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Examining The Linkages Among Brics Countries Using Volatility Indices

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Abstract
This study investigates the relationship between implied VIX throughout the capital markets of the BRICS (Brazil, Russia, India, China and South Africa) members, which will be helpful in developing a reliable volatility prediction for market players. The timeline of the daily VIX data used for the study extends from Nov 2013 to Dec 2019. The Gregory Hansen test was utilized to analyse VIX price information. The study examines data stationarity using breakpoint unit root tests and the Augmented Dickey fuller Test. It employs statistical tools for co-integration among VIX and examines long-run relationships using the Vector Error Correction Model (VECM). The study also examines pair-wise time-varying conditional correlations using the dynamic conditional correlation (DCC) model of Generalized Autoregressive Conditional Heteroscedasticity (GARCH).
The Gregory Hansen Co integration test shows that BRICS countries track a shared average value over the long term, which can be used for hedging purposes. The study reveals high uncertainty shocks, likely to persist in future variance projections, with the BRICS nation's VECM pairing highlighting the importance of information linkages.
Key Words: *BRICS, VIX, Gregory Hansen Method, GARCH Model, Vector Error Correction Model*

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I. Introduction

BRIC is an abbreviation representing the developing nations of Brazil, Russia, India, China, and South Africa, which are regarded as the world's major emerging economies. Jim O'Neill, a Goldman Sachs economist, invented the acronym BRIC (Brazil, Russia, India, and China) in 2001. Later in the year 2010, South Africa, was added to this group to strengthen the south - south relations, giving rise to the abbreviation 'BRICS.' South Africa may benefit from BRICS programmes such as security and justice, statistics, agriculture, and so on. In BRICS 15th summit in Johannesburg held in August 2023, the BRICS leaders announced the inclusion of six more countries i.e. Argentina, Egypt, Ethiopia, Iran, Saudi Arabia, and the United Arab Emirates as full members from January 1, 2024. Following this partnership, BRICS will be known as BRICS+.

When the BRICS nations gathered in India in 2012 to explore pooling resources and establishing a development bank, BRIC countries were responsible for 18 percent of the world's GDP, 40 percent of the world's population, and occupied one-fourth of the world's territory and when the globe was in crisis in 2008, BRICS emerged as a significant engine of global growth. Unlike the European Union, the BRICS nations are not interested in forming a political alliance or engaging in any other type of formal trading; instead, they are a formidable economic bloc with low production and labour costs.

According to the BRICS trade relations, the total contribution of the BRICS nations to global import and export was USD 2339 billion and USD 2902 billion, respectively, at the end of 2016. This statement implies that the BRICS countries had a significant trade surplus in aggregate during this year. They account for around 14.87 percent of worldwide imports and 18.57 percent of total global exports. China has emerged as the world's greatest trading country, both in terms of imports and exports, both within the BRICS nations and globally.

Under the BRICS nations the rapid economic and demographic growths of both India and China are expected to provide boom to a huge portion of middle class and further whose consumption would promote the economic development and expansion of the world's economy. The BRICS nations of China, India, and Brazil account for an exponential surge in spending for scientific research, increasing from 45 percent to $1,500 billion as they have now quadrupled their investments in such streams and raised their combined stake in R&D from 17 percent to 24 percent.

BRICS nations have expanded the number of their cooperation in recent years as it can be seen in various numbers of forums and annual BRICS conferences. As accordance of the Fortaleza Agreement, 2014, the BRICS nations established their own New Development Bank (NDB) and Contingency Reserve Arrangements (CRA) in order to promote more financial cooperation among themselves. The BRICS group of nations has immense potential and opportunity for the global economy, policymakers, and investors. They must be investigated from the viewpoints of investors, asset managers, and legislators since they have such tremendous potential (Hammoudeh, Sari, Uzunkaya,& Liu, 2013; Mensi, Hammoudeh, Kang, & Nguyen, 2016). BRICS financial markets are expanding and providing strong risk-adjusted returns as well as sufficient diversification options to global investors. The BRICS countries, which makes up one-third of the world's GDP and 17% of global trading, is crucial in determining global economic policy and advancing financial stability. By 2030, it is predicted that the BRICS nations, with their intended enlargement, might contribute more than 50% of the world's GDP, further establishing their position on the world arena. With a much greater liberalisation of financial and economic integration among the emerging economies of the world, BRICS nations have also improved their liquidity and depth of the markets, enhanced their regulatory standards and also strengthened their investor's protection (Mensi, Hammoudeh, & Kang, 2017. As a result of this legislation, the BRICS countries have emerged as a key destination for investors aiming to attain high risk-adjusted returns. (Buchanan, English, & Gordon, 2011).

It is important of the global investors who are willing to diversify and earn returns from the markets offered by BRICS nations, they need to study the dynamic changes of each nation's market alone and try to find out how they are integrated among themselves. The BRICS nation's market is not homogenous in nature as some of them are much more developed than others hence their respective financial markets may have varied levels of depth, regulatory systems, and market microstructure patterns.

In this paper, we examine that how well the nations in BRICS are linked to each other using their respective Volatility Indexes. Because market volatility fluctuates more than returns, examining cross-country volatility can reveal more about market developments, notably market integration through the spill-over effect (Peg & Ng, 2012), and for the global investors it would be of great interest to gain knowledge about the level and direction of linkages in the markets in terms of volatility. This can also help in determining unexpected shocks in one market's volatility would impact on other markets of the BRICS nations or not. And if there is an impact than what is the amount of impact. This will lead to a better understanding of the international markets and, as a result, improved decision making by investors and managers. The aims of the study is to develop an analysis of spill-over impacts of BRICS emerging economies as they are evolved into bigger players in the world of financial economy and the global investors and managers with the objective of harnessing the benefits of higher returns from portfolio diversification.

