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Cointegration and Causality among BRICS Stock Markets during Covid-19 Crisis

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Abstract: The BRICS nations-Brazil, Russia, India, China, and South Africa-represent significant emerging economies that have engaged in collaborative efforts in terms of trade, financial aid, and technical expertise despite their geopolitical differences. This study investigates the interconnectedness of these markets, particularly amid the global financial crisis triggered by the Covid-19 pandemic, based on their stock market data from October 24, 2019, to October 23, 2020. The research identifies causal links and long-term cointegration among the stock indices, by segregating the entire study period under three defined sub-periods: pre-crisis, crisis, and post-crisis. The indices examined include IBOVESPA (Brazil), MOEX (Russia), SENSEX (India), SSECI (China), and JTOPI (South Africa). Findings suggest that significant long-term co-movements among these markets predominantly occurred during the pandemic-induced crisis, with notable two-way causal relationships existing between the Indian market and both the South African and Russian markets. In the pre-crisis phase, the Indian market was influenced by the other two, while in the post-crisis transition, the only causal relationship noted involved the Indian market and Brazil. These insights may imply that Indian policymakers may strengthen economic ties with BRICS countries in the usual scenario. However, during global crises, exercising caution has been advised to mitigate potential spill-over effects.

1. Introduction

BRICS, an economic block comprising Brazil, Russia, India, China and South Africa, represents five major emerging economies of the world. Despite their Geopolitical diversity, these countries have collaborated with each other in trade openness, financial cooperation, and exchange of technical know-how by virtue of globalisation and growth in information and communication technology (Shahbaz et al., 2018). BRICS nations, barring Russia, have shown remarkable similarities in terms of their tendency to maintain a high amount of foreign reserves, a low level of cushioning against external debts, focus on the production of consumer goods, etc. (Movcham, 2015). All these factors have gone a long way towards building a sustainable economic integration among the BRICS nations. Naturally, an economic shock in one country resonates with the others through the channels of economic integration. Just before the Covid-19 pandemic, the real Gross Domestic Product (GDP) of the BRICS nations, on average, was growing at a rate of 2.48% (IMF, 2020).

In December 2019, in the Wuhan city of Hubei province, China, the first case of Covid-19 coronavirus disease (2019-nCov) was diagnosed. Soon after, World Health Organisation (WHO) declared it as a pandemic when the number of deaths from the virus crossed 20000. By then, China had controlled the outbreak to some extent. However, the centre of the Covid-19 pandemic has been shifted to emerging markets (Roy and Saha, 2020). By the end of August 2020, there had been a serious increase in the number of cases in Brazil and Russia. In India, the outbreak started at the end of March and, due to a high population density, the number of confirmed cases surged in no time

(Figure 1). As a measure of solution, the governments in BRICS countries have set a country-wide economic lockdown in motion (Ayittey et al., 2020). While it achieved its desired effect of capping the number of cases, the pandemic and its ensuing economic shutdowns resulted in stalled global trade and manufacturing production (John Hopkins University, 2020); reduction in domestic and export demand; decline in exchange rate; rising unemployment; and disruption in the supply chain network.

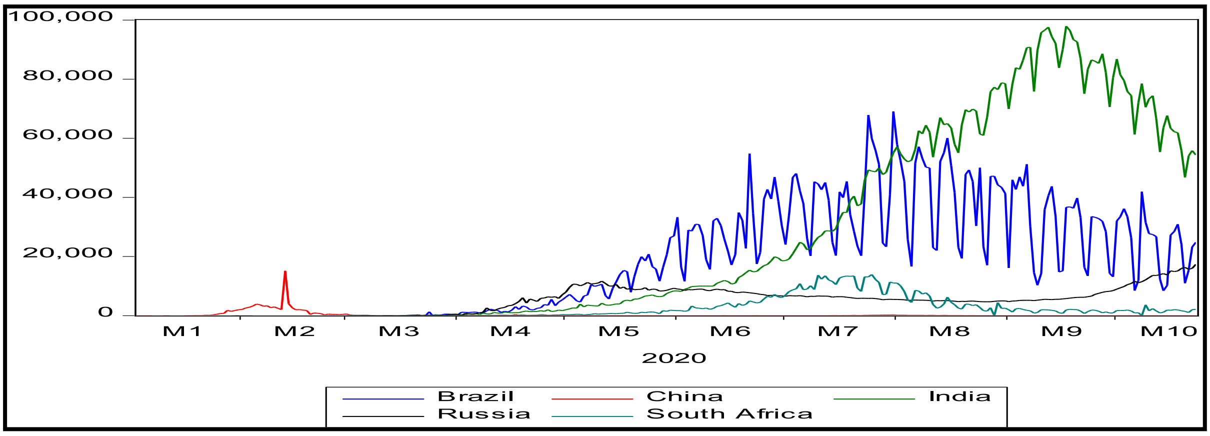

Figure 1: Number of New Cases in BRICS Countries

Source: Compilation of secondary data from WHO Covid Dashboard (WHO, 2020)

