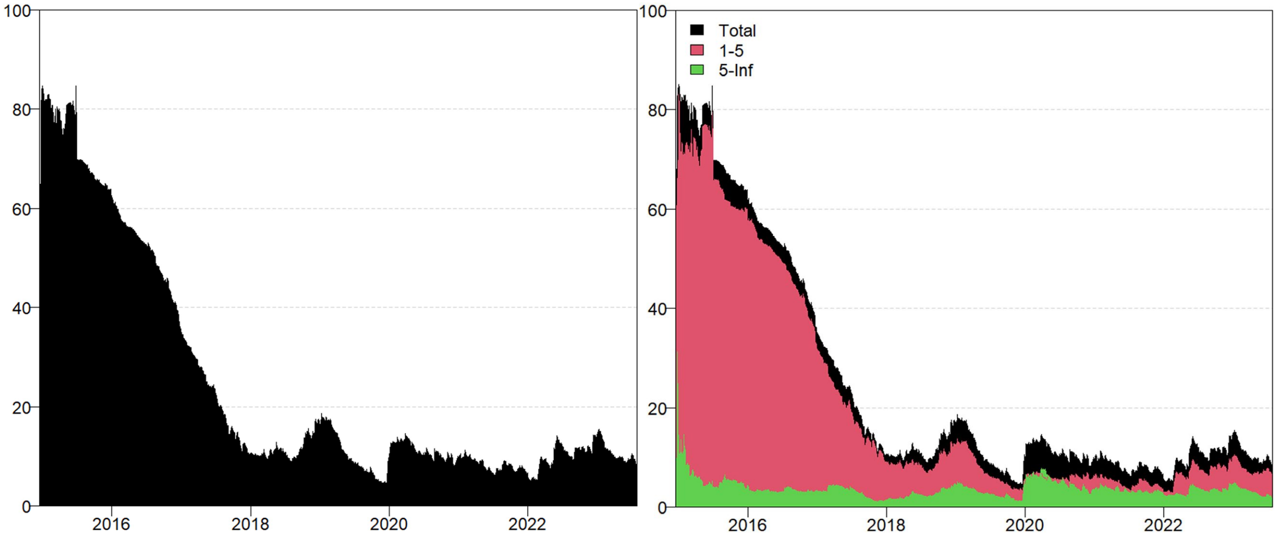
According to Chatziantoniou et al. (2021b), the values located on the main diagonal of the table correspond to shocks in specific variables. That is, internal or idiosyncratic shocks. The values outside the diagonal represent the interaction between the different nodes in the network. A general observation shows that the total dynamic connectivity within the network (i.e., the BRVM market) is determined by the transmission of short-term shocks (or spillovers). We note that volatility or shocks within the same sector of activity have a greater impact, as justified by the high values of the indices in the diagonals of **Table A1**. These results are consistent with the work of Chirilă & Nuta (2025), who argue that information originating within a given sector has a greater impact than information originating in other sectors or flowing from that sector to others.

Idiosyncratic shocks within the oil market are higher than those in other sectors of the BRVM market, with a total of 87.31%, of which 67.12% are short-term and 20.19% are long-term. The volatility of international crude oil prices has little impact on the indices of the various sectors of the regional stock market of WAEMU member countries. Thus, the finance, industry, utilities, transport, distribution and agriculture sectors react weakly to positive and negative variations or shocks in oil prices. This phenomenon can be explained, on the one hand, by the weak integration of the BRVM market at the international level. Most WAEMU member countries are oil importers. Compared to a country such as China, for example, the eight WAEMU countries are considered "small countries" in terms of international trade because of their low weight on the international stage in terms of imports and exports of petroleum products. Furthermore, the BRVM market is a modest market, characterized by low transaction volumes and, as a result, low investor responsiveness to new information.

For the financial sector (see **Table A1** in **Appendix**), 69.84% of connectivity, of which 55.97% is short-term (one trading week, i.e., five days) and 13.86% is long-term (six days over a sufficiently long horizon), can be explained by shocks caused by the financial sector index itself. Furthermore, 30.16% of connectivity may be due to interconnection throughout the network. In terms of total connectivity, the financial sector of the BRVM market is more open and more sensitive to shocks from other sectors of activity, as it receives more spillover from other sectors (30.16%), followed by the transport and distribution sectors with 27.68% and 25.46% respectively. The sectors that contribute most to the transmission of spillover effects within the market are still finance and industry, with 37.98%, followed by distribution (34.88%). The sectors with the least impact are mainly agriculture and oil, with contributions of 9.07% and 6.01% respectively. The agricultural sector is less sensitive to volatility from other sectors et also less able to absorb shocks within the market. In other words, the assets of companies operating in the agricultural sector are less likely to transmit or receive shocks. The oil market contributes little to the overall connectivity of the BRVM financial market, as it accounts for only 6.01%.