II. Literature Review

The present study reviewed various previous studies to better understand BRICS nations' Volatility Index and their relationship to each other. Some of the important studies are mentioned here.

Sharma, G. et al. (2017) examining the knowledge linkages of the forward-looking volatility index indexes for the BRICS nation's underlying stock market indices is very important for foreign investors and different decision-makers in the decision-making process. According to their findings, the relationship between the BRICS nation's pairs is long-term. Return and volatility spill-over matrix show the varying degree of BRICS VIX connectivity over the whole study period. There is also a clear contemporary negative association between the frequent shifts in VIX and the returns on the US stock exchange. **Sarwar, G. (2012)** When index volatility is large and unpredictable, the proved relationship in his research grows stronger. He also established that the negative relationship between the volatility index and stock returns exists between China and Brazil between 1993 and 2007, as well as between India and China between 1993 and 1997. There is a clear asymmetrical association between the volatility index and daily stock market returns in the U.S., China and Brazil, indicating that VIX is more of a gage of investor anxiety than bullish feelings of investors. And the asymmetry between stock market returns and VIX is even stronger when VIX is bigger and more volatile. As a result, VIX is not just an investor-fear index for the US capital market, but also for the financial markets of China, India, and Brazil.

Narwal, K.P. et al. (2012) as shown in the study the Asian – Pacific and Western capital markets have a significant and broader international systemic activity. Their tests of the BEKKGARCH bivariate model are unexpected, since spill overs of uncertainty are outward from developing to developed markets. However, in the real world, where developed economies are the dominant force, it is not the same, because the financial fluctuations of those nations frequently have an influence on the economies of emerging economies. The regular adjustments in the volatility indices in relation to the underlying indices provide an accurate picture of the market knowledge distribution.

Li & Giles (2014) find out that Global investors should place or call a number of volatility derivatives to diversify the risk associated with the investments on the international market. As a result, it is stated in their study that, in terms of their uncertainties, knowing the reality and accurate explanation behind the market connections would be a very crucial aspect for global investors.

Aloui et al. (2011) found in their study, Russia and Brazil have stronger connections with developed markets. As per the findings, these countries may be categorized as commodity price-driven since their revenue is derived from product exports, whereas China and India are export-oriented countries with finished goods.

While the relationship between China and other developed economies has grown significantly since the 2007 crisis, its strength remains low (0.072 between China and the US stock market). One possible cause is that the US and Chinese economies lose synchronisation for lengthy periods of time. According to **Zhang, B. et al. (2013)** findings, the 2007 financial crisis triggered lasting shifts in the long-term link between the BRICS country and other established stock markets as per the research conducted by Bing Zhang. On the other hand, the capital market of Brazil and Russia has stronger similarities with the developing countries than those of India and China.

Divya Gupta, D. & Kamilla, U. (2015) stated the financial crisis began in the United States in the summer of 2007 as a result of the housing bubble, it did not reach the world's emerging economies until November of the same year. This leads to homelessness, higher loan rates, and even more stock market volatility. After applied ADF Test and VAR model on the necessary time series, the conclusion is that intelligence relations exist between the various BRIC nations - Brazil, India, China, and Russia. This is especially true for the VIX (USA), which has the greatest influence on causality over the other market indices. According to the study, VIX (USA) explained 6%, 25%, 9.6%, 4.3% and 5% respectively, of the predicted error variances of VXEWZ, VXFXI, RTSVX, IVIX and VXJ, on average.

From **Hammoudeh, S. et al. (2012**) study, it is also worthwhile to consider the BRICS nations' diplomatic, financial, and economic country risk scores for their national stock markets. China was also found to be immune to all impacts. In general, financial risk ratings are more sensitive than economic and political risk ratings, whereas political risk ratings are equivalent to financial and economic risk ratings. In the study amongst all the five nations under the BRICS, Brazil has achieved a higher degree of exposure to both financial and economic threats, while Russia and China are more sensitive to political risks, while India is prone to higher oil prices.

Mensi, W. et al. (2017) examine an asymmetric long-term memory for the developed economies of the United States, Europe, and Japan, as well as all other BRICS nations, by using the multivariate DECO-FIEGARCH formula to regular spot indices from 1998 to 2016. However, there is a significant variation in the time shifting conditional correlation between the stocks included in the market, particularly from 2007 to 2008, during both bullish and bearish periods. Clear partnerships have also been recognized with respect to diversification gains and downside risk mitigation that affirm the utility of the BRICS equity portfolio risk management to use established market stocks.

Soumya Ganguly, S. & Bhunia, A. (2022) find out the volatility of the stock market and its correlation with the stock returns of the BRICS (Brazil, Russia, India, China, and South Africa) have been attempted in this paper to tracked over the time period between November 18, 2019, and May 7, 2021. The statistical analysis of the GARCH family model and the ARDL model is used in this paper. The GARCH model demonstrates the volatility of the Russian and Indian stock markets. The leverage effect is only present in the Indian stock market, according to the EGARCH model. The ARDL test reveals a short-run association between the stock markets of Brazil and a few other selected countries, as well as between the stock markets of India and South Africa and Brazil and South Africa. It is concluded in the study that investors in the BRICS stock markets should create proper safeguards to preserve their assets by putting into practice suitable hedging strategies.

