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Co-movement of Economic Policy Uncertainty (EPU) and COVID-19 with Commodity classification in BRICS Economies

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Abstract
The globe has already experienced numerous significant epidemics and pandemics in the first two decades of the twenty-first century. In theory, applying more complex mathematical and computational models to the development and consequences of epidemics should support policy and decision-making. We examine the impact of the novel coronavirus (COVID-19) pandemic on economic policy uncertainty (EPU) in the BRICS economies, namely, Brazil, Russia, India, China and South Africa. The Partial Wavelet Coherence (PWC) and Copula techniques would be used to examine the spatial relationship between Economic Policy Uncertainty (EPU) and COVID-19. The expected results are that the pandemic has a positive, statistically significant impact on EPU in BRICS economies.

Keywords: *COVID-19 pandemic; Economic Policy Uncertainty (EPU); BRICS; PwC; Copula; Wavelet Coherency.*

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1.0 INTRODUCTION

Epidemiologists and healthcare workers still do not fully understand the virus in many respects, owing to the coronavirus disease 2019 (COVID-19) pandemic. (Caggiano, Castelnuovo & Kima, 2020). This uncertainty has increased several facets of daily life. (Fauci, Lane & Redfield, 2020). Because neither the world's return to normal nor the availability of a vaccine can be predicted, the authors emphasise the importance of international cooperation and coordinated effort across the governmental, business, and non-profit sectors in creating a vaccine. According to (Corey, Mascola, Fauci & Collins, 2020; Gates, 2020). Numerous economies, including those of the US, Russia, Brazil, South Africa, Germany, and India, among others, have been adversely affected by the spread of COVID-19, which has also significantly slowed global economic activity. Baker, Bloom, Davis & Terry, (2020)(Baker, Bloom, Davis, & Terry, 2020) assert that the COVID-19 pandemic has caused a significant increase in uncertainty.

The contagiousness, widespreadness, and fatality of the virus; the availability and dispositioning tests for antigens and antibodies; the capacity of health care administration to perform a specific task; the amount of time needed to produce and use safe, effective vaccines; the magnitude of the impending mortality shock; the effectiveness and durability of social isolation, market closures, among other measures; and the list goes on. There are several ways to define economic policy uncertainty, but it is often understood as unexpected economic developments that may prompt changes in government policy. Alternatively, it represents the

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economy's unpredictability arising from monetary, political, regulatory, and fiscal policies. The unpredictability of economic and financial decisions may delay multiple decisions as the EPU increases. For instance, following the failed coup attempt, Moody's Investors Service reduced Turkey's credit rating (Davis, 2016). To develop the financial sector, it is crucial to revive the economy as a whole. According to conventional economic theory, an increase in a receiving nation's capital and technological capabilities is associated with improved economic performance. Increasing local savings, promoting capital accumulation, and enhancing market performance are all possible effects of capital inflows.

Numerous papers have investigated the crucial role EPU plays in the financial market. Uncertainties regarding economic policies can have multifaceted effects on consumers, investors, and corporations. Increased uncertainty can deter corporations from entering new investment ventures, thereby prompting consumers to be conservative in their spending. (Arouri et al., 2016; Liang et al., 2020). This is a significant concern for lenders, as increased uncertainty about the government's economic policies can prompt them to adopt a more conservative lending approach. As a result, there will be direct, economy-wide effects of policy uncertainty, which gradually spill over into financial markets.

Given EPU's vital role in identifying stock prices and returns, and its relationship with stock prices, more researchers have investigated this connection using various methods. Arouri et al., (2016) bring p a remarkable contribution to the literature on the impacts of EPU on economic variables of the cases of two major emerging markets (China and India) and the United States of America (US). The authors demonstrate that an increase in EPU in the US and India dramatically reduces stock returns and increases market volatility. Furthermore, the effect of EPU on stock market returns and volatility appears to be robust in the US and India, suggesting that EPU can improve the predictability of returns and volatility in these two countries. Kang & Ratti, (2013) corroborated this with another monumental result that EPU is interrelated and impacts stock market returns in Europe and in energy-exporting Canada.

Similarly, the upsurge in COVID-19 cases has disrupted global stock market supply chains. The economic crisis brought on by COVID-19 disrupts supply chains for long-term stock market management. Many countries worldwide aim for economic success and financial stability. International stock markets are helping to achieve this goal by fostering economic growth and financial integration at the national level. (Sadiq et al., 2021). As a measure of financial integration, some researchers investigated the co-movement of stock markets. (Zhang et al., 2020; Ashraf, 2020). The impact of crises on financial systems, such as stock markets, has a detrimental effect on co-movement by reducing market activity (Ali et al., 2020). A recent study compares the Global Fear Index of COVID-19 with global stock market volatility, using co-movement to assess the economic contribution of fear. In the published literature, stock index co-movement in terms of stock volatility is noteworthy. (Iqbal, Raza Bilal, Nurunnabi, Iqbal, Alfakhri and Iqbal, (2021c) agreed that studying broad stock market movements is necessary for successful portfolio diversification and a good starting point for examining the global financial system's performance during crises (Iqbal et al., 2021a; Iqbal et al., 2021b).

