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Long Run Relationships and Causality among Stock Markets of BRICS Nations: An Econometric Analysis in the Backdrop of Covid-19 Global Financial Crisis

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Abstract

The paper investigates into the long-run cointegrating relationships and causality among stock markets of BRICS nations in the backdrop of Covid-19 global crisis considering study period from October 24, 2019 to October 23, 2020 as full sample period. With a view to investigating into the long-run relationships and causality among the stock markets of BRICS nations, stock indices like IBOVESPA (Brazil), MOEX (Russia), SENSEX (India), SSECI (China) and JTOPI (South Africa) are selected based on judgmental sampling technique. The daily data on select indices have been collected from available data of website: *www.investing.com* and transformed into their natural logarithmic form to control skewness. Datasets of select indices have been made consistent through data mining. Stationarity of the data series for the sample period is estimated using Augmented Dickey Fuller (ADF) test. Long-run cointegrating relationships among stock markets are examined using Johansen cointegration based on order of integration of the data series. Short-run causality among them is also explored using Block Exogeneity test with an underlying VAR model. The study evidenced that Indian market has bi-directional causality with Russian market, while the Indian market has unidirectional causality with Brazilian market. On the other side, Indian market causes the movement of South African and Chinese market during the study period.During the first wave of Covid-19, the economic vulnerabilities in each country in BRICS resonate to the others through the channels of economic integration. The study is an attempt to find out whether their economic interconnectedness has been spilled over to their stock market relationships too along with their potential causes.
Keywords: BRICS; Block Exogeneity test; Covid-19; Johansen Cointegration.