As there has been very little empirical study on the information connections of VIX (in general and BRICS in particular), which give crucial cues for forward-looking volatility indicators that effect the interconnection of equities markets. The present study will attempt to determine the degree to which the Volatility Indexes of the BRICS nations are related to one another. This study report will help international investors, executives, and a variety of decision-makers who want to participate in certain financial markets. It produces a correlation by estimating that if they are related, a surprise in one market will cause changes in the other markets.

III. Research Methodology

The VIX of Brazil, Russia, India, China, and South Africa is included in the data. The Study made use of daily VIX values from these respective countries. The timeline of the daily VIX data used for the study extends from Nov 2013 to Dec 2019. The COVID-19 era is not included in the data collection period because volatility indices during COVID-19 period frequently capture short-term market movements rather than long-term economic realities. These short-term fluctuations may not necessarily reflect the true long-term BRICS Countries Information Linkages in volatility indices.

The VIX time-series data began in November 2013 since it was the earliest accessible VIX data for Russia at the time. VIX pricing are taken in USD to limit foreign exchange risk and to ensure comparability. The data for the study ranges from 2013 to 2019, and was obtained from the official websites of CBOE, Bloomberg, and the NSE. Separate data for each country has been collected, where VIX data for Brazil, China, Russia and USA is sourced from CBOE, INDIA VIX is sourced from NSE website.

The Time Series Data Transformation Variable/Natural Log by using the equations:

$$\Delta Country\_R = Log[\frac{Country_t}{Country_{t-1}}]$$

Further in this research we have examined the stationarity in data using breakpoint unit root tests with the help of the Augmented Dickey fuller Test at different level of lag methods with the help of various statistical tools. Furthermore, for co integration among VIX, we employ the Gregory and Hansen (1996a, 1996b) model that is tested at a 5% significant level. For the analysis of the existence of co-integration pairing of two has of the BRICS nation has been done. Following the investigation of the long-run relationship between the BRICS VIX price series, we examine their short-run dynamics using the Vector Error Correction Model (VECM) test. In this study, we paired the BRICS nations to use VECM. We then study pair-wise time-varying conditional correlations through dynamic conditional correlation (DCC) model of Generalized Autoregressive Conditional Heteroscedasticity (GARCH) proposed by Engle (2002).

Augmented Dickey Fuller Test

The Augmented Dickey Fuller Test (ADF) is the unit root test for stationarity. Testing the stationarity is a very frequent step in autoregressive models. The first step in ARIMA time series forecasting is to determine the number of differencing required to make a given time series completely stationary. The word Unit Root here means to the characteristics if available in a time series can make a particular times series non-stationarity and the number of roots in a series relates to the number of differential operations necessary to achieve stationarity in the test series. A unit root is technically accessible in a time series of the value when Alpha = 1 in the equation provided below:

$$Z_t = \alpha Z_{t-1} + \mu X_e + \epsilon$$

Where, Z_t is the value of the time series at time't' and X_e is the exogenous variable (a separate explanatory variable, which is also in the time series). A Dickey Fuller test that examines the null hypothesis α=1 in the equation model shown below:

$$z_t = c + \mu t + \alpha z_{t-1} + \emptyset \Delta Z_{t-1} + e_t$$

Where,
α is the coefficient of the first lag on the time series Z
Zt-1 is the lag one of the tome series Z
Delta Z (t-1) is the first difference of the time series at time t-1.
The ADF test, on the other hand, extends the Dickey Fuller test equation to include a high order regressive process to the aforementioned equation.
That is,

$$z_t = c + \mu t + \alpha z_{t-1} + \emptyset_1 \Delta Z_{t-1} + \emptyset_2 \Delta Z_{t-2} \dots + \emptyset_p \Delta Z_{t-p} + e_t$$

A important point to mention here is that, because the null hypothesis implies the presence of the unit root, that is, =1, the p-value obtained should be smaller than the significance level (say, 0.05) in order to reject the null hypothesis. As a result, we may conclude that the series is stationary.

Gregory Hansen Method

Structural breaks comes under observation when an event has affected the trend of a particular series. But the question rises that can these structural breaks can be detected in a series? Answer is yes. These Structural breaks can be exogenously detected if one knows the break date in the series and if doesn't know the break date than it can be endogenously. The structural breaks can be modelled and estimated as well. Here we are undertaking the Gregory Hansen co Integration test. We know that under an Ideal model if variable are integrated of different orders it is bounce test of for integration that is used but what is there is break in any of the series, it means that the bounce test will now yield inconsistent results in that situation Gregory and Hansen

(1996) test that is designed for co integration testing when controlling for the structural breaks in a data. Based on the extensions of the standard ADF, Z Alpha, and Zt Test types, the authors extended the Engle and Granger (1987) approach, which entails testing the null hypothesis of co integration versus an alternative of co integration with a single break in unknown dates.

The Gregory Hansen test hypothesis is as follows:
H_0: No Co integration at the break Point.
H_1: There is Co integration at the break point.

If the absolute value of Zt is greater than the 5% critical value, we reject the null hypothesis, and vice versa. If the null hypothesis is rejected, it suggests that even if there is a structural break, the linear combination of the variables exhibits stable properties in the long term.

GARCH Model

The General Autoregressive conditional heteroscedasticity (GARCH) model is a statistical model that is used to analyse different type of financial data specially that are Marco by nature. The information resulting from GARCH Model is used by various financial institutions to help them determine pricing of various assets and that further leads to help them in judging that which asset will provide them with higher returns. Autoregressive Models works under the assumption that past values of the time series do have an effect on the present and the future values of the time series.