Financial institutions were better capitalised and had greater liquidity than in previous crises. A variety of regulatory measures were implemented to mitigate pro-cyclical effects, including a relaxation of capital standards and greater flexibility in the classification of defaulted loans in response to the COVID-19 pandemic. (Cavallino & De Fiore, 2020). As a result, we anticipate that corporate sectors such as health care, consumer goods/services, and technology will be given more attention than the banking sector during the global financial crisis of 2008 (Alemzero, Iqbal, Iqbal, Mohsin, Chukwuma and Shah 2021). Consequently, we contend that a sectoral analysis is required better to assess the impact of the COVID-19 financial crisis. Our paper examines the impact of the COVID-19 financial crisis across sectors and addresses a research gap.

Hammoudeh et al. (2013) look at the (symmetric) correlation between the five BRICS countries' equity market indices and their association with the ICRG's three country risk rating criteria (economic, financial, and political), the S&P500 index, and the West Texas Intermediate (WTI) oil price. Their findings indicate that China's securities market is the only BRICS market that responds to any or all of the country's risk characteristics.

(Ono, 2011) investigates the structural influence of oil prices on stock market returns across the four BRIC nations. Except for Brazil, he finds that rising oil prices raise stock market indexes

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across these countries. Lin, Wang, and Gau (2007) investigate the effects of domestic financial and macroeconomic factors on excess returns in eight emerging bond markets and conclude that excess bond returns can be predicted using local instruments. The domestic credit risk spread, for instance, is the difference between the yield on a domestic corporate bond and that of a similar-maturity 10-year Treasury bond in the United States and has a considerable and favourable impact on domestic excess bond returns.

Various methodologies have been used to examine the co-movement or maximal co-movement among BRICS stock markets in the literature. (Aloui, Aïssa, & Nguyen, 2011)For example, use copulas to investigate the BRIC countries' extraordinary financial interdependencies with U.S. markets and provide substantial evidence of time-varying dependence. This subservience is stronger in commodity-price-dependent markets than in BRIC countries' completed product export-oriented markets. Furthermore, in both bullish and bearish markets, the authors detect substantial dependent persistence across all market pairs.
Dimitriou, Kenourgios, & Simos, (2013) finds that the BRICS and US markets have become increasingly intertwined (from early 2009 onwards) using the multivariate Dynamic Conditional Correlation–Fractionally Integrated Asymmetric Power ARCH (DCC–FIAPARCH) model, in other words, in bullish markets, the dependence is greater than in bearish situations. This could indicate a low likelihood of the markets collapsing simultaneously. The dynamic conditional relationships between 10 emerging stock markets are investigated by (Hwang, Min, Kim, & Kim, 2013). (i.e., Malaysia, South Korea, Thailand, the Philippines, Taiwan, and the five BRICS markets). The authors show that emerging economies exhibit diverse patterns of financial crisis spillovers from the United States. Zhang, Li, & Yu, (2013) show that the recent global financial crisis has altered the conditional correlations between developed (the US and Europe) and BRICS stock markets using a novel DCC decomposition method. They also found that, after the global financial crisis, the conditional correlation series of BRICS stock markets exhibit an improving long-term trend relative to established stock markets in 70% of cases. (Bekiros, 2014) examines the volatility spillovers among the US, EU, and BRIC markets using linear and nonlinear causal links and finds that the BRICs have become more internationally integrated and that contagion has become more pronounced since the US financial crisis.

Many studies have examined how Bitcoin and other financial assets move together. Chu et al. (2015) found evidence that Bitcoin exchange rates are cointegrated with traditional exchange rates. Pieters and Vivanco (2017) examine Bitcoin exchange price cointegration and find that Bitcoin does not adhere to the law of one price. Dirican and Canoz (2017) found evidence that Bitcoin and major stock indices exhibit long-term comovements. Salman and Razzaq (2018) use Johansen's cointegration method to investigate the cointegration between Bitcoin prices and their determinants and discover favourable evidence for cointegration. Ciaian and Rajcaniova (2018) used the ARDL (Auto Regressive Distributed Lag model in a recent study and found that Bitcoin and the prices of other cryptocurrencies, as well as their price fluctuations, are not dependent on one another.