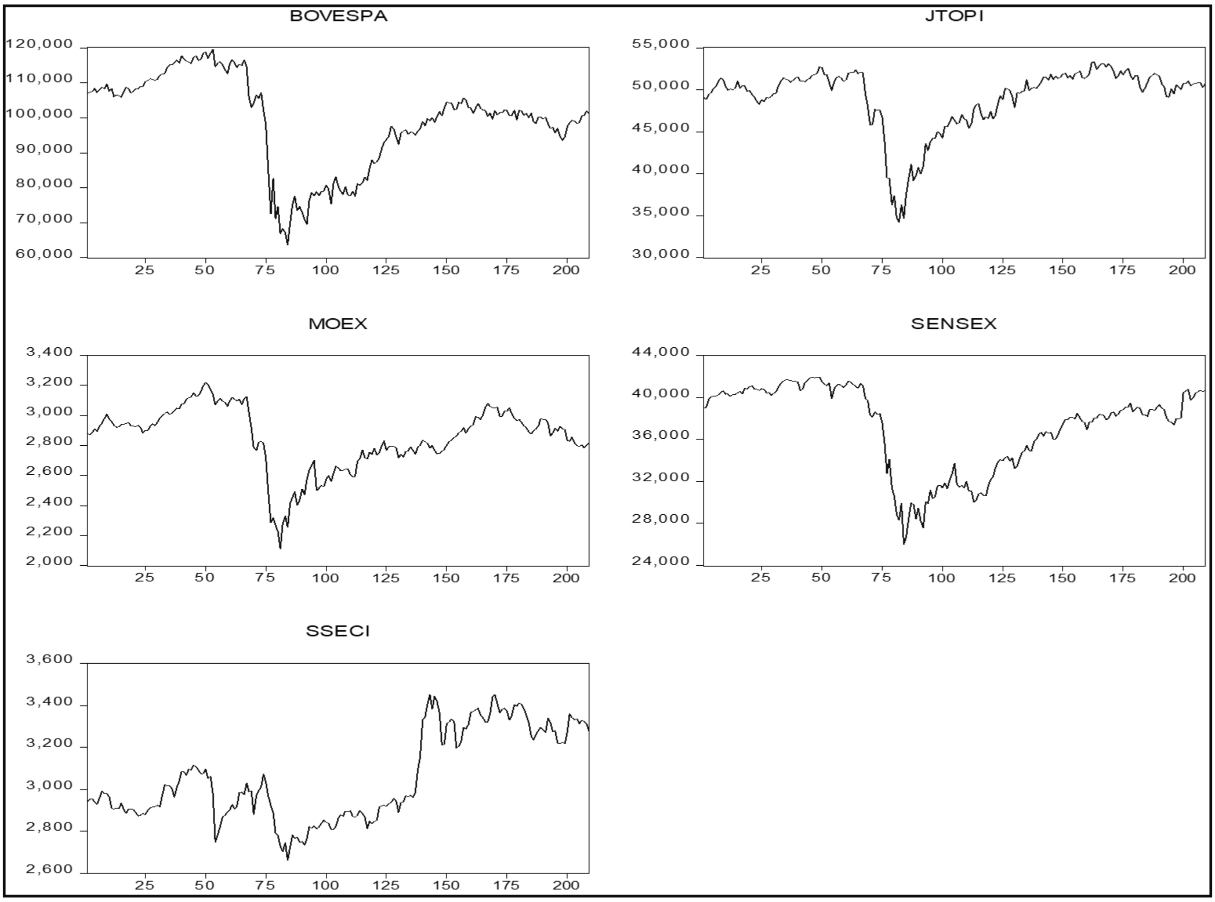
1. Introduction

China's attempt to conceal the outbreak followed by an extraordinary mobilization of resources may have contained their financial turmoil to some extent. However, when the outbreak transcended beyond Chinese borders, other members of the BRICS, either denied its presence for a long time and when they did, they may have used it to consolidate their political image. Barring China, efforts to restore the economic balance by other members of BRICS were not adequate. In Brazil and Russia, they were initiated as a response to public protest, while in South Africa; a high level of corruption crippled the supply chain network. India too may have failed to address the issue of health care and migrant workers with a practical approach (Nilson & Holdt, 2020). Naturally, impact of Covid-19 on financial markets was ignored for a long time. When the stock markets in the European Union (EU) or the United States (US) started to face the hit of Covid-19, the volatility in those markets spilled over to the BRICS nations (Ngwakwe, 2020). Data reveals that from February, 2020, the stock markets of all the BRICS countries started showing signs of recessions

(Figure 1), when number of cases and deaths from Covid-19, as compared to the EU or the US were insignificant. However, in June, 2020, when number of cases and deaths tripled and had drawn world's attention, markets started to correct itself probably due to Governments' initiative to contain the spread, declarations about economic stimulus and possibility of a vaccine. While BRICS countries are economically interconnected, question arises as to whether their stock markets are integrated too, and how Covid-19 global crisis have impacted their causal relationship. Addressing this, the present research may aid policy decisions in order to prevent the financial contagion in Indian market that may have flown from other BRICS nations and assist investors in diversifying their portfolio among BRICS markets.

A few studies have been reviewed in this context. Pradhan, et al. (2015) investigated into the cointegration and causal relationship among economic growth, inflation and stock market based on a study of 34 Organizations for Economic Cooperation and Development (OECD) countries using panel vector auto-regression (VAR) model for 1960-2012. Singh and Singh (2016) captured the long-run and short-run causal relationship between the US and BRICS equity market during pre-global financial crisis, crisis and post-crisis periods employing Johansen Cointegration, VAR, vector error correction model (VECM), Granger causality, generalised impulse response, variance decomposition, and spill-over index approach (Diebold & Yilmaz, 2015) during the period 2004-2014. Jin and An (2016) analysed the contagion effect between BRICS and the US markets using volatility impulse response framework (VIRF) in the backdrop of 2007-2009 financial crisis.