The average total connectivity index (TCI) is 23.92%, adjusted to 27.91% (cTCI), i.e., 20.31% in the short term and 3.61% in the long term. Therefore, according to Chatziantoniou et al. (2021b), the remainder, i.e., 72.09%, can be attributed to other factors that are taken into account by the internal components of each specific sector or market. Thus, we note that most of the connectivity in the BRVM network is attributed to short-term shocks, justified by the low rate of long-term connectivity (4.21%).

However, the results of connectivity matrices do not provide all the information on the connectivity links between the different components within a network. For example, they do not provide information on specific events during the study period, such as periods of high turbulence, which mostly affect the assets of publicly traded companies. For this reason, it is necessary to introduce total dynamic connectivity in terms of time and frequency, as well as network connectivity by variable pair. Unlike the analysis by Diebold & Yilmaz (2014), which focuses solely on overall connectivity, whether temporal or frequency-based, the analysis by Chatziantoniou et al. (2021b) is based on the decomposition of connectivity at the aggregate level. Thus, connectivity analysis is broken down into overall connectivity, short-term connectivity, and long-term connectivity. The overall connectivity index (TCI) is represented by a shaded area (black), which measures the overall interconnection between all components of the network (**Figure 4**). The latter is broken down into a short-term scale (represented by the pink shaded area) and a long-term dynamic (represented by the green shaded area). The results of the total connectivity index are established on the basis of a 200-day sliding window, over a forecast horizon of 100 days. An overall analysis of the results shows a downward trend in the degrees of connectivity within the network, marked by peaks following the temporal and frequency dynamics. Most peaks occur in the first few months of 2014, 2020, and 2023. Total connectivity (black shaded area) shows very significant peaks: as we can see (Figure 4), it is around 80% at the beginning of the study period. However, total connectivity (black shaded area) is short-lived.



(a) (b)

Figure 4. Total dynamic connectedness of BRVM sector indices and the prise of Brent crude oil.

Connectivity focused on short-term dynamics, corresponding to five (5) trading days, expresses the connectivity movements of the various nodes (indices and oil prices) over a period of up to one week. This high level of connectivity observed over the very short term indicates a risk of contagion between sectors of activity and oil prices. This risk of contagion is very evident within the network, where there is a large pink band, particularly over the period from 2014 to 2018. During this period, there is strong connectivity between the various sectors of activity on the BRVM, with a downward trend from 80% to 10%. The pink shaded area largely dominates the green and black shaded areas. This implies that the total connectivity between sectoral stock market indices and oil price fluctuations appears to be caused by short-term shocks within the financial market. In other words, the relationship between the BRVM financial market and the oil market is, in a way, influenced more by short-term exogenous shocks (crises), generally lasting one trading week. This short-term connectivity can be understood by the low impact of shocks within African stock markets, due to their low level of integration on the international stage, compared to the stock markets of developed countries, which are highly integrated. But also, thanks to measures to adjust and rebalance securities portfolios, the propagation of shocks within the network is not very significant. These results are consistent with the claims of Naeem et al. (2021), who estimate that connectivity between global financial markets is mostly influenced by short-term shocks, due to the speculative nature of active investors (active traders), who are motivated by short-term investments. Connectivity on long-term dynamics (green shaded area) refers to the lower frequency band, which reflects a dependency relationship between financial market sectors and the oil market. It is noticeable that this relationship is short-lived.