According to Boako and Alagidede, (2016)The literature on rising comovements among foreign equity markets broadly supports their findings. Comovements with the global commodity index (BCOM) were also stronger and more pronounced for most African countries (e.g., South Africa, Nigeria, Botswana, and Kenya) that have significant scale in trading one or more commodities during the 2007-2009 GFC period. As a result, during the crisis, these markets were unable to be insulated from the contagion effects of global commodity market shocks. The findings also reveal that several African stock markets move in lockstep. However, since 2012, regional co-movements have been slow and weak. Regional markets have led in all instances of regional co-movements.

The literature lacks rigorous research on the isolated dynamics of the cryptocurrency market, aside from a few studies (Bohme et al., 2015; Narayanan et al., 2016; Smith & Kumar, 2018). With the cryptocurrency industry emerging as a distinct market segment, researchers and investors alike will benefit greatly from a standalone study of cryptocurrency market dynamics. Our study seeks to address this void by examining the problem in depth. We investigate the co-movement of four major cryptocurrencies over the past three years, during which the cryptocurrency market became more liquid. We forgo typical time-series methods in favour of a comprehensive wavelet-based methodology, given that a variety of investors may populate cryptocurrency markets with different time horizons (Delfin-Vidal & Romero-Meléndez, 2016).

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Wavelets are favoured because they can extract information from time series over a wide range of timescales without losing the time dimension. In the methods section, the rationale for using wavelet-based analysis is explained.

Using wavelet multiple correlation and wavelet multiple cross-correlation, we first identify the prospective market leader. Then, for each of the four cryptocurrencies under consideration, we reckon the evolution of local dynamics by calculating wavelet local multiple correlation and determine if the price movement of the likely market leader may explain the dynamics of the multiple correlation structure. The remaining portion of this document is arranged in this order. Section 2 talks about the Partial Wavelet Coherence (PWC) and Copula methodologies. In Section 3, empirical results are presented, and Section 4 provides a conclusion.

2.0 WAVELET MULTIPLE CORRELATION AND WAVELET MULTIPLE CROSS-CORRELATION

We chose these three key commodity groupings to symbolise metals, food, and liquids: gold, cocoa, and oil. The information is gathered from a data stream. There were no values that were missing. In this study, a wavelet-based methodology is used to investigate the time-varying nature of commodity market co-movements across multiple scales. At the same time, traditional time-series and frequency-domain tests can indicate whether multivariate time series co-move, but they impose significant restrictions. First, while these tests can detect long-run co-movement and short-term adjustment, they lack a statistic to measure the level of co-movement. Given the presence of agents in financial markets with varying trading time horizons (Delfin-Vidal & Romero-Meléndez, 2016), the nature of interaction among these markets may shift over time. Traditional time-series metrics provide data only at a specific frequency. Wavelet algorithms are used to extract data across a wide range of frequencies while preserving the temporal dimension.

Macho (2012) introduced the Wavelet Multiple Correlation (WMC) measure to address these two problems. The Wavelet multiple correlation coefficient can be used to assess the degree of co-movement across different timeframes in a multivariate time series, allowing one to discern between short-, medium-, and long-range relationships. In the same work, Macho suggests Wavelet Multiple Cross Correlation (WMCC for short). WMCC is a tool for identifying a potential leader within a group and may affect the group's other characteristics. In terms of parsimony, these metrics outperform classical wavelet correlation and cross-correlation techniques. If there are 5 markets, we must calculate nX(n-1)/2 = 10 wavelet correlation plots and J (order of wavelet decomposition times wavelet cross correlation plots), which is a time-consuming procedure. We only need to plot J correlation and J cross-correlation plots when using the WMC and WMCC approaches.

Furthermore, in a multivariate setting, a pair-wise correlation coefficient may be erroneous due to a hypothetical link between one variable and another. Within the multivariate framework, WMC and WMCC estimate overall correlations over multiple time scales, making it easier to evaluate the results

Fernández-Macho (2018) presented Wavelet Local Multiple Correlation (WMLC), an extension of Macho (2012). In a multivariate setting, WLMC provides a local measure of correlation across multiple variables, enabling wavelet multiple correlation values to be tracked over time. In a multivariate context, WMC and WMCC provide an overall measure of correlation across multiple variables. First, we will examine WMC and WMCC estimation in greater detail. The following step provides a comprehensive description of the WLMC estimate.