Here, an AR(1) autoregressive process is one in which the current value is determined by the value immediately preceding it, whereas an AR(2) process is one in which the current value is determined by the previous two values, and so on. For white noise, an AR(0) process is utilised, which has no term dependency.

Heteroscedasticity occurs when a given variable's standard variable is tracked over time. The tell-tale characteristic of heteroscedasticity is that residual errors tend to spread out with time. When future periods of high and low volatility cannot be foreseen, conditional heteroscedasticity indicates non-constant volatility. When futures periods of high and low volatility can be determined, unconditional heteroscedasticity is applied.

The main distinction between the GARCH (1, 1) model and the ARCH (1) model may be found in their conditional covariance equations.

ARCH (1) conditional covariance equation:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \mu_{t-1}^2$$

GARCH (1, 1) conditional covariance equation:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \mu_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

Under GARCH (1, 1) model Variance of the error term is also captured at the previous time period. As the GARCH (1, 1) is better than the ARCH (1) model as it better captures volatility clusters in the financial assets. All of this indicates that if volatility was high in the prior time period, the forecast will anticipate a lot more volatility. The ARCH (1) model, on the other hand, does not have that capacity.

As per the variance equation formed from the estimate output following are the variables that are identified:
C = α_0
Resid(-1)^2 = μ_{t-1}^2
GARCH(-1) = σ_{t-1}^2

In order to apply GARCH model to specific time series we first find if there is any ARCH effect or not in the series. If there is an ARCH effect in the time series than only we will apply the GARCH model and reject the Null Hypotheses of there is no ARCH effect.

The presence of the ARCH effect in the time series is determined by the HETEROCEDACITY test after applying the regression equation.

The regression equation used to determine the presence of the ARCH effect is:

$$R_{Country\ i,t} = C + R_{country\ i,t-1} + e$$

Vector Error Correction Model

The vector Autoregressive is a type of model that is generally used for the description of the dynamic interrelationship between the variables that are at their stationary position. So the major thing to check is that the date is stationary or not at first differences or the levels (lag-levels) of the time series. At all the level if the data does not come out as stationary as the vector Autoregressive Model is needed to be reframed.

After all the measure if the given data or the time series comes out to be stationary than for those particular time series Vector Error correlation Model becomes a special model of VAR.

Just like VAR Model, VECM also undertake any co integration relationship among the variables. Vector Error Correction is a model that can be called as a very restricted model of the Vector Auto regression that deals with the series that are non-stationary in nature but are co integrated in nature. Hence it is necessary for one to undertake stationarity tests well as the co integration test in order to identify the number of lags available in the series as well as the number of co integrating equations. The co integrating terms are also hence called as the error correction term because the deviation from long-run equilibrium is progressively addressed by a series of partial short-run adjustments.

The following is an example with two variables, one co-integrating equation, and no lagged difference terms. As a result, the co-integrating equation seems to be:

$$Z_{2,t} = \beta Z_{1,t}$$

The corresponding Vector Error Correction model becomes:

$$\Delta Z_{1,t} = \alpha_1 (Z_{2,t-1} - \beta Z_{1,t-1}) + \epsilon_{1,t}$$
$$\Delta Z_{2,t} = \alpha_2 (Z_{2,t-1} - \beta Z_{1,t-1}) + \epsilon_{2,t}$$

In the above given equations ε is the error term, which is zero in the long run.

The error term will only non-zero only when the terms Z1 and Z2 will deviate from their original values in the long run. And the coefficient alpha measures the rate at which the endogenous variable moves towards equilibrium.

IV. Empirical Analysis And Results

Table 1: Representing the Descriptive statistics for the BRICS nation

	BRAZIL_R	CHINA_R	INDIA_R	RUSSIA_R	SOUTH_AFRICA_R
Mean	2.01E-05	-5.81E-05	-0.000145	-1.58E-05	1.59E-06
Median	-0.000958	-0.001265	-0.001324	-0.000127	0.0001
Maximum	0.140693	0.158851	0.215793	0.67061	0.012815
Minimum	-0.26908	-0.088077	-0.179962	-0.368088	-0.019307
Std. Dev.	0.020482	0.022474	0.021731	0.035826	0.003274
Skewness	-1.043948	0.973981	0.316111	4.206112	-0.425726
Kurtosis	25.62545	7.837243	15.56947	101.4822	5.52081
Jarque-Bera	32395.96	1706.391	9939.047	613037	444.2359
Probability	0	0	0	0	0
Sum	0.030242	-0.08756	-0.218579	-0.023814	0.002398
Sum Sq. Dev.	0.631386	0.760154	0.710744	1.931673	0.016132

Source: authors' calculation.

Note: This table provides a brief description of the data. Maximum standard deviation was found to be highest for the Russia followed by China (within BRICS).

Skewness and Kurtosis measurements reveal that, with the exception of Brazil and South Africa, the sample return series was positively skewed and strongly leptokurtic with respect to the normal distribution. The Jarque–Bera test of sample return series normalcy was rejected with 95% confidence.

(Refer Appendix 1)

Table 2: Representing ADF test statistic for BRICS nation

Country	ADF T-Statistic	5% Critical Value	Probability	Reject H_0 of Time series has unit root
Brazil	-14.63979	-2.863227	0	Yes
Russia	-18.60989	-2.86322	0	Yes
India	-29.76617	-2.863256	0	Yes
China	-13.84187	-2.863228	0	Yes
South Africa	-27.92153	-2.863233	0	Yes

Source: authors' calculation

Note: This table provides the results for unit root test of the BRICS nation with the help of Augmented Dickey Fuller Test. All the values for each nation has come out stationary at level.