Since BRICS countries, especially China, had already proved their contribution to global growth, their struggle with the Covid-19 induced economic crisis hurt emerging market sentiments. However, China has showcased a strong capacity to fund proactive policy responses that contained the financial turmoil to some extent. Brazil, on the other hand, despite a strong healthcare system, ignored the impact of Covid-19 for a long time, which resulted in its economic collapse. Brazil, Russia being major oil exporters within BRICS, also faced a hit due to the Covid-19 induced oil price collapse. In countries like India and South Africa, meagre growth, high indebtedness, weak institutional capacity to mobilise fiscal or financial resources, huge social disparities, limited health infrastructure, and vulnerable informal groups limited their abilities to combat the crisis (Park and Garcia-Herreo, 2020). Covid-19 has exposed the faults in the administrative process in all five countries in navigating between health and economic priorities and its unavoidable impact on the livelihood of the common mass. However, even during this crisis, BRICS nations not only resorted to any hostile action against one another, but also have supported China and Russia when they became subject to the United States (US) confrontation on Covid-19 and subsequent vaccination issues, and US-China competition has become a focal point of international relations (Grigoryeva, 2020). Amid Covid-19, India too had entered into bilateral trade ties with other member countries (Rajagopalan, 2020) and jointly moved to the World Trade Organisation (WTO) to ease trade norms (The Hindu, 2020). However, India has recently gotten into several clashes with China (e.g. defence breach, banning of Chinese Apps, propaganda to disallow Chinese products, etc.), which may disrupt Sino-Indian economic relations in the future (Brar, 2020).

The stock market, being the barometer of economic performance in a country, signalled these economic vulnerabilities in BRICS countries (Mroua and Trabelsi, 2020). During February to June 2020, when Covid-19 was at its peak, stock markets went into an acute recession. In this backdrop, it becomes imperative to study whether the economic interconnectedness among the countries during the crisis has spilled over to their stock market relationships too.

In the stock market, black-swan theory (Taleb, 2010) is commonly used as a metaphor to designate an event which is highly unlikely as a black swan. It is used to describe the crises and financial turbulence that have come to the stock markets by shock and have large and harmful effects. In the last 20 years, the stock markets globally experienced multiple 'black-swan' events, such as the internet bubble burst (2001), sub-prime crisis (2007), leading to the global financial crisis (2008-09), European public debt crisis (2009), etc. These events have led to a deep depression in global stock prices and increased instability in the markets. Due to its increasing trend, policy makers and investor communities have placed greater attention on the long-run and short-run correlations among global stock markets, to prevent unwarranted volatility spill-over or to reap the benefit of portfolio diversification (Bekiros et al., 2017). Since countries under an economic block (e.g. BRICS, ASEAN, G7, G20, etc.) are interconnected by virtue of multilateral trade relations and other strategic partnerships, the effect of a black-swan is significantly felt in their stock markets. Covid-19 and its immediate economic aftershock had an unprecedented effect on global stock markets, especially the stock markets of BRICS nations. Since India is economically interconnected with its foreign counterparts under BRICS through multilateral trade ties and other strategic collaborations, stock market recession in one country is likely to spill over to other countries, leading to a stock market slump there as well. However, it would happen only if the BRICS stock markets are integrated in the long-run and a causal relationship exists among them, specifically during times of crisis. It would also limit the benefits of cross-country portfolio diversification for international investors.

The present study has attempted to address the following research questions:

(a) Were the BRICS stock markets integrated in the long run just prior to the Covid-19 led global financial crisis?
(b) Were the BRICS stock markets integrated in the long run during the Covid-19 led global financial crisis?
(c) Were the BRICS stock markets integrated in the long run in the transition period after the Covid-19 led global financial crisis?
(d) Were there any causal relationships among the BRICS stock markets just prior to the Covid-19 led global financial crisis?
(e) Were there any causal relationships among the BRICS stock markets during the Covid-19 led global financial crisis?
(f) Were there any causal relationships among the BRICS stock markets in the transition period after the Covid-19 led global financial crisis?