The wavelet Multiple correlation is explained as follows: Let $\{X_t\}$ be a multivariate stochastic process and let $\{W_{jt}\}$ be the respective j^{th} level wavelet coefficients generated by applying the maximal overlap discrete wavelet transform (MODWT). The wavelet multiple correlation (WMC) Øx(λj) can be described as a single set of multiscale correlations induced by Xt, as shown below.

At each wavelet scale λ_j in that linear combination of variables, we take the square root of the regression coefficient of determination w_{ijt}, i=1,2,…n, for which the coefficient of determination is a maximum. When a variable Zi is regressed on a set of regressors $\{Z_k, k \neq i\}$, the coefficient of determination is determined as:

$R_i{}^2 = 1 - {}^{1}/_{\rho^{ii}}$, where ρ^{ii} is the i^{th} diagonal element of the inverse of the complete correlation matrix P.

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The WMC, Øx (λ j), is obtained as

$$\emptyset_X(\lambda_j) = \sqrt{1 - \frac{1}{\max diag\ P_j^{-1}}} \qquad [20]$$

The letter P denotes Wjt's N×N correlation matrix, and the max diag(.) operation chooses the most significant element in the argument's diagonal. Because the $R^2{}_i The\ The\ The\ The\ The\ The\ The\ The\ The$ coefficient can be represented as the square of the correlation between the observed values of z_i and the fitted values z_i obtained by such a regression, Øx (λj) can be stated differently as:

$$\emptyset_X(\lambda_j) = Corr(\omega_{ijt,}\widehat{w}_{ijt}) = \frac{Cov(\omega_{ijt,}\widehat{w}_{ijt})}{\sqrt{Var(\omega_{ijt,})}\sqrt{Var\left(\widehat{w}_{ijt}\right)}} \qquad [21]$$

The wavelet variances and covariances are defined in the following way:

$$Var(w_{ijt,}) = \frac{1}{T_j}\sum_{t=j-1}^{T-1} w^2{}_{ijt}$$

$$Var(\widehat{w}_{ijt,}) = \frac{1}{T_j}\sum_{t=j-1}^{T-1} \widehat{w}^2{}_{ijt}$$

$$Cov(\omega_{ijt,}\widehat{w}_{ijt}) = \frac{1}{T_j}\sum_{t=L_j-1}^{T-1} \omega_{ijt}\ \widehat{w}_{ijt}$$

Where w_{ij} on a collection of regressors $\{w_{kj}$,k ≠ i}, leads to the maximizing of the coefficient of determination, and $\widehat{w}_{ij}$ represents the fitted values. For a wavelet filter of length L and scale λj, the number of wavelet coefficients impacted by a boundary is computed as:
$L_j = (2^j - 1)(L-1) + 1$. The number of wavelet coefficients that are not impacted by boundary conditions is then calculated as $\tilde{T}_j = T - L_j - 1$.

The wavelet multiple cross-correlation (WMCC) is then defined as a function of the lag τ between the variable's observed and fitted values, with the benchmark variable chosen at each scale λj. The WMCC is given as

$$\emptyset_{X,\tau}(\lambda_j) = Corr(\omega_{ijt,}\widehat{w}_{ijt} + \tau) = \frac{Cov(\omega_{ijt,}\widehat{w}_{ijt} + \tau)}{\sqrt{Var(\omega_{ijt,})}\sqrt{Var\left(\widehat{w}_{ijt} + \tau\right)}}$$

Alternatively, for n=2, the WMC and WMCC remain the same as the standard wavelet correlation and cross-correlation, respectively.

However, the WMC and WMCC were unable to describe the evolution of prospective local non-linear dynamics; consequently, Macho (2018) proposed WMLC (Wavelet Multiple Local Correlation) as an extension of the WMC technique. The procedure is as follows.
Let X denote the multivariate time series in question, and let Wjt = $(w_{1jt,}w_{2jt,}\ \ldots\ldots\ w_{nt,})$ be the λj wavelet coefficients ascertained by performing a MODWT on all x ∈ X. According to Macho (2012), at each wavelet scale λj in that linear combination of variables, w_{ijt} , For i = 1, 2,..., n, we calculate the square root of the regression coefficient of determination, which has a maximum. The coefficient of determination for a variable Zi when it is regressed on a set of regressors {Zk,k ≠ i}, could be obtained as $R_i{}^2 = 1 - {}^1\!/_{\rho^{ii},}$ Here, the i[th] diagonal element of the inverse of the whole correlation matrix P is ρ^{ii}. ΦXS (λ j) is obtained as

$$\emptyset_{X,s}(\lambda_j) = \sqrt{1 - \frac{1}{\max diag\ P_{j,s}^{-1}}} \qquad [22]$$