Thus, an external shock such as an oil crisis affecting the financial sphere of the WAEMU, leads to increased connectivity within financial market networks. As a result, when connectivity is created at low frequencies, this indicates the persistence of a shock and its transmission over the long term within the network. More explicitly, connectivity spikes can be explained by the impact of certain exogenous shocks on the stock markets. For example, the connectivity spike observed at the beginning of the study period can be explained by the 2014-2015 crisis. Concerns about oil price volatility in the oil markets, mainly due to geopolitical tensions in the Middle East. The dramatic fall in the price of a barrel of oil by nearly 50% (IMF, 2015), which began in the summer of 2014 and continued until 2016, had a significant impact on the overall oil supply of producing countries. Given that there is a strong correlation between oil and financial markets, the fall in crude oil prices, in this case Brent, can affect the prices of companies' assets. The oil crisis of 2014 and the collapse of share prices led to an increase in the connectivity of business sectors within networks. In addition, the slowdown in economic growth in most emerging countries, including China, which is the global benchmark in terms of oil imports, and the increase in supply from oil-producing countries have led to an upheaval in the oil market. Despite the downward trend in connectivity (**Figure 4**), there was a peak in connectivity in 2019, coinciding with the onset of the Covid health crisis. Several studies have demonstrated the causal relationship between oil price fluctuations and stock market assets (Antonakakis & Gabauer, 2017; Křehlík & Baruník, 2017; Ferrer et al., 2018; Li et al., 2020). This confirms the view that asset prices rise significantly during periods of turbulence or crisis.

In the context of the BRVM market, these slight peaks observed at the start of the Covid-19 crisis in 2020 and the war in Ukraine in 2022 can be explained by low speculative activity on the part of investors in a market with modest capitalization compared to the stock markets of developed and emerging countries. As a result, oil price volatility will not have a greater impact on business sectors over time. Thus, an exogenous shock such as an oil shock can have a slight influence on sector index returns over a relatively short period (one trading week). The WAEMU financial market therefore shows a certain resilience to oil price volatility.

4.2. Net Total Directional Connectedness (NET)

For a much more in-depth analysis of the connectivity of the BRVM financial market network and the international crude oil market, we introduce net directional connectivity. Net directional connectivity then makes it possible to identify the main shock (or fallout) emitters and receivers within a network. The net connectivity of a sector is the difference between the volatility impact emitted by a sector and the impact originating from one or more other sectors in the network.

In Table A1, by analyzing the net connectivity indices (NET) for each variable, we find that the sectoral indices for finance (BRVM-Fin = 7.82%, of which 6.70% is short-term and 1.11% is long-term), public services (BRVM-Spu = 1.64%, of which 0.63% is short-term and 1.01% is long-term), transport (BRVM-Trans = 5.23%, of which 4.62% is short-term and 0.61% is long-term) and distribution (BRVM-Dis = 4.31%, of which 479% is short-term and −0.48% is long-term) are the main transmitters of shocks within the network. The agriculture, industry and oil sectors contribute less to network connectivity, with −8.37% (including −8.25% in the short term and 0.12% in the long term); −3.94% (with 3.74% in the short term and 0.20% in the long term) and -6.6% (with −4.76 in short term and −1.93 in long term), respectively, which are the main net recipients of shocks, which are affected in the short term.

The net connectivity of assets in different sectors of activity and the price of crude oil within the BRVM market is shown in Figure 5. The decision rule is such that when a fringe is on the positive side, then the variable in question is a net transmitter or receiver of shocks to other entities in the network. On the other hand, when the fringe is on the negative side, in this case, the variable is a receiver of shocks. In other words, it is an entity that is influenced by one or more other entities. All entities within the network can be transmitters or receivers. There are entities that alternate their role within the network, acting at times as transmitters and at times as receivers of volatility. We note both significant positive values,