2. Review of Literature

Policymakers and investors have always been interested in the economic ties between various economic groups, such as the G7, BRICS, and the Organisation for Economic Cooperation and Development (OECD). Previous research demonstrated that in OECD nations, there were significant causal relationships between economic growth, inflation, and stock markets (Pradhan et al. 2015). Over the past ten years, the US and BRICS have shared a commercial partnership. Due to their trading connections, the US and BRICS economies were seen to partially integrate during the global financial crisis. The Standard and Poor's (S&P) 500, which represents the US stock market, experienced a financial shock that had a major impact on the stock returns in China, South Africa, and Brazil. Strong economic integration between the US and BRICS countries is what caused the conflict (Singh and Singh, 2016; Jin and An, 2016).

Stock market movements in BRICS and other emerging economies were found to be vulnerable to volatilities in select macro-economic variables, such as gold price, oil price, foreign exchange rate, etc. In one of the studies, a time-varying asymmetric dependence structure between gold and stock prices in the emerging markets had been identified (Bekiros, et al., 2017). It showed that gold often acted as a means of risk diversification for stock market investors in emerging economies (Raza, et al., 2016). However, the associated volatilities of gold and oil prices were found to have negative impact on the stock market returns. Since gold and oil were among India's top imported commodities, studies suggested that future volatilities in their prices might affect inflation and India’s stock market sentiments. Furthermore, gold and oil prices at the international markets and Indian stock market returns were observed to be cointegrated with non-linear bi-directional causality between them. Implied volatilities of gold and oil prices were found to have positively impacted the implied volatility of Indian stock market returns (Bouri, et al., 2017). The studies also showed that despite projecting a high growth rate, BRICS economies were susceptible to the fluctuations in external shocks, especially in gold and oil prices. However, when it came to the impact of foreign exchange rates on stock returns, especially during the global financial crisis, it was observed that volatilities in stock returns due to variations in foreign exchange rates had spilled over from one country to another within BRICS bloc (Sui and Sun, 2017).

A few studies had specifically analysed the impact of pandemics on different macro-economic variables, including stock market performances. It was observed that since 1900 many infectious diseases (e.g. Spanish Flu) had caused volatilities in macro-economic variables, including stock returns. However, studies reported that the impact of Covid-19 on stock markets all over the world had been unprecedented (Baker, et al., 2020). Sethi, Dash, Swain and Das (2021), in their study, used a sample of 37 nations and considered data from January 4, 2020, to April 30, 2021, to investigate how Covid-19 affected their currency exchange rate behaviour. The study used fixed-effect regression to show that the exchange rate responded favourably to the Covid-19 pandemic, especially to the number of confirmed cases and deaths per day.

Several studies that had specifically focused on the impact of Covid-19 on stock market returns had shown that stock markets of Japan, Korea, Singapore, the US, Germany, Italy and the United Kingdom (UK) had gone into recession immediately after the outbreak, and the situation was worst in Asian markets. Covid-19 led to pessimistic market sentiments, which were found to have adversely affected the post-listing abnormal returns. The study suggested that had policymakers and regulators apprehended the financial contagion effect of Covid-19 and taken appropriate steps to prevent its impact on the economy, such a catastrophe could be avoided (Liu, et al., 2020). One of the studies also showed that Covid-19 impacted six Latin American and the US stock markets in a non-linear way. However, it was observed that the Argentinean market managed to remain out of its clutch. According to the authors, insignificant contagion effect among these markets allowed the international investors there to carry out efficient portfolio diversification strategies and allowed the policy makers to carry out institutional reforms in ensuring market efficiency (Helidoro, et al., 2020). Khilar, Singh, Dash and Sethi (2022) in their study, used a sample of 34 nations from both emerging and developed economies to investigate how the stock markets of those nations responded to verified cases, deaths, and government-imposed lockdowns caused by Covid-19 based on a data from January 4, 2020, to September 30, 2020. The findings showed that the Covid-19 outbreak, specifically the daily confirmed cases and lockdown in both emerging and developed nations, had a detrimental impact on their stock markets.