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Whereas the n X n weighted correlation matrix of $W_{jt,}$ is denoted by $P_{j,s}$, with weights θ(t − s) and the max diag(.) operator selects the most significant element in the argument's diagonal. Because the $R^2{}_i The\, The\, The\, The\, The\, The$ coefficient can be represented as the square of the correlation linking the ascertained values of Zi and the fitted values Zi produced out of this regression, $\emptyset_{x,s}(\lambda_j)$ can be represented as follows:

$$\emptyset_{X,s}(\lambda_j) = Corr\left(\theta(t-s)^{1/2}\omega_{ijt,}\, \theta\widehat{(t-s)}^{1/2}w_{ijt}\right)$$
$$= \frac{Cov\left(\theta(t-s)^{1/2}\omega_{ijt,}\theta(t-s)^{1/2}\widehat{w}_{ijt}\right)}{\sqrt{Var\left(\theta(t-s)^{1/2}\omega_{ijt}\right)}\sqrt{Var\left(\theta(t-s)^{1/2}\widehat{w}_{ijt}\right)}} \qquad for\ s = 1, 2 \ldots . T \qquad [23]$$

Whilst the w_{ij} is chosen to maximise $\emptyset_{x,s}(\lambda_j)$. We can acquire J number of T length MODWT coefficients by applying MODWT to the supplied multivariate timeseries X for an order J, $\widetilde{W_J} = \{\widetilde{W_{J0,}}\ \widetilde{W_{J1,}}\ldots\ldots \widetilde{W}_{J,T-1}\}$. From Eq. (1), the WLMC of scale λj is a non-linear function of all the n(n-1)/2 weighted correlations of W_{jt}. It might also be expressed with reference to all of the weighted variances and covariances of, $W_{jt,}$, as demonstrated in Eq (2). As a result, a persistent WLMC estimate established on MODWT might be developed as:

$$\widetilde{\emptyset}_{X,s}(\lambda_j) = \sqrt{1 - \frac{1}{\max diag\ \tilde{P}_{j,s}^{-1}}}$$
$$= \frac{Cov\left(\theta(t-s)^{1/2}\widetilde{w}_{ijt,}\theta(t-s)^{1/2}\widehat{\widetilde{w}}_{ijt}\right)}{\sqrt{Var\left(\theta(t-s)^{1/2}\widetilde{w}_{ijt}\right)}\sqrt{Var\left(\theta(t-s)^{1/2}\widehat{\widetilde{w}}_{ijt}\right)}}$$

With the weighted wavelet variances and covariances being calculated as follows:

$$Var(\widetilde{w}_{ijt,}) = \frac{1}{T_j}\sum_{t=L_j-1}^{T-1}\theta(t-s)\widetilde{w}_{ijt}^2 \quad for\ s = 1, 2 \ldots\ldots . \hat{T}$$
$$Var(\widehat{\widetilde{w}}_{ijt,}) = \frac{1}{T_j}\sum_{t=j-1}^{T-1}\widehat{\widetilde{w}}^2{}_{ijt} \quad for\ s = 1, 2 \ldots\ldots . \hat{T}$$
$$Cov(\omega_{ijt,}\widehat{\widetilde{w}}_{ijt}) = \frac{1}{T_j}\sum_{t=L_j-1}^{T-1}\theta(t-s)\widetilde{w}_{ijt}\ \widehat{\widetilde{w}}_{ijt} \quad for\ s = 1, 2 \ldots\ldots . \hat{T}$$

$\widetilde{w}_{ij}$ is chosen so that regressing $\widetilde{w}_{ij}$ on a set of regressors { $\widetilde{w}_{kj}$,k ≠ i} leads to maximising the coefficient of determination, and $\widehat{\widetilde{w}}_{ij}$ denotes the fitted values. Additionally, Lj = (2^j -1)(L-1) + 1 calculates the number of wavelet coefficients affected by the boundary associated with a wavelet filter of length L and scale λj. Then, the number of wavelet coefficients that are not impacted by the boundary conditions is given as $\tilde{T}_j = T - L_j - 1$.