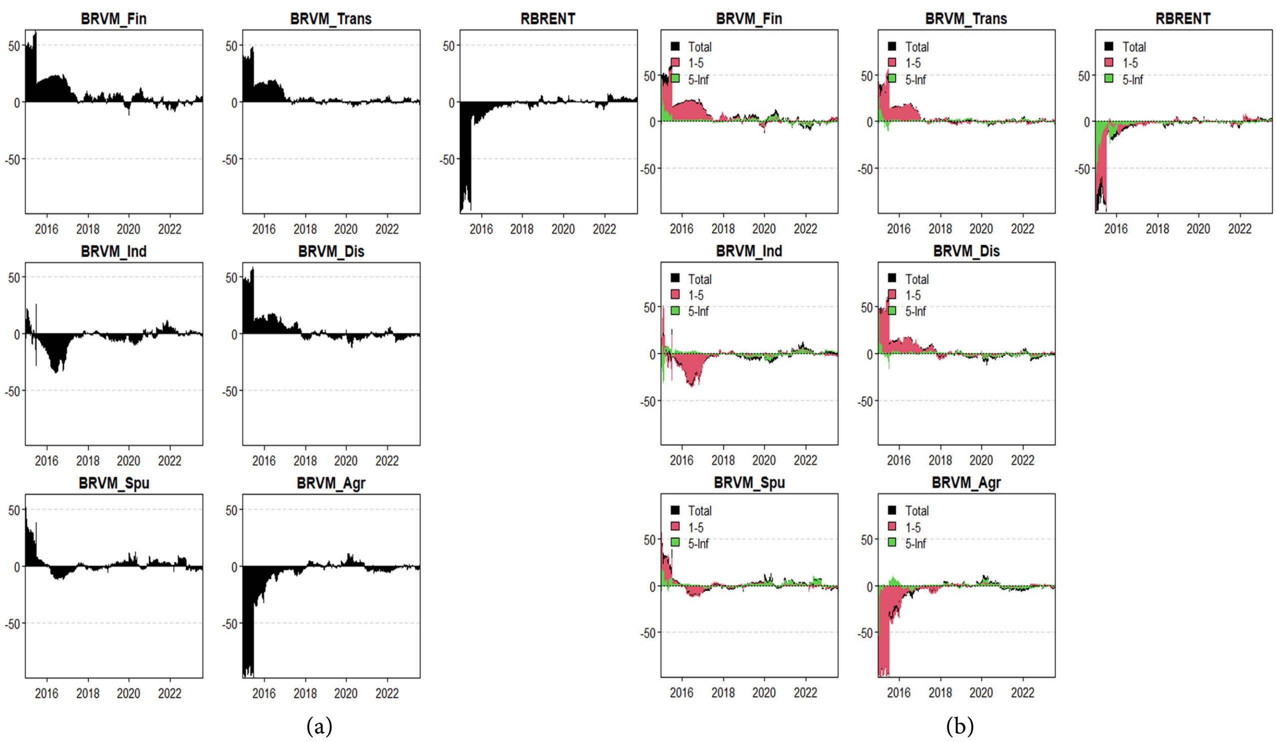


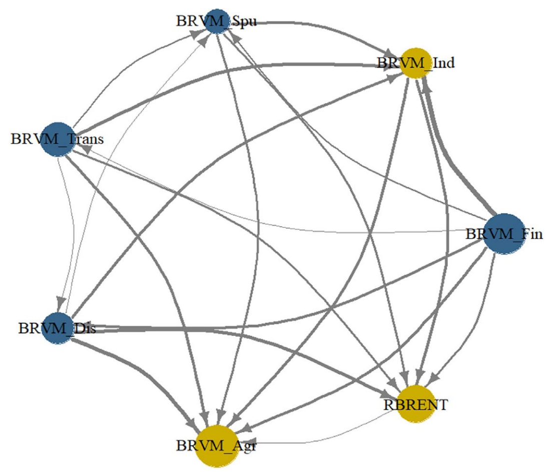
Figure 5. Net total connectivity of BRVM sector indices.

generally at the beginning of the study period, and low negative values for the indices of the finance, transport, distribution and public services sectors. We also observe significant negative values and low positive values for the indices of the industry, agriculture and Brent crude oil market sectors. We note that the indices for the finance, transport, distribution and public services sectors are net transmitters of volatility within the BRVM network, while the indices for the industry, agriculture and oil market sectors are net receivers of fallout. All sectors of activity are either net receivers or transmitters of short-term shocks (dominance of the pink fringe) on the stock market.

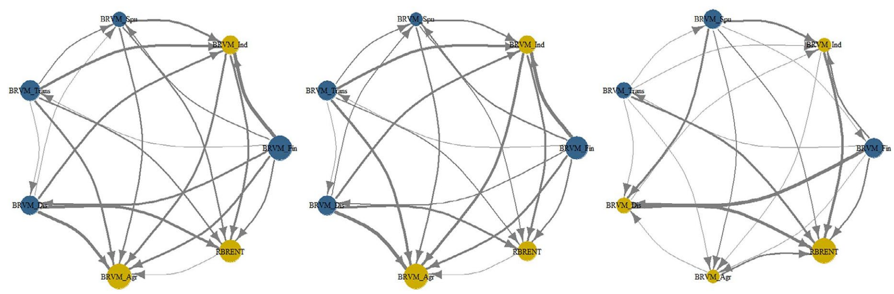
The volatility of international Brent crude oil prices does not have a significant impact on the share prices of publicly traded companies in different sectors. Thus, using the FROM and TO indices (see Table A2) for each sector index, it is possible to rank the sectors of the BRVM stock market.