Bhardwaj, Sharma, and Mavi (2022) revealed the potential effects of Covid-19 on the short- and long-term relationships among five growing Asian economies in a relatively recent study. In addition to South Korea, Indonesia, Taiwan, China, and India were included in their analysis, even though they did not specifically select the BRICS as their sample. According to the report, Covid-19 made it harder for the chosen economies to integrate. In actuality, those five nations' stock markets were not eventually integrated. Only the stock markets of South Korea and China reported short-term links following the outbreak, but the stock markets of those five countries had both unidirectional and bidirectional causal associations prior to the Covid-19 pandemic. On the other hand, Mishra and Mishra (2022) examined the impact of Covid-19 on the degree of integration among the BRICS stock markets. Their analysis indicates that during the epidemic, the markets were not interconnected. Such findings were actually influenced by vulnerable real interest rates, inflation rates, real currency rates, and a reduction in trade links between the countries.

While the BRICS countries' stock markets' lack of long-term integration allowed foreign investors to diversify their portfolios, it was also crucial to manage macroeconomic variables like inflation, interest rates, and exchange rates during the global crisis in order to promote steady economic growth and, ultimately, guarantee economic interconnectedness. There are relatively few studies that include BRICS, even though much of the research that was particularly examined in the paper examined the economic interconnectivity of the member countries of various economic blocs. Additionally, the authors have not found any noteworthy Indian research on the short-term causal relationships and long-term integration of the stock markets of the BRICS countries, particularly in times of global financial crises. Additionally, the literature reviewed thus far has not examined the effects of short-term causal links and long-term integration on the economic interconnection among the member countries. Given these gaps in the literature, the current work aims to fill them.

Based on the gaps in existing research reviewed so far and with a view to addressing the research questions, the study has been undertaken with the following major objectives:

(i) To estimate the long-run relationship among stock markets of BRICS nations in pre-; during and post-Covid-19 induced global crisis period.
(ii) To estimate causality among stock markets of BRICS nations in pre-; during and post-Covid-19 induced global crisis period.

3. Research Methodology

3.1. Sampling Design

With a view to analysing the long-run cointegration and causality among the stock markets of BRICS nations, their largest stock exchanges based on their market capitalisation have been identified (WEF, 2019). The stock index that best represents the market movements of each identified stock exchange is selected based on existing literature (Panda and Thiripalraju, 2021; Rout and Das, 2024). Selection of stock indices are shown below in Table 1:

Table 1: Stock indices taken in the study

Country	Stock Exchange	Stock Index
Brazil	Brazil Stock Exchange and Over the Counter Market	IBOVESPA (BOVESPA)
Russia	Moscow Exchange	MOEX
India	Bombay Stock Exchange Ltd. (BSE)	Sensitivity Index (SENSEX)
China	Shanghai Stock Exchange (SSE)	SSE Composite Index (SSECI)
South Africa	Johannesburg Stock Exchange Ltd. (JSE)	JTOPI

Source: Authors' compilation.

3.2. Data Collection

The period of study selected is October 24, 2019 to October 23, 2020. Data on the adjusted closing price of the aforesaid indices during the period is collected from www.investing.com. to remove the inconsistency in the dataset arising out of different operating days in different stock exchanges, appropriate data mining has been made. Ultimately, the study is made with 209 observations that conform to the same dates of operation of the select stock exchanges. The data for all the stock indices is then plotted (Figure 2). It is observed that stock markets in all the countries under consideration have passed through a recession, presumably due to the Covid-19 pandemic and its ensuing economic shutdown from February to June 2020, which falls between the full sample periods (October 24, 2019 to October 23, 2020). Based on this observation, the full-sample period has been segregated into three sub-sample periods: (a) pre-Covid-19 global crisis period (October 24, 2019 to February 23, 2020); (b) Covid-19 global crisis period (February 24, 2020 to June 23, 2020); and (c) post-Covid-19 global crisis period with transition (June 24, 2020 to October 23, 2020). The total of 209 observations of the full sample period have also been distributed almost equally among the pre-Covid-19 global crisis period (69 obs.), Covid-19 global crisis period (68 obs.) and the post-Covid-19 global crisis period (72 obs.). For further analysis, the data is then converted into their natural logarithmic form (LNBOVESPA; LNJTOPI, LNMOEX, LNSENSEX; and LNSSECI) to reduce skewness in the data.