(Refer Appendix 2)

Table 3: Gregory Hansen Test for Co integration

Countries	Co integration Models	ADF Test Statistic	Zt*	Critical Values at 5%	Zα*	Critical Values at 5%	Reject H_0 of No Co integration
	Level Shift	-6.26	-6.17	-4.61	-80.7	-40.48	Yes
Brazil and Russia	Level Shift with Trend	-6.67	-6.3	-4.99	-82.4	-47.96	Yes

	Regime Shift	-7.35	-7.23	-4.95	-114	-47.04	Yes
	Level Shift	-5.18	-5.08	-4.61	-50.3	-40.48	Yes
Brazil and India	Level Shift with Trend	-5.6	-5.68	-4.99	-57	-47.96	Yes
	Regime Shift	-5.89	-5.88	-4.95	-67	-47.04	Yes
	Level Shift	-5.7	-5.45	-4.61	-61.8	-40.48	Yes
Brazil and China	Level Shift with Trend	-5.88	-5.62	-5.45	-64.8	-57.28	Yes
	Regime Shift	-6.04	-5.56	-4.95	-64.7	-47.04	Yes
	Level Shift	-4.88	-4.79	-4.61	-45.8	-40.48	Yes
Brazil and South Africa	Level Shift with Trend	-5.42	-5.52	-4.99	-56.5	-47.96	Yes
	Regime Shift	-5.12	-5.1	-4.95	-51.7	-47.04	Yes
	Level Shift	-5.57	-5.53	-4.61	-63.7	-40.48	Yes
China and India	Level Shift with Trend	-6.61	-6.33	-4.99	-81.5	-47.96	Yes
	Regime Shift	-6.85	-6.43	-4.95	-85.2	-47.04	Yes
	Level Shift	-5.57	-6.88	-4.61	-98.2	-40.48	Yes
China and Russia	Level Shift with Trend	-5.8	-7.12	-4.99	-103	-47.96	Yes
	Regime Shift	-6.65	-9.32	-4.95	-184	-47.04	Yes
	Level Shift	-5.72	-5.44	-4.61	-60.9	-40.48	Yes
China and South Africa	Level Shift with Trend	-6.33	-6.07	-4.99	-74.2	-47.96	Yes
	Regime Shift	-5.96	-5.72	-4.95	-66.6	-47.04	Yes
	Level Shift	-5.41	-5.96	-4.61	-68.9	-40.48	Yes
India and Russia	Level Shift with Trend	-5.59	-6.13	-4.99	-72.5	-47.96	Yes
	Regime Shift	-5.44	-5.99	-5.47	-69.7	-57.17	Yes
	Level Shift	-5.34	-5.82	-4.61	-64.8	-40.48	Yes
India and South Africa	Level Shift with Trend	-5.52	-6.07	-4.99	-70.3	-47.96	Yes
	Regime Shift	-5.43	-5.85	-4.95	-65.7	-47.04	Yes
	Level Shift	-5.29	-6.87	-4.61	-91.6	-40.48	Yes
Russia and South Africa	Level Shift with Trend	-5.77	-7.4	-4.99	-104	-47.96	Yes
	Regime Shift	-5.36	-6.94	-4.95	-93.6	-47.04	Yes

Source: authors' calculation

Notes: The critical values are from Gregory and Hansen (1996a).

The results of the Gregory and Hansen (1996a, 1996b) cointegration test are shown in this table. When the time of a single breaks in the intercept and/or slope coefficients is uncertain, this test indicates cointegration. If the crucial value, calculated by altering the Mackinnon (1991) approach, is larger than the associated ADF, Zt, and Za statistics, the null hypothesis of no cointegration with structural breakdowns is rejected. **(Refer Appendix 3)**

Table 4: Heteroscedasticity Test: ARCH –BRICS

Country	Obs*R-squared	RESID^2(-1)	Prob. Chi-Square(1)
Brazil	1.40409	0.03025	0.236
Russia	255.766	0.42101	0
India	1.68159	0.09768	0.1947
China	38.5054	0.45627	0
South Africa	104.082	0.54542	0

Source: authors' calculation.

Note: This table provides the results for the ARCH effect present in the time series in the BRICS nation that is taken into account for this research.

The significance values for prob and Residual values taken into consideration are from Engle (2003). The availability of the ARCH effect noticed from the above data will lead the nations to further application of GARCH model on their time series.

(Refer Appendix 4)

Table 5: GARCH variance equation table for BRICS nation

Country	Variance Equation			
China	C	0.0000402	0.0012	Prob.
	RESID(-1)^2	0.319014	0	
	GARCH(-1)	0.627961	0	
Russia	C	0.000472	0	Prob.
	RESID(-1)^2	0.4171	0	
	GARCH(-1)	0.1446	0.0015	
South Africa	C	0.000000335	0.0238	Prob.
	RESID(-1)^2	0.11039	0	
	GARCH(-1)	0.8646	0	

Source: authors' calculation.

Note: This table provides the results for the GARCH effect for the nations in the BRICS group that have ARCH effect in them. In the GARCH effect the probability values of Residual and GARCH are examined at 5 percent significance level. The Significance values are taken from Engle (2003).