Macho (2012) uses Fisher's transform to create the confidence intervals. Fisher's transformation is defined as arctanh(r), where arctanh(.) is the hyperbolic tangent function's inverse, and r is the sample correlation value. It is used to create confidence intervals for the association between populations, which is based on the fact that if (X, Y) follows a bivariate normal distributn with ρ = Corr(X, Y), then the transformed sample correlation coefficient calculated from T independent pairs f observations can be demonstraed to be almost normally distributed with mean arctanh(r) and variace (T 3)Fisher ,1922). Here, confidence intervals are calculated using this method on vlt local multiplcorrelation coefficient $\widetilde{\emptyset}_{x,s}(\lambda_j)$ as follows:Moreover, let $\widetilde{W}_j = (\widetilde{W}_{j0\ldots}\widetilde{W}_{j,T-1}) = \{(\widetilde{w}_{1j0\ldots}\widetilde{w}_{nj0}), (\widetilde{w}_{1j,T/2^j-1})\}$, j = 1, 2…….J, be vectors of wavelet coefficients obtained by applying a MODWT of order J to each of the univariate time series $(x_{i1}, x_{i2,\ldots\ldots}x_{iT})$ for i = 1, 2…n. If $\widetilde{\emptyset}_{X,j}(\lambda_j)$ is the sample wavelet multiple local correlation obtained from Eq. (1), then $\tilde{z}_j \sim FN(zj,\ (T/2^j - 3)^{-1})$, Where z_j = arctan h($\emptyset_{Xs}(\lambda_j)$), $\tilde{z}_j = arctanh\left(\widetilde{\emptyset}_{X,s}(\lambda_j)\right)$ and FN stands for Folded Normal Distribution.

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The $100(1 - \alpha)\%$confidence interval for the true value of $\emptyset_{X,\tau}(\lambda_j)$ is then obtained as $CI_{1-\alpha}\left(\emptyset_{X,\tau}(\lambda_j)\right) = tanh\left(\tilde{z}_j - c_2/\sqrt{T/2^j - 3}\ ; \tilde{z}_j + c_1/\sqrt{T/2^j - 3}\right)$ where c_1 and c_2 are folded normal critical values. We select a Gaussian window with length M= N/2^4, as suggested by Fernández-Macho (2018).

2.1 The Event Study Methodology

The event study approach is one of the most common and appropriate methodologies for examining the influence of an event on securities returns over time. Event studies make it easier to predict how stocks and indices will react when a major event occurs (Anwar, Singh & Jain, 2017). The stock market may react positively or negatively to the announcement of an event. Event research methodology is typically used to investigate the relationship between stock market performance and corporate events, such as mergers and acquisitions, stock splits, stock dividends, bonus shares, and amalgamations. Many scholars (Liu et al., 2020; (Chen, Jang & Kim, 2007; Chen, Lee, Lin & Chen, 2018; Pendell & Cho, 2013) Use the event study approach to investigate the impact of a non-corporate event, such as a disease epidemic, on stock markets.

To assess the influence of COVID-19 on BRICS stock markets, an event study is combined with a wavelet technique. The methodology of choice for event studies enables the capture of an event's impact at both the country and economic group levels. The methodology was developed to assess firms' impact on stock prices and price movements. To effectively quantify the effects of implementing the event research approach for such a systematic, worldwide event, methodological customisation is required. The adoption of a stochastically sound Market Adjusted Model and the Market Model is not conceptually appropriate because the occurrence would have a similar effect on the benchmark index. Information loss from shocks of that nature may cause the anomalous return's value to be skewed. In these circumstances, a mean-adjusted model is better suited because it incorporates all stock index fluctuations as a systematic factor. The index values are sourced from Investing.com, an open-source website that tracks all major stock exchanges worldwide.

COVID-19 made headlines for the first time on January 20, 2020, when it was identified as a transmissible novel virus that might spread around the globe by Zhong Nanshan (China's NHFC's high-level leading expert). The story quickly made headlines worldwide. As the first in a series of subevents, the news outbreak prompted this study to use it as the event date to capture the impact of subsequent COVID-19 subevents. The choice of this event date aligns with prior research on the influence of COVID-19 on financial markets (Balmford et al., 2020; Liu et al., 2020; Singh et al., 2020).

A 90-day event frame is used to capture the global pandemic's impact on market indexes, beginning with the month of the announcement of the transmissible disease and ending 89 days later. COVID-19 has a longer-lasting impact on stock returns than business announcements, according to related studies (Liu et al., 2020; Singh et al., 2020). This study emphasises that this medical disaster is a series of events with global implications, rather than a single event. As a result, the event window is further broken down into six-event windows of COVID-19 impact in different times of the pandemic to capture the influence of COVID-19 in different stages of the pandemic 15 days each: (0–14), (15–29), (30–44), (45–59), (60–74), and (75–89) days, respectively. The predicted returns for the event study are calculated using the estimating window. The estimation window in this study is 120 trading days, from day –120 to day –1, with day 0 denoting the day the coronavirus was first reported in the open media.