Figure 1: Stock Market Performance of BRICS Countries



Source: Compilation of secondary data using Eviews 9

Raza, et al. (2016) examined the long-run and short-run asymmetric impact of associated volatilities of gold and oil prices on stock markets using monthly data from January 2008 to June 2015 based on auto-regressive distributed lag (ARDL) model. Bekiros, et al. (2017) analysed interactions of gold price with stock market movements in BRICS economies using multi-scale wavelet approach and a Generalised Autoregressive Conditional Heteroscedasticity (GARCH) based copula methodology. Sui and Sun (2017) examined the dynamic relationship among the stock returns of BRICS markets, foreign exchange rates (under a managed floating rate regime), interest rate differential and Standard & Poor's (S&P's) 500 index. Bouri, et al. (2017) used implied volatility indices to study cointegration and non-linear causality among international gold and oil prices and Indian stock markets. Baker, et al. (2020) studied the stock market movements since 1900 with special emphasis on stock market volatility since 1985 and concluded that none of previous infectious diseases including the Spanish flue had this unprecedented impact on the stock market like Covid-19 does. Liu, et al. (2020) evaluated short term impact of Covid-19 on stock market sentiments in Japan, Korea, Singapore, the USA, Germany, and Italy and the UK using event study and panel fixed effect regressions. Helidoro, et al. (2020) analysed financial contagion in six US and Latin American markets during the period 2015-20 using Autocorrelation test, and BDS test.

While the literature reviewed present a comprehensive outlook on BRICS market and possible impact of Covid-19 on the stock markets of developing nations, cointegrating relationship and causality among the BRICS markets in the backdrop of Covid-19 has not been studied in literature reviewed so far. Keeping this gap in view, the study is made to fulfil the following objective.

2. Objectives of the Study

The major objective of the study is to estimate the long-run relationship and causality among stock markets of BRICS nations.

3. Data and Methodology

In order to analyse the long-run relationship and causality among the stock markets of Brazil, Russia, India, China and South Africa (BRICS), the largest stock exchanges in those five countries are identified based on their market capitalization [World Federation of Exchanges (WFE), 2019]. They are: (a) B3: Brazil Stock Exchange and Over the Counter Market (Brazil); (b) Moscow Exchange (Russia); (c) Bombay Stock Exchange Ltd. (BSE) (India); (d) Shanghai Stock Exchange (SSE) (China); and (e) Johannesburg Stock Exchange Ltd. (JSE) (South Africa). In all those exchanges, the most prominent index in each stock exchange that often works as a barometer of the economic movement is selected for the purpose of the current study. Accordingly, (a) IBOVESPA (BOVESPA) (Brazil); (b) MOEX (Russia); (c) Sensitivity Index (SENSEX) (India); (d) SSE Composite Index (SSECI) (China); and (e) JTOPI (South Africa) are selected. In order to capture the effect of Covid-19 global crisis stock market performance in those countries, a one-year window from October 24, 2019 to October 23, 2020 is selected and the data on the adjusted closing price of the aforesaid indices during the period is collected from www.investing.com. An appropriate data mining is made to remove the inconsistency in the dataset arising out of different operating days in different stock exchanges. Finally, 209 observations remain that conform to same dates of operation under different stock exchanges. The data (209 obs.) is converted into their natural logarithmic form to reduce skewness in the data. Further analyses are done with these logs transformed data (LNBOVESPA; LNJTOPI, LNMOEX, LNSENSEX; and LNSSECI).

The basic nature of the data in terms of their central tendency, volatility, skewness, kurtosis and normality is captured with the help of descriptive statistics. The correlation among the log-transformed values of the stock indices during the full sample period and 3 sub-sample periods is calculated using Pearson's Correlation Coefficient (r) = Cov (x, y)/ $\sigma_x \sigma_y$ (where X and Y are the log-transformed values of a pair of stock indices). Significance of 'r' is measured based on the following hypothesis: H_0: r=0; against H_1 = r$\neq$0. At n-2 df and 5 per cent level of significance, if the Prob. of t-statistic is less than 0.05, H_0 cannot be accepted and vice versa. Finally, stationarity of the data is measured with the help of Augmented Dickey Fuller (ADF) test which is an extension of DF test.