Following is the variation equations formed from the above table 5:
China:

$$\sigma_t^2 = 0.000004 + 0.319014\mu_{t-1}^2 + 0.627961\sigma_{t-1}^2$$

As the constant variance term, this time changing variation has 0.000004, 0.627961 being the GARCH term and 0.319014 being the ARCH term. Those terms are positive. With P – Value as 0 both ARCH and GARCH are highly significant. The sum of the ARCH and GARCH coefficients which is 0.319014 plus 0.627961 is close to 1 which means the shocks to the conditional variance will be persistence.

Russia:

$$\sigma_t^2 = 0.00004 + 0.4171\mu_{t-1}^2 + 0.1446\sigma_{t-1}^2$$

This time variable variation comprises 0.00004 as the term of continuous change, 0.1446 as the term of GARCH and 0.4171 as the term of ARCH. These words which have been listed are optimistic. With P – Price as 0.0015 both ARCH and GARCH are extremely important. The sum of the ARCH and GARCH coefficients which is 0.4171 + 0.446 is similar to 1 and implies the shocks of conditional variance would be continuity.

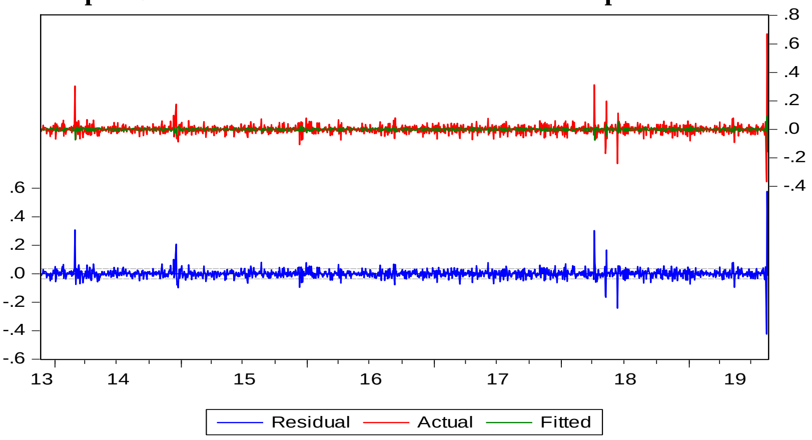
South-Africa:

$$\sigma_t^2 = 0.00000003 + 0.11039\mu_{t-1}^2 + 0.8646\sigma_{t-1}^2$$

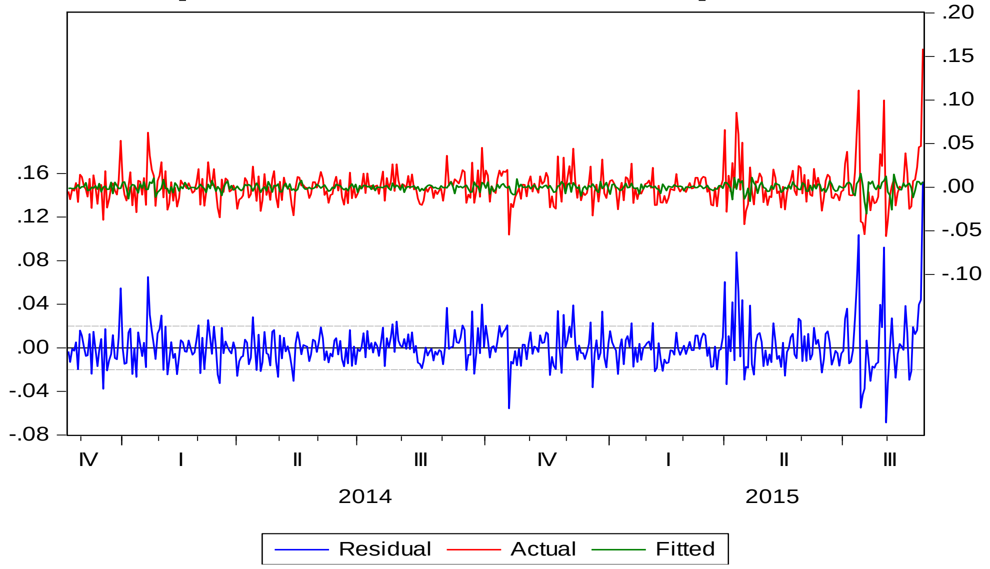
This time-varying volatility involves 0.00004 as the term of constant variation, 0.8646 is the term GARCH and 0.11039 is the term ARCH. These words which have been listed are optimistic. With P – Value as 0.0 both ARCH and GARCH are highly important. The sum of the ARCH and GARCH coefficients which is 0.8646 plus 0.11039 is similar to 1 which means persistence would be the shocks of conditional variance.

Since the GARCH term is important for all GARCH model nations, it implies that a large excess return value is generated which will result in a high future variance forecast for an extended period of time. It also means that, in the time of high uncertainty, the GARCH model would definitely be the better predictive model than the arch model.