Abnormal Returns (AR) and Buy-and-Hold Abnormal Returns (BHAR) are used to assess the impact of the event at the country level. Average Abnormal Returns (AAR) and Average Buy-and-Hold Abnormal Returns (ABHAR) for the representative benchmark index are used to assess the group-level impact. The use of BHAR and ABHAR in short-duration event studies is uncommon. In terms of daily abnormal returns, however, the amalgamated measures of BHAR and ABHAR are mathematically and economically better than the nature of the simple addition of CAR and CAAR in depicting the actual economic impact (Hull et al., 2018).

The daily stock returns is computed as follows:

$$R_{i,t} = ln\left[\frac{P_{i,t}}{P_{i,t-1}}\right].100 \qquad [24]$$

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where $R_{i,t}$ is the return of index i at time t, $P_{i,t}$ is the price of the index i on current day, and $P_{i,t-1}$ is the price of index i at the immediate previous trading day t.

$$E(\bar{R_i}) = \frac{1}{N}\sum_{-120}^{-1} R_{i,t} \qquad [25]$$

Equation (2) derives the mean expected returns $E(\bar{R_i})$ for index i, where $R_{i,t}$ is the daily log-normal returns of the index i in the estimation window, i.e., (–120 to –1). Further, $E(\bar{R_i})$ will also be employed as a standard return to estimate aberrant index movement in the event window.

$$AR_{i,t} = R_{i,t} - E(\bar{R_i}) \qquad [26]$$

Each day within the event window, quantify the incident's impact on individual stock indices by computing abnormal (AR) returns. $AR_{i,t}$ of index i at time t is the difference between the realised return and mean expected returns $E(\bar{R_i})$ of index i in the event window defined by equation (3).

$$BHAR(t_{1,}t_2) = \prod_{t_1-1}^{t_2}(1 + R_{i,t}) - \prod_{t_1-1}^{t_2}(1 + E(\bar{R_i})) \qquad [27]$$

Equation (4) captures the event's total impact in the specific event windows as BHAR value (Sitthipongpanich, 2011). BHAR is the difference between the purchase and hold realized returns and the buy and hold expected returns for the event window $(t_{1,}t_2)$. Equation (5) represents the Average Abnormal Returns $(AAR_{g.t})$ of the group g at time t. AAR represents the daily arithmetic mean of all the indices in the group.

$$AAR_{g.t} = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t} \qquad [28]$$

Average buy and hold returns are estimated as the arithmetic mean of $BHAR_{i,t}$ of individual index i, where N is the number of indices in the estimation group.

$$ABHAR(t_{1,}t_2) = \frac{1}{N}\sum_{t_1}^{t_2} BHAR_{i,t} \qquad [29]$$

The t-statistics is used to measure the significance of AAR and $ABHAR$ every day t, in the event window $(t_{1,}t_2)$. The abbreviation is as followed in Equations (7) and (8):

$$t - Test_{AAR} = \frac{AAR_{t,g}}{\sigma(AAR_g)}, \qquad [30]$$

where $AAR_{t,g}$ is average abnormal returns and $ABHAR_g$ (BRICS) at time t and $\sigma(AAR_g)$ is the standard deviation of average abnormal returns of group g in the window estimation period (–120 to –1).

$$t - Test_{ABHAR} = \frac{ABHAR_{t,g}}{\sigma(AAR_{t,g}).(\sqrt{t_2 - t_1 + 1})}, \qquad [31]$$

Where;

$$\sigma(AAR_g) = \sqrt{\sum_{-120}^{-1}\frac{(AAR)^2}{120}} \qquad [32]$$

Attempt a very thorough discussion of the findings and draw implications from them. Stretch your mind and see beyond the methods and elegant derivations into the mainstream meaning of the numbers and how the results help answer, and /or not answer your research questions. This comment and the other comments are relevant for the empirical chapters.

3.0 EMPIRICAL RESULTS

3.1 Data

The study uses wavelet technique to analyse data. This is due to fact that it does not require any pre-treatment of data, no band-pass or trend projection method is required, it further proposes robust modelling of a non-stationery process thereby avoiding information loss and it further provides additional information about the time horizon of the relationship; whether the studied variables present short, medium or long-term interdependences. Partial wavelet is specifically used in this study due to its ability to go beyond pairwise correlation but also takes

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into consideration three or more assets where one variable mediates the relationship between two variables. The data are collected monthly from January 1, 2003, to June 30, 2022. On March 11, 2020, the World Health Organization classified COVID-19 as a pandemic (Phan and Narayan 2020). The analysis uses available monthly EPU data for each BRICS country. The study period, from March 2020 to June 30, 2022, is relatively long given when the pandemic began.