4.3. Net Pairwise Directional Connectedness for BRVM Network

Network connectivity provides information about the nature of the nodes (transmitters or receivers), their market share and the intensity of the connection. Total connectivity provides overall information on the interconnection relationship between the different nodes in the network. However, it does not provide information on connectivity relationships between pairs of variables. Figure 6(a) presents the network connectivity diagrams of the results from the connectivity table. This network can be broken down according to short- and long-term dynamics (Figure 6(b)). The BRVM market is structured as a network, within which there are different nodes representing the sectors of activity and the oil market with Brent prices. The blue nodes (circles) are the shock transmitters within the network. The yellow nodes are the shock receivers. The size of the nodes shows the share of the sector of activity or index in the network connectivity. The thickness of the arrows refers to the strength or intensity of the connection between two nodes or between several nodes. Total connectivity is broken down into short-term and long-term frequency connectivity. Oil is mainly a shock receiver within the stock market. This implies that oil price variations are influenced by price variations in the assets of other sectors of activity within the stock market. The finance sector is the main source of shocks to other sectors of activity, as it is the sector that is connected directly or indirectly to virtually all other sectors of the stock market. This result can be understood through the central role of the financial sector in a country's economy. Indeed, finance acts as an intermediary for the various capital flows of the different sectors of the economy. It plays a central role in a network (financial market) by participating in or managing various investment operations and granting credit to companies in the distribution, industry, transport, public services and agriculture sectors. Thus, a shock originating in the finance sector can easily spread to other sectors of the BRVM market. This sector generally includes banks and certain financial institutions, most of which are responsible for financing companies belonging to other sectors of the market.



(a)



(b)

Figure 6. Network connectivity between sector indices and the price of Brent crude oil.

Furthermore, the agricultural sector is the main shock absorber within the BRVM network. This weak connectivity may be linked to different economic structures between agricultural indices and the Brent price. Indeed, in the African On the other hand, this weak connectivity may be linked to different economic structures between agricultural indices and the price of Brent. Indeed, agricultural indices in the African context are mostly influenced by climatic factors and seasonal cycles, as well as support policies from central authorities (governments) through subsidies or tax exemptions. As for the variation in the price of Brent crude oil, its price is set on the London stock market, which generally depends on geopolitical conditions, demand and global energy production, as well as international energy policy. As a result, these two entities depend on different economic structures. The transmission of shocks between the agricultural index and the price of Brent crude oil can occur indirectly through another sector of activity such as transport, via the costs of transporting agricultural products, the price of fertilizers (petroleum derivatives) and inputs. Public services within the BRVM network occupy a balanced position, as they are both net issuers and receivers of spillover effects. Public services, a sector in which some WAEMU member states hold assets, despite being a net transmitter of shocks within the network, is sensitive to receiving spillovers from volatility originating in other shock-emitting sectors such as distribution, finance and transport.

Figure 7 describes the net directional connectivity by index pair. We note that the relationship between the variation in the international price of Brent crude oil is more connected to the sectors of activity on the stock exchanges of WAEMU countries than at the beginning of the study period in 2016. On the other hand, there is weak connectivity during other periods of high tension (2020 and 2022). Thus, this weak influence does not rule out a certain interdependence between the sectors of activity on the market and the dynamics of the oil market.