If all the log-transformed data series are non-stationary and integrated of same order, long-run relationship among them is estimated using Johansen Cointegration technique. If the stock indices are not cointegrated, short-run causality among them can be estimated using unrestricted VAR model.

4. Results and Analysis

4.1. *Descriptive Statistics*

Central tendency of the data is measured with the help of mean $[\frac{1}{n}\sum_{t=1}^{n} Y_t]$ (where Y is the log-transformed value of a stock index, and n is the number of observations) and median (mid-value of a distribution). During the period under consideration (Table 1), LNBOVESPA projects the highest central tendency (mean and median) among its peers in the BRICS, while LNMOEX has lowest central tendency figures. It goes on to prove that Brazilian stock market projected a better stock market performance as compared to that of other members of the BRICS.

Volatility in the dataset is measured with the help of maximum and minimum value in a dataset; Standard Deviation (SD) $[\sqrt{\frac{1}{n-1}\sum_{t=1}^{n}(Y_t - \bar{Y}_t)^2}]$ (where $\bar{Y}_t$is the mean); and Sum of Squared Deviation (SS) $[\sum_{t=1}^{n}(Y_t - \bar{Y}_t)^2]$. In terms of maximum and minimum values and SD and sum of squared deviation, LNBOVESPA projects highest volatility as compared to LNSSECI, which is least volatile during the period.

Table 1: Descriptive Statistics

Parameters	LNBOVESPA	LNJTOPI	LNMOEX	LNSENSEX	LNSSECI
Mean	11.49273	10.79722	7.951883	10.51711	8.021810
Median	11.52527	10.82616	7.968593	10.55491	7.998513
Maximum	11.69130	10.88465	8.077112	10.64430	8.146445
Minimum	11.05989	10.44113	7.655694	10.16513	7.886145
Std. Dev.	0.143889	0.085941	0.076625	0.114513	0.069064
Skewness	-0.934550	-2.166172	-1.191326	-0.984169	0.311295
Kurtosis	3.076511	7.700529	4.639081	2.883859	1.753234
Jarque-Bera	30.47387	355.8589	72.83312	33.85665	16.91197
Probability	0.000000	0.000000	0.000000	0.000000	0.000213
Sum	2401.981	2256.620	1661.944	2198.077	1676.558
Sum Sq. Dev.	4.306435	1.536243	1.221259	2.727567	0.992122

Source: Compilation of secondary data using Eviews 9

Skewness is the degree of distortion from symmetrical normal distribution. It indicates whether the data is symmetrical (skewness between -0.5 to 0.5); positively skewed (skewness>0.5, highly positively skewed, if skewness>1) and negatively skewed (skewness<-0.5, highly negatively skewed if skewness<-1). The distribution for LNBOVESPA and LNSENSEX are negatively skewed (<-0.5) during the period, LNJTOPI and LNMOEX are highly negatively skewed (<-1) during the period. On the other hand, LNSSECI is normally distributed.

Kurtosis measures the presence of outliers in the dataset. A data may be Mesokurtic (normal) (Kurtosis=3); Platykurtic (low on outliers) (Kurtosis<3); and Leptokurtic (high on outliers) (Kurtosis>3). From the kurtosis values, it is observed that LNSENSEX and LNSSECI are Platykurtic (<3) (low on outliers), while others are leptokurtic (>3) (high on outliers).

Normality of the dataset can be measured with the help of Jarque-Bera (JB) test based on the following hypothesis: Null hypothesis (H_0): JB statistic = 0; against alternate hypothesis (H_1): JB statistic ≠ 0. The JB statistic is (n-k+1)/6 x $[S^2 + \frac{1}{4}(C-3)^2]$, where n=number of observations; k = number of regressors (1 in case of single data); S = sample skewness; C = sample kurtosis. At 'n' degree of freedom (df) and 5 per cent level of significance, if the probability (Prob.) of obtaining the calculated value of JB statistic in Chi-square distribution table is less than 0.05, H_0cannot be accepted and vice versa. Results of JB test suggests that none of the indices are normally distributed during the full sample period.