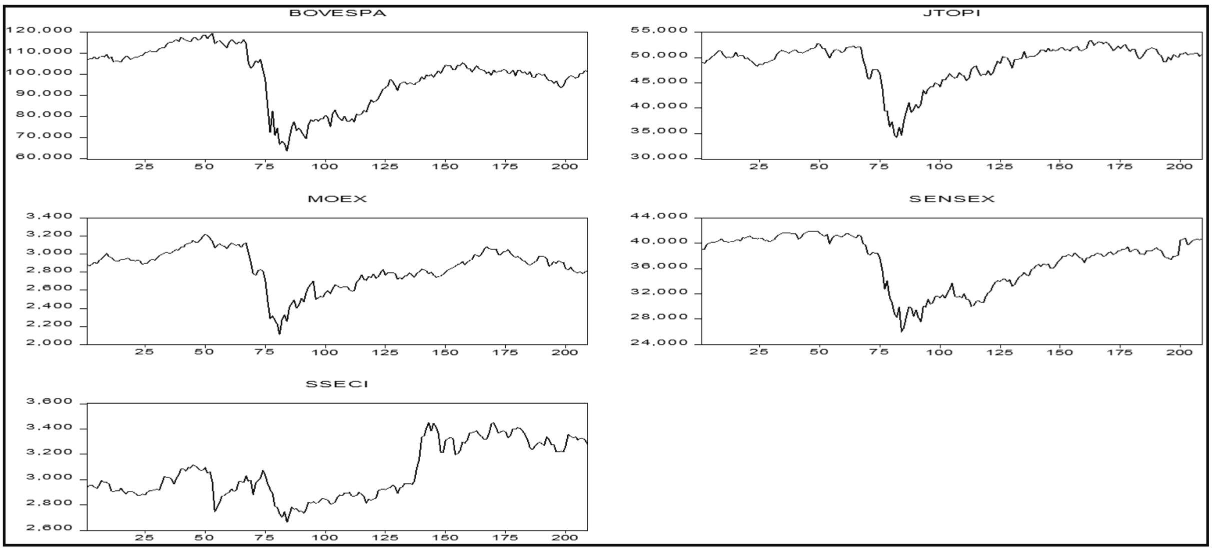

Figure 2: Stock Market Performance of BRICS Countries

3.3. Econometric Tools

Stationarity in the dataset is tested using the Augmented Dickey Fuller (ADF) test for each of the three sub-sample periods (McKinnon, 1991; Enders, 2004). In each sub-sample period, if the data series are integrated of the same order, long-run relationship among them is estimated using Johansen Julius (JJ) cointegration technique (Johansen, 1988). If the data series are cointegrated in the long run, long-run or short-run causality among them may be identified based on the underlying Vector Error Correction Model (VECM) (Thierry et al. 2016). However, if they are not cointegrated in the long run, their short-run causality may be estimated using the Vector Auto-regression (VAR) model (Toda and Phillips, 1991). If the data series are integrated of different orders, long-run relationships among them will be measured with the help of Bounds Test under the Auto-regressive Distributed Lag (ARDL) model (Pesaran et al., 2001). In this situation, short-run causality among the data series may be estimated using the Pair-wise Granger causality test (Rahman and Kashem, 2017; Granger, 1969).