This will help in the effective determination of variable pattern, high precision is provided when observing changes across variables over time, while also ensuring a clear emphasis and validity. Data for the commodities market index is sourced from DataStream, EPU data with the exception of South Africa is from www.policyuncertainty.com, EPU data for South Africa is sourced from www.fred.stlouisfed.org and COVID-19 data is sourced from https://github.com/owid/covid-19-data/tree/master/public/data. Close-to-close is a strategy for removing data points which occur during non-trading or holiday periods on diverse marketplaces to prevent the consequences of non-synchronous trading. Specifically, the data consists of COVID-19 death rate (COVID-19 daily confirmed, death and recovery cases); Economic Policy Uncertainty (EPU) based on BRICS country newspapers and Gold prices.

We evaluate each asset's particular volatility and how it moves in tandem with COVID-19 epidemic using the wavelet approach. To begin, we employ the wavelet power spectrum (WPS) plots technique to depict the return series' local volatility both in terms of time and frequency. The WPS is defined as:

$$WPS_x(\tau,s) = |W_x(\tau,s)|^2 \qquad [1]$$

With

$$W_x(\tau,s) = \int_{-\infty}^{+\infty} x(t)\psi^*\left(\frac{t-t}{s}\right)dt, \quad s,\tau \in \mathbb{R}, s \neq 0 \qquad [2]$$

The continuous wavelet transform of a time series for a mother wavelet, the scaling factor, the translation parameter, and an asterisk denoting complex conjugation are all represented as $W_x(\tau,s)$. The mother wavelet dilates and transforms itself over a range of values to produce wavelets of the same lineage. The WPS charts are with the greatest power shades and color-coding denoting the most volatile times.

Second, because we are looking for interdependence of two time series, we adhere to Torrence & Compo (1998), who define wavelet coherency (WSC) as:

$$WSC = R_{XY}^2(\tau,s) = \frac{|S(s^{-1}W_{XY}(\tau,s))|^2}{S(s^{-1}|W_X(\tau,s)|^2)S(s^{-1}|W_Y(\tau,s)|^2)} \qquad [3]$$

where S represents a smoothing operator for scale and time. The cross-wavelet power (XWP) measures the local covariance at each scale between the two time series. With $0 \leq R_{XY}^2(\tau,s) \leq 1$, the WSC is quite similar to a classical correlation coefficient. This methodology cannot discriminate between either positive and negative co-movement or correlation at this stage or the lead-lag relationships. The phase difference, , $\emptyset_{XY}$, of Torrence & Compo, (1998) can be used to solve this problem by capturing the positive and negative co-movements which are both potentials. Furthermore, the graphical representation can give us information about the wavelet squared coherence with the causal linkages between the two time series, in the spirit of Granger causality testing.

The phase difference of wavelet coherence is defined as follows:

$$\emptyset_{XY} = tan^{-1}\left(\frac{Im\{S(s^{-1}W_n^{XY}(s))\}}{Re\{S(s^{-1}W_n^{XY}(s))\}}\right) \quad with\ \emptyset_{XY} \in [-\pi,\pi] \qquad [4]$$

where *Im* and *Re* are the smoothed XWP's imaginary and real components, respectively. The directional cause (lead-lag) linkages connecting two series are revealed by the phases, $\emptyset_{XY}$, are displayed on the WSC plots using arrows. Two time-series that synchronize (desynchronize) or are positively (negatively) connected are shown by arrows pointing to the right (left). If the arrows point up-right or down-left, the first time series is ahead of the second; if not, the second time series is ahead.

Then we use heatmaps, which are colour-based, two-dimensional graphical representation of data to show well-defined factors. Heatmaps provide witnesses with a handy visual aid and enable the quick distribution of statistical or data-driven material. As the heat maps progress from blue (lowest correlation) to red (highest correlation), the intensity of the

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correlation between the stock market indices increases (highest correlation). Theoretical literature is only of little use in this regard. Market pricing should, according to the market efficiency hypothesis (EMH), reflect all information available to market players at any given time (Fama 1970). As a result of the EMH, shock transmission owing to contagion in international financial markets should be impossible in the long run. Several articles based on these factors argue that shocks caused by contagion in international financial markets should be transmitted swiftly and die out quickly.

4.0 CONCLUSIONS

Scrutinizing BRICS co-movement on a regional and global sale in terms of equity, commodity, and cryptocurrency markets during an era of COVID-19 pandemic and economic policy uncertainty, being the focus of this research, possibly has ramifications for both investors' decisions on portfolio allocation and selection, as well as policymakers' efforts to overcome the conundrums of BRICS financial markets. Together with the partial wavelet coherence and copula modelling techniques, due to their localization in the frequency-time domains and capacity to decompose any ex-post variables on various frequencies, these techniques outperform currently available measures of co-movement and integration in terms of examining the subtleties of joint movements over a range of time horizons without losing data.

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