4.2. *Correlation among the Stock Indices*

It is evident from Table 2 that all the stock indices have significant (Prob.<0.01) positive correlation (r>0) among themselves. SENSEX has high correlation (r>0.5) with BOVESPA, MOEX and JTOPI. However, it has comparatively low positive correlation with SSECI.

Table 2: Pearson's Correlation Coefficient and Results of t-test

Indices	LNBOVESPA	LNJTOPI	LNMOEX	LNSENSEX
LNJTOPI (r)	0.828290			
Prob.	0.0000			
LNMOEX (r)	0.909474	0.890997		
Prob.	0.0000	0.0000		
LNSENSEX (r)	0.948459	0.786378	0.857356	
Prob.	0.0000	0.0000	0.0000	
LNSSECI (r)	0.397221	0.642256	0.451154	0.471276
Prob.	0.0000	0.0000	0.0000	0.0000

Source: Compilation of secondary data using Eviews 9

4.3. *Stationarity of the Data Series*

A time series (Y_t) representing log-transformed value of a stock index depends upon its lagged value is represented as: $\Delta Y_t = \delta Y_{t-1} + u_t$Where, $\delta = \rho - 1$ where, ρ is the autocorrelation between Y_t and Y_{t-1}. Stationarity of the series is tested based on the following hypothesis: H_0: $\delta = 0$ against H_1:$\delta \neq 0$. The test statistic under DF test is $\frac{\hat{\delta}}{SE(\hat{\delta})}$ which is compared with its critical value to take decision about H_0 **(McKinnon, 1991)**. In case of ADF test, the DF regressions are augmented by including 'm' lags of the Dependent Variable (DV) to correct serial correlation in the disturbance term (u_t). Where m= Int. $12*(T/100)^{1/4}$. In the present study, all the log-transformed data series are tested for RW with drift ($\Delta Y_t = \alpha + \delta Y_t + \sum_{i=1}^{m} Y_i \, \Delta Y_{t-1} + \mu_t$) and RW for trend and drift $\Delta Y_t = \alpha + \beta t + \delta Y_t + \sum_{i=1}^{m} Y_i \, \Delta Y_{t-1} + \mu_t$. Appropriate lag length is selected based on Schwarz Bayesian Criterion (SBC). If H_0 in both these models are accepted, the series is a non-stationary series and vice versa **(Enders, 2004)**. If a log-transformed series is stationary at level, it is integrated of order 0 [I(0)], and if a series is non-stationary at level and stationary at first difference, it is integrated of order 1 [I(1)].

Results of the ADF tests (Table 3) with 'intercept' and 'trend and intercept' suggest that all the indices are non-stationary at level and stationary at first difference. They all are I(1) series.

Table 3: Results of ADF Test

Index	Level			First Difference			Nature of the Data Series at Level
	Prob. (Intercept)	Prob. (Trend and Intercept)	Nature of the Data Series	Prob. (Intercept)	Prob. (Trend and Intercept)	Nature of the Data Series	
LNBOVESPA	0.4939	0.8271	Non-Stationary	0.0000***	0.0000***	Stationary	I(1)
LNJTOPI	0.4379	0.7271	Non-Stationary	0.0000***	0.0000***	Stationary	I(1)
LNMOEX	0.4395	0.7562	Non-Stationary	0.0000***	0.0000***	Stationary	I(1)
LNSENSEX	0.6218	0.9087	Non-Stationary	0.0000***	0.0000***	Stationary	I(1)
LNSSECI	0.6337	0.5618	Non-Stationary	0.0000***	0.0000***	Stationary	I(1)

*significant at 10% level of significance
**significant at 5% level of significance
***significant at 1% level of significance