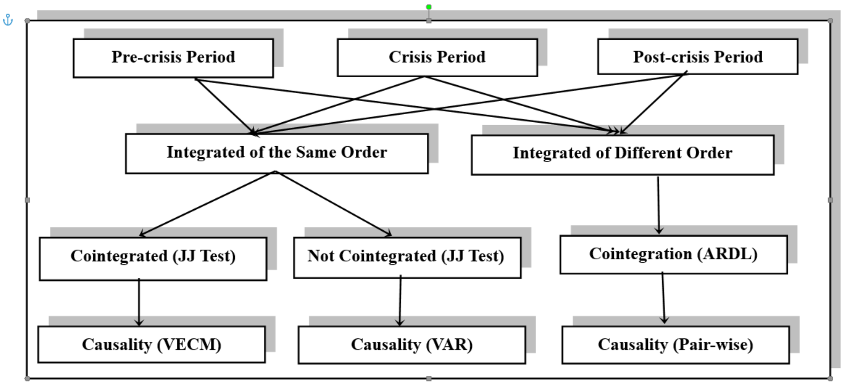

Figure 3: Research Design

4. Results and Discussion

4.1. Data Stationarity

DF test is based on following hypothesis: H0: $\delta = 0$ against H1:$\delta \neq 0$ where ρ is the autocorrelation between Yt and Yt-1 in the equation: $\Delta Y_t = \delta Y_{t-1} + u_t$. The test statistic under DF test is $\frac{\hat{\delta}}{SE(\hat{\delta})}$ which is compared with its critical value to make a decision about H_0. 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 ADF test is to be conducted to test whether the data series are random walk (RW) with drift ($\Delta Y_t = \alpha + \delta Y_t + \sum_{i=1}^{m} Y_i \Delta Y_{t-1} + \mu_t$) and RW with 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. 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 ADF tests during three intermittent sub-sample periods exhibit that during pre-Covid-19 global crisis period (Panel A, Table 3), at 1% level of significance, all the data series are non-stationary at level (Prob.>0.01) and stationary at first difference (Prob.<0.01). During Covid-19 global crisis period (Panel B, Table 3), all the data series are non-stationary at level and stationary at first difference. Hence, all the data series during these two periods are I(1) series. However, during post-Covid-19 global crisis period with transition, all the data series are I(1) barring LNSSECI (Panel C, Table 3). It is an I(0) series.

4.2. Long-Run Relationship and Causality During Pre-Covid-19 Global Crisis Period

4.2.1. Long-Run Relationship

Since all the stock indices during pre-Covid-19 global crisis period are I(1), long run relationship among them is estimated using JJ Cointegration technique. There are two tests under this technique – (a) Trace test and (b) Max-Eigen value test. Trace test is conducted based on following hypothesis H_0: $r = r_1 < k$ [where r is number of distinct cointegrating vector(s)], against H_1: r=k. 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 i^{th} largest value of cointegrating matrix Π and T is the number of observations. Here, Π = -(I – A1 – A2 - ...Ap) where I is an identity matrix and A1, A2,…Ap are coefficients in the equation $Zt = A1\, Zt - 1 + A2Zt - 2 + \ldots.\, Ap\, Zt - p + ut$ where $Zt = \{\mathrm{LNBOVESPAt, LNJTOPIt, LNMOEXt, LNSENSEXt, LNSSECIt}\}$. On the other hand Max-Eigen value test is based on following hypothesis: H_0: $r = r_1 < k$ against H_1: $r = r_1 + 1$. 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 appropriate lag length is determined based on Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC), and Hannan-Quinn Criterion (HQC). The lag that reports the minimum value in AIC and SBC, is selected as the appropriate one. However, if there is an inconsistency in the lag length as per AIC and SBC, appropriate lag is selected based on HQC. The particular assumption for running the model is intercept but no trend in Cointegrating Equations (CE) and Vector Auto-Regression (VAR). 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 2: Results of JJ Cointegration Test (Pre-Covid-19 Global Crisis Period)

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	0.365	68.125	0.067	Accepted	29.473	0.153	Accepted
At most 1	0.232	38.651	0.274	Accepted	17.118	0.569	Accepted
At most 2	0.176	21.533	0.325	Accepted	12.611	0.488	Accepted
At most 3	0.072456	8.922124	0.3726	Accepted	4.888998	0.7558	Accepted
At most 4	0.060162	4.033126	0.0446*	Rejected	4.033126	0.0446*	**Rejected**

Note: *Significant at 5% level of significance.

Source: Authors' compilation.

At lag-length 1 (based on AIC, SBC, and HQC), the results of Trace test and Max-Eigen value test suggest that both trace statistic and max Eigen-value statistic are significant with at most 4 hypothesis CEs (Table 2). From the result, it may be concluded that at 5% level, there is no cointegration among the stock indices. Hence, there are no long-run relationships among stock indices in the pre-Covid-19 global crisis period.