Graph 1: Actual Fitted Residual GARCH Graph for Russia



Graph 2: Actual Fitted Residual GARCH Graph for China



Graph3: Actual Fitted Residual GARCH Graph for South Africa

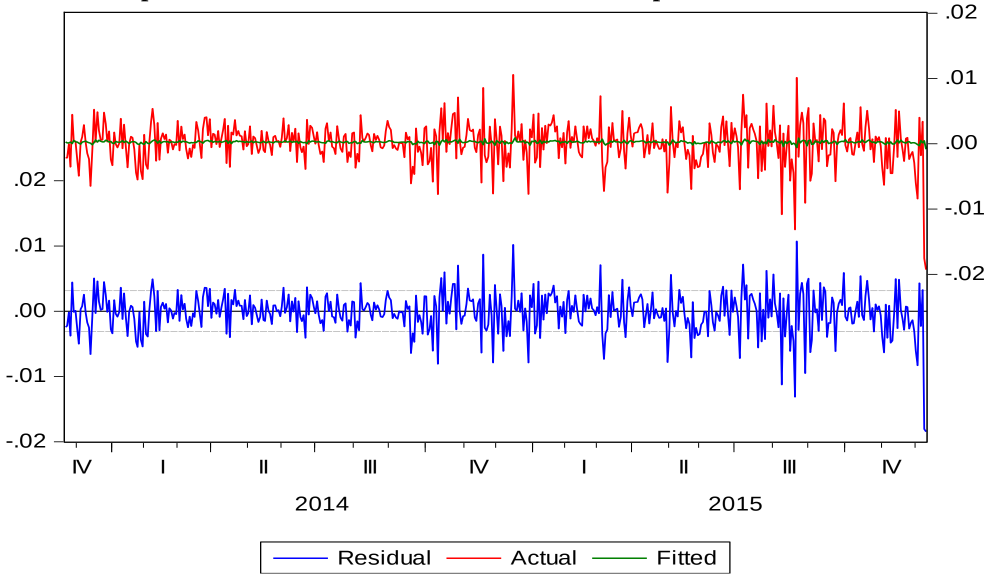


Table 6: Co integrating Equation table for BRICS Nation

Country	Co integrating Eq:	CointEq1	Country	Co integrating Eq:	CointEq1
	BRAZIL_R(-1)	1		CHINA_R(-1)	1
	RUSSIA_R(-1)	-2.01522		RUSSIA_R(-1)	-1.3442
Brazil and Russia		(-0.0977)	**China and Russia**		-0.068
		[-20.6271]			[-19.7559]
	C	-0.0000204		C	0.0000567
	BRAZIL_R(-1)	1		CHINA_R(-1)	1
Brazil and India	INDIA_R(-1)	2.089297	**China and South Africa**	SOUTH_AFRICA_R(-1)	4.19854
		(-0.07516)			-0.3377
		[27.7966]			[12.4336]
	C	0.000367		C	0.0000534
	BRAZIL_R(-1)	1		INDIA_R(-1)	1
Brazil and China	CHINA_R(-1)	-4.1358	**India and Russia**	RUSSIA_R(-1)	-3.017

		-0.1323			-0.1237
		[-31.2623]			[-24.3961]
	C	-0.0004		C	0.00016
	BRAZIL_R(-1)	1		INDIA_R(-1)	1
Brazil and South Africa	SOUTH_AFRICA_R(-1)	3.160349	**India and South Africa**	SOUTH_AFRICA_R(-1)	-0.5016
		-0.35973			-0.2198
		[8.78524]			[-2.28248]
	C	0.0000238		C	0.00019
	CHINA_R(-1)	1		RUSSIA_R(-1)	1
China and India	INDIA_R(-1)	-13.299	**Russia and South Africa**	SOUTH_AFRICA_R(-1)	0.11163
		-0.4485			-0.3144
		[-29.6530]			[0.35502]
	C	-0.0024		C	0.0000337

Source: authors' calculation

Note: This table provides co integrating equations resulting from Vector error correction Models.

Following are the co integrating equations formed for each pair of countries:

China and South Africa

$$ECT_{t-1} = 1.0000China\_R_{t-1} + 4.198SOUTH\_AFRCICA\_R_{t-1} - 0.00000534$$

Estimated VECM with China VIX as the target variable:

$$\Delta China\_R_t = -0.994ECT_{t-1} - 0.058\Delta China\_R_{t-1} - 0.0147\Delta China\_R_{t-2} - 0.00687\Delta China\_R_{t-3} - 0.0138\Delta China\_R_{t-4} + 3.63\Delta SOUTH\_AFRICA\_R_{t-1} + 3.382\Delta SOUTH\_AFRICA\_R_{t-2} + 2.69\Delta SOUTH\_AFRICA\_R_{t-3} + 1.533\Delta SOUTH\_AFRICA\_R_{t-4} + 0.000000458$$

Estimated VECM with South Africa VIX as the target variable:

$$\Delta SOUTH\_AFRICA\_R_t = -0.0834ECT_{t-1} + 0.061\Delta China\_R_{t-1} + 0.0493\Delta China\_R_{t-2} + 0.0361\Delta China\_R_{t-3} + 0.01755\Delta China\_R_{t-4} - 0.4660\Delta SOUTH\_AFRICA\_R_{t-1} - 0.378\Delta SOUTH\_AFRICA\_R_{t-2} - 0.253\Delta SOUTH\_AFRICA\_R_{t-3} - 0.152\Delta SOUTH\_AFRICA\_R_{t-4} + 0.000000415$$

The long-term equilibrium variations from the previous year was adjusted at an adjustment level of 99.43 per cent in the current year. A percentage increase in South Africa VIX is correlated with a decline in China VIX by 0.337 per cent, with other factors remaining stable in the short term.