Source: Compilation of secondary data using Eviews 9

4.4. Long-Run Relationship among Stock Markets

Since all the data series are I(1) at level (Table 4), long run relationship among the stock markets can be estimated using (a) Trace test and (b) Max-Eigen value test under Johansen technique (Johansen, 1988). Appropriate lag length is determined based on Akaike Information Criterion (AIC), SBC, and Hannan-Quinn Criterion (HQC) technique is 1. Hence, with the assumption of linear deterministic trend The test statistic for trace can be specified as $\lambda_{Trace} = -T \sum_{i=r+1}^{n} Ln(\lambda - 1)$. Where λ_i is the ith largest value of cointegrating matrix Π and T is the number of observations. It tests the following hypothesis. H_0: $r = r_1 < k$ [where r is number of distinct cointegrating vector(s)], against H_1: $r=k$. The test statistics under Max-Eigen value test can be specified as $\lambda_{Max} = -T \ln(1-\lambda_{r+1})$ (where λ_{Max} is the (r+1)th largest squared Eigen value. The hypothesis for the test are: H_0: $r = r_1 < k$ against H_1: $r = r_1 + 1$. The number of cointegrating relationship among the variables depends on number of hypothesised CEs for which the results of trace and max-Eigen values are significant (Prob.<0.05 and H_0 cannot be accepted).

Table 4: Results of Johansen Cointegration Test

No. of Hypothesised CE(s)	**Eigen Value**	**Trace Test**			**Max Eigen Value Test**		
		Statistic	**Prob.**	**Decision on H_0**	**Statistic**	**Prob.**	**Decision on H_0**
None	0.112591	58.51198	0.2839	Accepted	24.72597	0.4038	Accepted
At most 1	0.064613	33.78601	0.5136	Accepted	13.82652	0.8344	Accepted
At most 2	0.058867	19.95949	0.4256	Accepted	12.55897	0.4935	Accepted
At most 3	0.025241	7.400520	0.5315	Accepted	5.291983	0.7046	Accepted
At most 4	0.010134	2.108538	0.1465	Accepted	2.108538	0.1465	Accepted

Source: Compilation of secondary data using Eviews 9

Since there are five stock indices, there will be four cointegrating relationships (vectors) among the variables. Eigen values from none to at most 4 CEs have been computed. Since the probability (Prob.) of trace statistic and max-Eigen value statistic is greater than 0.05 for all hypothesised CEs, the H_0 cannot be accepted. Hence, there are no cointegrating long-run relationships among the stock indices during the full sample period.

4.5. Short-Run Causality among Stock Markets

Since the stock markets are not cointegrated in the long run, short-run relationship among them can be estimated using unrestricted VAR model (Eqn. 1 to 5). The data is transformed into stationary by taking their first difference. The differenced log transformed stock indices data is nothing but the stock market returns of the BRICS nations.

$\Rightarrow$ $\Delta LNBOVESPA_t = a_0 + \sum_{j=1}^{p} a_{1p}\, \Delta LNBOVESPA_{t-j} + \sum_{j=1}^{p} a_{2p}\, \Delta LNJTOPI_{t-j} + \sum_{j=1}^{p} a_{3p}\, \Delta LNMOEX_{t-j} + \sum_{j=1}^{p} a_{4p}\, \Delta LNSENSEX_{t-j} + \sum_{j=1}^{p} a_{5p}\, \Delta LNSSECI_{t-j} + \mu_t$....(1)

$\Rightarrow$ $\Delta LNJTOPI_t = b_0 + \sum_{j=1}^{p} b_{1p}\, \Delta LNBOVESPA_{t-j} + \sum_{j=1p}^{p} b_2\, \Delta LNJTOPI_{t-j} + \sum_{j=1}^{p} b_{3p}\, \Delta LNMOEX_{t-j} + \sum_{j=1}^{p} b_{4p}\, \Delta LNSENSEX_{t-j} + \sum_{j=1}^{p} b_{5p}\, \Delta LNSSECI_{t-j} + \mu_t$....(2)