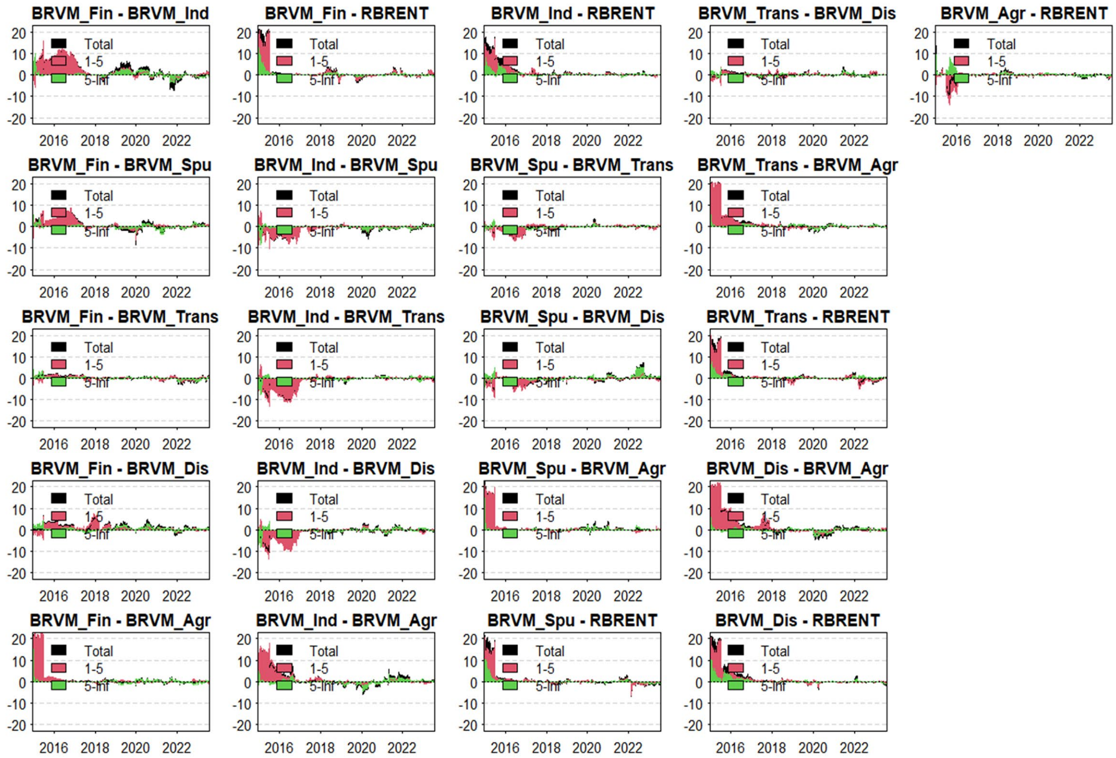


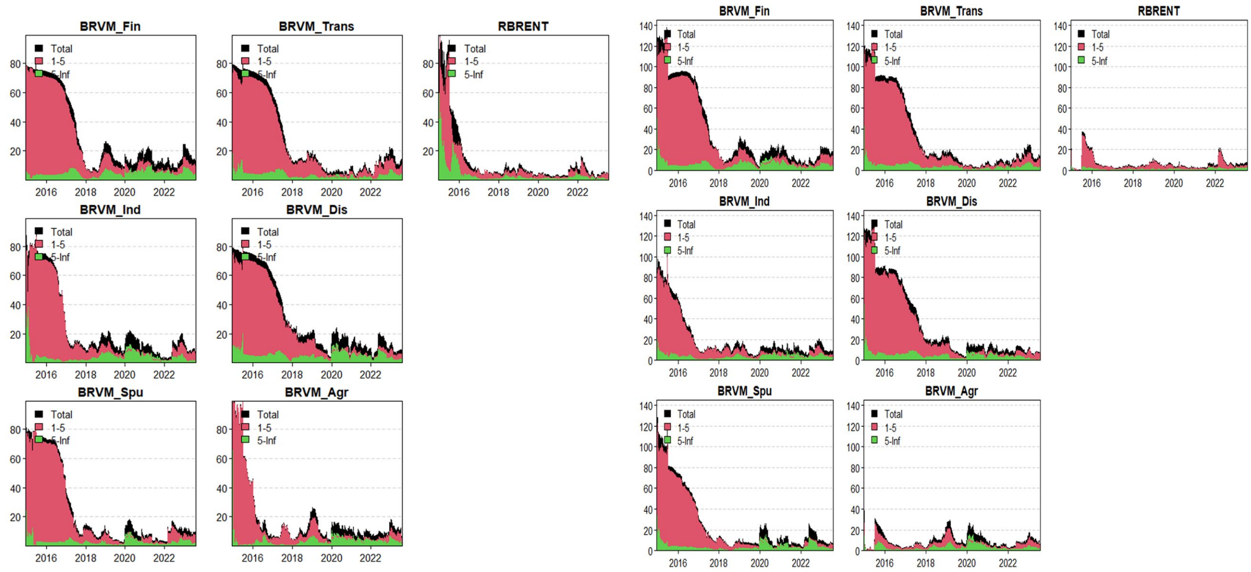
Figure 7. Network connectivity between sector indices and the price of Brent crude oil.

4.4. Ranking of BRVM Market Activity Sectors According to Outgoing, Incoming and Net Connectedness

We have ranked the various indices of the BRVM financial market sectors according to incoming connectivity (FROM), outgoing connectivity (TO) and net connectivity (NET). This ranking helps to identify the sector(s) that are most sensitive to risk or that contribute most to the spread of risk at the network level. The finance sector contributes most to connectivity or shocks at the stock market level. The transmission of shocks or volatility from one sector to other sectors of activity, as well as the reception of shocks from other sectors of activity by one sector, are shown in **Figure 8**. The numerical results are shown in **Table A2**. This contrasts with the agriculture sector, which contributes only 9.07%. Variations in Brent crude oil prices have little impact on the connectivity of market entities.