India and South Africa

$$ECT_{t-1} = 1.0000India\_R_{t-1} - 0.5016SOUTH\_AFRICA_{t-1} - 0.00019$$

Estimated VECM with India VIX as the target variable:

$$\Delta India\_R_t = -1.07181ECT_{t-1} + 0.08652\Delta India\_R_{t-1} - 0.32601\Delta SOUTH\_AFRICA\_R_{t-1} + 0.00000127$$

Estimated VECM with South Africa VIX as the target variable:

$$\Delta SOUTH\_AFRICA\_R_t = 0.008639ECT_{t-1} - 0.00631\Delta India\_R_{t-1} - 0.4539\Delta SOUTH\_AFRICA\_R_{t-1} + 0.0000000137$$

The long-term equilibrium deviations from the previous year are corrected at an adjustment speed of 107.18 per cent in the current period. South Africa VIX is associated with a decrease of 0.219 per cent in India VIX, with other things being constant in the short run.

Russia and South Africa

$$ECT_{t-1} = 1.0000Russia\_R_{t-1} + 0.11163SOUTH\_AFRICA_{t-1} + 0.00000337$$

Estimated VECM with Russia VIX as the target variable:

$$\Delta Russia\_R_t = -1.6727ECT_{t-1} + 0.393\Delta Russia\_R_{t-1} + 0.170\Delta Russia\_R_{t-2} + 0.076\Delta Russia\_R_{t-3} + 0.3146\Delta SOUTH\_AFRICA\_R_{t-1} + 0.094\Delta SOUTH\_AFRICA\_R_{t-2} - 0.204\Delta SOUTH\_AFRICA\_R_{t-3} + 0.00000118$$

Estimated VECM with South Africa VIX as the target variable:

$$\Delta SOUTH\_AFRICA\_R_t = 0.010202ECT_{t-1} - 0.007\Delta Russia\_R_{t-1} - 0.0055\Delta Russia\_R_{t-2} - 0.0040\Delta Russia\_R_{t-3} - 0.6918\Delta SOUTH\_AFRICA\_R_{t-1} - 0.483\Delta SOUTH\_AFRICA\_R_{t-2} - 0.243\Delta SOUTH\_AFRICA\_R_{t-3} + 0.000000358$$

The previous year's deviations from long run equilibrium are rectified at a rate of 167.27 percent in the current period. In the near term, a percentage change in South Africa VIX is related with a 0.314 percent reduction in Russia VIX, with all other variables being constant.

V. Findings and Conclusion

Under BRICS the time series for every country is constant at point. Their mean, deviation, self-correlation etc. are also all stable over time. Volatility on the stock exchange requires all of the related details accessible.

All the ten pairs of nations established under the Gregory Hansen Co integration test have dismissed the null hypothesis of no co-integration, thereby showing that the component tracks a shared average value over the long term. The definition can also be used for purposes of hedging.

The period series BRAZIL and INDIA did not reach the amount of unknown variables or residual factors resulting in the absence of ARCH impact in both series rendering GRACH an ineffective model for their study. Cantered on the subsequent GARCH sense meanings, past VIX time series data is extremely useful in forecasting potential developments for RUSSIA, CHINA and SOUTH – AFRICA. Hence we may also assume that the impact of today's shocks should stay in the prediction for several cycles with potential variances.

The findings also reveal that the magnitude of shocks of uncertainty, as measured by the sum of ARCH and GARCH, is high (near to 1). Results signify that the impact of today's shocks will in the future continue in the variance projection for long times. The information linkages were made clear through the BRICS nation's VECM pairing.

Just South Africa VIX took the lead of all the study indices pairs when combined with each of the other VIX indices to address the short-term divergence from the long-term equilibrium partnership with the other Member States.

As a result, similar conclusions may be expected from South Africa VIX, given that South Africa is the newest member of the BRICS club, with a smaller population, scale, and economy than other states.

VI. Conclusion

Since its inception, the VIX has acquired popularity among customers, investment managers, and regulators alike, since it is seen as valuable in making informed / sensible judgments regarding future volatility in the financial markets. This study explores the link of implied VIX across BRICS member nations' capital markets, which will be valuable in creating a decent volatility forecast for market players.

The Gregory Hansen test, which incorporates endogenous structural breaks, was used to the VIX price information to determine the presence of any long-run equilibrium linkages between the various BRICS VIX sequences. The existence of a long-run equilibrium relationship between the sample series allowed the VECM model to be used to analyse the short-run equilibrium adjustment course and the Granger causality test to confirm the causality route. Because implied volatility is a more forward-looking indicator of uncertainty, dependence details may help to arrive at a clearer estimate of the underlying stock indices. Investors may use the details on an estimation of expected volatility to develop their plans for risk-hedging. Understanding such interconnections between forward-looking volatility indexes would be extremely beneficial to volatility traders seeking arbitrage advantages in certain markets.

Term performance levels of underlying stock indexes will also have a significant impact on potential share values and, as a result, risk market pricing, which is an important input for fund managers and corporates.

It will contribute to the calculation of equity costs for companies in such specific markets. The interconnectivity of forward-looking volatility indicators may provide critical insight for policymakers considering the efficacy of their monetary-policy initiatives and researching the effects of contagion. Indeed, policymakers would want to investigate the relationships between the forward-looking volatility indicator and their underlying stock benchmarks in order to better understand the instability of asset markets, which is a major worry for global financial stability. Because implied VIX is regarded as a forward indicator of institutional investors' sentiment, and given their dominance in the foreign derivatives markets, an examination of their interconnections will enable such investors to realign their aspirations and change their portfolio to reap the same diversification benefits. The examination of BRICS nations' conditional correlation in VIX will also help hedge fund managers who regard BRICS as a homogenous group obtain risk-adjusted profits by searching for correlations within BRICS member countries' pairings to increase their alpha returns.

The study has crucial implications for academics since it examines in depth the interconnections between VIX for BRICS member nations, which are expected to be future drivers of economic development and wealth.

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