$\Rightarrow$ $\Delta LNMOEX_t = c_0 + \sum_{j=1}^{p} c_{1p}\, \Delta LNBOVESPA_{t-j} + \sum_{j=1}^{p} c_{2p}\, \Delta LNJTOPI_{t-j} + \sum_{j=1}^{p} c_{3p}\, \Delta LNMOEX_{t-j} + \sum_{j=1}^{p} c_{4p}\, \Delta LNSENSEX_{t-j} + \sum_{j=1}^{p} c_{5p}\, \Delta LNSSECI_{t-j} + \mu_t$....(3)

$\Rightarrow$ $\Delta LNSENSEX_t = d_0 + \sum_{j=1}^{p} d_{1p}\, \Delta LNBOVESPA_{t-j} + \sum_{j=1}^{p} d_{2p}\, \Delta LNJTOPI_{t-j} + \sum_{j=1}^{p} d_{3p}\, \Delta LNMOEX_{t-j} + \sum_{j=1}^{p} d_{4p}\, \Delta LNSENSEX_{t-j} + \sum_{j=1}^{p} d_5\, \Delta LNSSECI_{t-j} + \mu_t$....(4)

$\Rightarrow$ $\Delta LNSSECI_t = e_0 + \sum_{j=1}^{p} e_{1p}\, \Delta LNBOVESPA_{t-j} + \sum_{j=1}^{p} e_{2p}\, \Delta LNJTOPI_{t-j} + \sum_{j=1}^{p} e_{3p}\, \Delta LNMOEX_{t-j} + \sum_{j=1}^{p} e_{p4}\, \Delta LNSENSEX_{t-j} + \sum_{j=1}^{p} e_{5p}\, \Delta LNSSECI_{t-j} + \mu_t$....(5)

The short-run causality among the stock indices is estimated using Granger causality in VAR (Wald test) with the following hypothesis. H_0: $R_\alpha=0$; against H_1: $R_\alpha \neq 0$ (where α is the vector of all VAR coefficients and R is suitably chosen non-causality restriction matrix having full row rank. The Wald statistic is $T\hat{\alpha}R'(R\widehat{\sum_{\hat{\alpha}} R'})^{-1}$where T=sample size; $\hat{\alpha}$ is the asymptotically normally distributed estimator of α; $\sum_{\hat{\alpha}} R$ is the covariance matrix of the asymptotic distribution and $\widehat{\sum_{\hat{\alpha}} R'}$is its estimator (Toda & Phillips, 1991). Wald statistic for testing Granger causality follows χ^2(p-1) distribution. At 5 per cent level of significance, if prob.<0.05, H_0 cannot be accepted and vice versa. If H_0 of non-causality cannot be accepted, causal relationship exists among two variables. For each equation in the model, causal effects of exogenous stock indices individually and together on the endogenous stock index are measured separately.

Table 5: Results of VAR Granger Causality Test

Dependent Variable	Independent Variables	Chi-Square	Prob.	Decision Rule	Decision on H_0	Results
DLNBOVESPA	**DLNJTOPI**	0.086281	0.7690	Prob.>0.05	Accepted	DLNJTOPI ↛ DLNBOVESPA
	DLNMOEX	4.626987	0.0315	Prob.<0.05	Rejected	**DLNMOEX→ DLNBOVESPA**
	DLNSENSEX	2.648115	0.1037	Prob.>0.05	Accepted	DLNSENSEX ↛ DLNBOVESPA
	DLNSSECI	0.564100	0.4526	Prob.>0.05	Accepted	DLNSSECI↛ DLNBOVESPA
	All	8.558899	0.0731	Prob.>0.05	Accepted	All↛ DLNBOVESPA
DLNJTOPI	**DLNBOVESPA**	0.726909	0.3939	Prob.>0.05	Accepted	DLNBOVESPA↛ DLNJTOPI
	DLNMOEX	27.62238	0.0000	Prob.<0.05	Rejected	**DLNMOEX→ DLNJTOPI**
	DLNSENSEX	22.17889	0.0000	Prob.<0.05	Rejected	**DLNSENSEX→ DLNJTOPI**
	DLNSSECI	0.002759	0.9581	Prob.>0.05	Accepted	DLNSSECI↛ DLNJTOPI
	All	51.13568	0.0000	Prob.<0.05	Rejected	**All→ DLNJTOPI**
DLNMOEX	**DLNBOVESPA**	5.056135	0.0245	Prob.<0.05	Rejected	**DLNBOVESPA→ DLNMOEX**
	DLNJTOPI	1.158742	0.2817	Prob.>0.05	Accepted	DLNJTOPI↛ DLNMOEX
	DLNSENSEX	14.55776	0.0001	Prob.<0.05	Rejected	**DLNSENSEX→ DLNMOEX**
	DLNSSECI	0.417013	0.5184	Prob.>0.05	Accepted	DLNSSECI↛ DLNMOEX
	All	22.40219	0.0002	Prob.<0.05	Rejected	**All→ DLNMOEX**
DLNSENSEX	**DLNBOVESPA**	8.086995	0.0045	Prob.<0.05	Rejected	**DLNBOVESPA→ DLNSENSEX**
	DLNJTOPI	0.253934	0.6143	Prob.>0.05	Accepted	DLNJTOPI↛ DLNSENSEX