In terms of the ranking of sector indices that receive more connectivity or volatility from shocks, the distribution and finance sector indices receive 30.56% and

30.16% respectively of the volatility spillover from other sectors of activity on the BRVM market. The finance index measures the performance of companies operating in the finance sector that are listed on the WAEMU stock exchange. In general, the finance index for most financial markets includes banks, insurance companies and certain financial institutions, but the BRVM market is partly composed of banks. The shares of banking companies are more sensitive to the volatility of other assets of other companies. This can be explained by the intermediary role of banks between the various economic agents. The agriculture sector and the oil market are also among the least susceptible to shocks from other sectors. The public services and industry indices are moderately susceptible to shocks or volatility from other sectors of activity in the BRVM network.



(a) (b)

Figure 8. Total connectivity originating from (FROM) or resulting in (TO) one or more entities in the network.

These results are confirmed by the ranking of different sectors and the oil market in terms of net connectivity. The financial, transport and distribution sector indices contribute most to market connectivity. The agriculture sector index brings up the rear with a low contribution to market connectivity and is considered a net receiver of volatility. The utilities index contains assets from large companies that show encouraging results in terms of performance.

5. Conclusion and Economic Policy Implications

Financial markets are constantly evolving at an exponential (or rapid) pace, so there is a growing need to use innovative and effective methods that are capable of exploiting information both inside and outside the markets. This involves a set of tools capable of performing rapid and efficient processing that will enable traders, market operators, and public and private decision-makers to make informed decisions. The objective of this study was to establish the dynamic temporal and frequency connectivity between the different sectors of activity of the UEMOA stock market, namely the BRVM and the oil market, using daily data for the period 2014 to 2023. The financial market is considered as a network containing different sectors of activity and oil price variations, all of which represent nodes. The connectivity analysis by Chatziantoniou et al. (2021b), based on the analysis of Diebold & Yilmaz (2009, 2012, 2014), using the time-varying autoregressive vector approach (TVA-VAR), was used to understand the interactions between the financial and oil markets.

Our results show that the total connectivity of stock market networks and the global oil market is greater in times of crisis or major geopolitical turmoil. The total connectivity index increases within the network from the first months of the crisis year. In other words, most connectivity occurs in the short term, hence the presence of contagion within the stock markets. The finance sector is the main entity (nodes) or hub responsible for transmitting shocks or volatility among the five (5) sectors of activity within the BRVM stock market. The oil market and the agricultural sector are the main recipients of risk at the network level. The industrial sector is both a recipient and transmitter of volatility within the network in the short term.

Most of the companies listed on the BRVM are banks or financial institutions, or companies operating in the food, services or telecommunications sectors. There are hardly any oil companies that do not depend directly on the variation in the price of oil on the financial market. Therefore, companies belonging to these sectors are less affected by the volatility of oil prices.

In terms of economic policy implications, investors can consider the WAEMU financial market as a stable market in the short term, which is less susceptible to exogenous shocks such as oil demand or supply shocks, from which they can expect profitable gains. On the other hand, they must exercise a degree of caution by diversifying their assets, due to the low level of market integration on the international stage. This means that the financial sphere of the WAEMU zone does not yet represent a channel for transmitting oil shocks to the real economy of the union's member economies. Despite the limited influence of the oil market on the BRVM financial market, central authorities must take into account the indirect (or asymmetric) effects of oil price volatility. Promote the strengthening of the regional financial market by developing financial literacy and encouraging companies to list on the stock exchange.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix

Table A1. Connectivity average of BRVM sector indices and oil price.

Total	BRVM_Fin	BRVM_Ind	BRVM_Spu	BRVM_Trans	BRVM_Dis	BRVM_Agr	RBRENT	FROM
BRVM_Fin	**69.84**	4.54	5.98	8.14	8.83	2.10	0.58	**30.16**
BRVM_Ind	7.07	**75.16**	5.33	5.12	4.50	1.86	0.95	**24.84**
BRVM_Spu	6.96	3.85	**75.95**	5.74	6.04	0.60	0.87	**24.05**
BRVM_Trans	8.34	3.43	4.97	**72.32**	8.94	1.08	0.93	**27.68**
BRVM_Dis	10.19	3.03	5.61	9.13	**69.44**	1.78	0.83	**30.56**
BRVM_Agr	3.58	3.43	1.89	2.75	3.93	**82.57**	1.85	**17.43**
RBRENT	1.82	2.62	1.92	2.04	2.65	1.64	**87.31**	**12.69**
TO	**37.98**	**20.90**	**25.69**	**32.91**	**34.88**	**9.07**	**6.01**	**167.43**
Inc.Own	107.82	96.06	101.64	105.23	104.31	91.63	93.31	cTCI/TCI
Net	**7.82**	**−3.94**	**1.64**	**5.23**	**4.31**	**−8.37**	**−6.69**	**27.91/23.92**
NPDC	6.00	2.00	3.00	5.00	4.00	0.00	1.00	
1 - 5 days	BRVM_Fin	BRVM_Ind	BRVM_Spu	BRVM_Trans	BRVM_Dis	BRVM_Agr	RBRENT	FROM
BRVM_Fin	**55.97**	3.64	5.15	7.31	7.81	1.42	0.46	**25.79**
BRVM_Ind	5.93	**57.58**	4.66	4.61	3.84	1.13	0.72	**20.89**
BRVM_Spu	6.22	3.49	**60.35**	5.24	5.28	0.45	0.66	**21.34**
BRVM_Trans	7.41	2.95	4.60	**59.45**	7.89	0.83	0.83	**24.49**
BRVM_Dis	8.65	2.40	4.52	8.00	**54.75**	1.22	0.67	**25.46**
BRVM_Agr	2.85	2.67	1.54	2.36	3.40	**62.66**	1.65	**14.47**
RBRENT	1.44	2.00	1.51	1.59	2.03	1.17	**67.12**	**9.74**
TO	**32.49**	**17.15**	**21.98**	**29.11**	**30.24**	**6.22**	**4.99**	**142.18**
Inc.Own	88.47	74.73	82.33	88.56	84.99	68.88	72.11	cTCI/TCI
Net	**6.70**	**−3.74**	**0.63**	**4.62**	**4.79**	**−8.25**	**−4.76**	**23.70/20.31**
NPDC	6.00	2.00	3.00	5.00	4.00	0.00	1.00	
5 days -inf	BRVM_Fin	BRVM_Ind	BRVM_Spu	BRVM_Trans	BRVM_Dis	BRVM_Agr	RBRENT	FROM
BRVM_Fin	**13.86**	0.90	0.83	0.83	1.02	0.68	0.11	**4.37**
BRVM_Ind	1.14	**17.58**	0.67	0.52	0.66	0.73	0.23	**3.95**
BRVM_Spu	0.74	0.36	**15.60**	0.50	0.76	0.15	0.20	**2.71**
BRVM_Trans	0.94	0.48	0.37	**12.87**	1.05	0.26	0.10	**3.20**
BRVM_Dis	1.54	0.63	1.09	1.13	**14.69**	0.56	0.17	**5.11**
BRVM_Agr	0.74	0.76	0.35	0.38	0.53	**19.91**	0.20	**2.96**
RBRENT	0.38	0.62	0.41	0.45	0.62	0.47	**20.19**	**2.95**
TO	**5.48**	**3.75**	**3.72**	**3.80**	**4.63**	**2.84**	**1.02**	**25.25**
Inc.Own	19.35	21.33	19.31	16.67	19.32	22.75	21.21	cTCI/TCI
Net	**1.11**	**−0.20**	**1.01**	**0.61**	**−0.48**	**−0.12**	**−1.93**	**4.21/3.61**
NPDC	5.00	2.00	5.00	5.00	2.00	2.00	0.00	

Table A2. Ranking of sector indices on the WAEMU financial market (BRVM) based on FROM, TO and NET connectivity during the period from 15 December 2014 to 31 July 2023.

Rang	Connectedness					
	Sectors	TO	Sectors	FROM	Sectors	NET
1	BRVM-Fin	37.98	BRVM-Dis	30.56	BRVM-Fin	7.82
2	BRVM-Dis	34.88	BRVM-Fin	30.16	BRVM-Trans	5.23
3	BRVM-Trans	32.91	BRVM-Trans	27.68	BRVM-Dis	4.31
4	BRVM-Spu	25.69	BRVM-Ind	24.84	BRVM-Spu	1.64
5	BRVM-Ind	20.90	BRVM-Spu	24.05	BRVM-Ind	−3.94
6	BRVM-Agr	9.07	BRVM-Agr	17.43	RBRENT	−6.69
7	RBRENT	6.01	RBRENT	12.69	BRVM-Agr	8.37