	DLNMOEX	11.92890	0.0006	Prob.<0.05	Rejected	**DLNMOEX→ DLNSENSEX**
	DLNSSECI	0.472450	0.4919	Prob.>0.05	Accepted	DLNSSECI↛ DLNSENSEX
	All	37.45999	0.0000	Prob.<0.05	Rejected	**All→ DLNSENSEX**
DLNSSECI	**DLNBOVESPA**	0.334591	0.5630	Prob.>0.05	Accepted	DLNBOVESPA↛ DLNSSECI
	DLNJTOPI	0.050405	0.8224	Prob.>0.05	Accepted	DLNJTOPI↛ DLNSSECI
	DLNMOEX	3.147204	0.0761	Prob.>0.05	Accepted	DLNMOEX↛ DLNSSECI
	DLNSENSEX	6.680623	0.0097	Prob.<0.05	Rejected	**DLNSENSEX→ DLNSSECI**
	All	10.12600	0.0384	Prob.<0.05	Rejected	**All→ DLNSSECI**

Source: Compilation of secondary data using Eviews 9

The results suggest that there is a bi-directional causality between DLNBOVESPA and DLNMOEX; DLNMOEX and DLNSENSEX. The results also suggest that there is unidirectional causality between DLNMOEX and DLNJTOPI; DLNSENSEX and DNLNJTOPI; DLNBOVESPA and DLNSENSEX; DLNSENSEX and DLNSSECI with former granger causing the later. It is also observed that barring Brazil, stock market returns of Russia, India, China and South Africa individually are Granger caused by the stock returns of remaining four countries.

5. Conclusion

The study observes that the stock market performances of the BRICS countries are not integrated in the long-run in the backdrop of Covid-19. One of the possible reasons may be that the member countries of BRICS are arguably homogenous in terms of their economic and political trajectories. Widening inequalities between South Africa and other BRICS countries, especially Russia in terms of level of poverty, accumulation of wealth and political presence could also be a possible reason behind absence of long term relationship among their stock markets. The study also points out a causal relationship among the BRICS countries in the backdrop of Covid-19. While they are not cointegrated in the long-run, such short-run causality could be due a short-term bubble in the indices led by some economic events. Indian stock market has bidirectional causality with Russian market, possibly due to their long-term bilateral trade treaties and economic cooperation (Embassy of India Moscow, 2018). South African stock market followed Indian market, possibly due to the competitive pressure faced by South African economy from India (Human Science Research Council, 2008). Despite growth in Indian export in the last one decade, China's share in it had shrunk by a considerable extent. These could have been possible reasons behind Indian market causing movement of the Chinese market (The Week, 2020). Recently, Brazil and India have projected a multilateral cooperation for improving international trade environment and reforms which tripled Indian trade volumes (Indian Embassy in Brazil, 2017) which may have caused Indian stock market to follow Brazilian market.

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