Table 3: Results of ADF tests for three intermittent sub-sample periods

Index	Level Prob. (Intercept)	Level Prob. (Trend and Intercept)	Result	First Difference Prob. (Intercept)	First Difference Prob. (Trend and Intercept)	Result	Data Series Nature at Level
Panel A: Pre-Covid-19 Global Crisis Period (Maximum Lag as per SIC = 10)							
LNBOVESPA	0.499	0.563	Non-Stationary	0.001***	0.001***	Stationary	I(1)
LNJTOPI	0.391	0.452	Non-Stationary	0.001***	0.001***	Stationary	I(1)
LNMOEX	0.634	0.721	Non-Stationary	0.001***	0.001***	Stationary	I(1)
LNSENSEX	0.016**	0.039**	Non-Stationary	0.001***	0.001***	Stationary	I(1)
LNSSECI	0.317	0.597	Non-Stationary	0.001***	0.001***	Stationary	I(1)
Panel B: Covid-19 Global Crisis Period (Maximum Lag as per SIC = 10)							
LNBOVESPA	0.429	0.397	Non-Stationary	0.001***	0.001***	Stationary	I(1)
LNJTOPI	0.683	0.229	Non-Stationary	0.001***	0.001***	Stationary	I(1)
LNMOEX	0.224	0.079*	Non-Stationary	0.001***	0.001***	Stationary	I(1)
LNSENSEX	0.171	0.471	Non-Stationary	0.001***	0.001***	Stationary	I(1)
LNSSECI	0.343	0.505	Non-Stationary	0.001***	0.001***	Stationary	I(1)
Panel C: Post-Covid-19 Global Crisis with Transition Period (Maximum Lag as per SIC = 11)							
LNBOVESPA	0.090*	0.159	Non-Stationary	0.001***	0.001***	Stationary	I(1)
LNJTOPI	0.092*	0.125	Non-Stationary	0.001***	0.001***	Stationary	I(1)
LNMOEX	0.514	0.905	Non-Stationary	0.001***	0.001***	Stationary	I(1)
LNSENSEX	0.248	0.098*	Non-Stationary	0.001***	0.001***	Stationary	I(1)
LNSSECI	0.001***	0.001***	Stationary	NA	NA		I(0)

Note: *, ** and *** show significance at 10%, 5% and 1% respectively.
Source: Authors compilation.

4.2.2. Short-Run Causality

Since stock indices are not cointegrated, the short-run causal relationship among them may be estimated using underlying VAR model after converting the data into first differences as follows:

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

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

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

$\Rightarrow$ $\Delta LNSENSEX_t = d_0 + \sum_{j=1}^{p} d_{1p}\,\Delta LNBOVESPA_{t-j} + \sum_{j=1}^{p} d_{2p}\,\Delta LNJTOPI_{t-j} + \sum_{j=1}^{p} d_{3p}\,\Delta LNMOEX_{t-j} + \sum_{j=1}^{p} d_{4p}\,\Delta LNSENSEX_{t-j} + \sum_{j=1}^{p} d_{5}\,\Delta LNSSECI_{t-j} + \mu_t$....(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 (Block Exogeneity 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. It follows χ^2(p-1) distribution. At 5% level of significance, if test statistics>critical value, H_0 cannot be accepted and vice versa. If H_0 cannot be accepted, causal relationship exists among two variables. For each equation in the model, causal effects of exogenous indices on endogenous index is measured individually and together.

Table 4: Results of VAR Granger Causality Test (Pre-Covid-19 Global Crisis Period)

DV	IV	χ^2	Prob.	Decision Rule	Decision on H_0	Results
DLNBOVESPA	**DLNJTOPI**	1.50	0.22	Prob.>0.05	Accepted	DLNJTOPI ↛ DLNBOVESPA
	DLNMOEX	0.05	0.81	Prob.>0.05	Accepted	DLNMOEX↛ DLNBOVESPA
	DLNSENSEX	0.83	0.36	Prob.>0.05	Accepted	DLNSENSEX ↛ DLNBOVESPA
	DLNSSECI	0.95	0.33	Prob.>0.05	Accepted	DLNSSECI↛ DLNBOVESPA
	All	3.96	0.41	Prob.>0.05	Accepted	All↛ DLNBOVESPA
DLNJTOPI	**DLNBOVESPA**	0.76	0.38	Prob.>0.05	Accepted	DLNBOVESPA↛ DLNJTOPI
	DLNMOEX	0.26	0.61	Prob.>0.05	Accepted	DLNMOEX↛ DLNJTOPI
	DLNSENSEX	0.02	0.88	Prob.>0.05	Accepted	DLNSENSEX↛ DLNJTOPI
	DLNSSECI	1.64	0.20	Prob.>0.05	Accepted	DLNSSECI↛ DLNJTOPI
	All	3.18	0.52	Prob.>0.05	Accepted	All↛ DLNJTOPI
DLNMOEX	**DLNBOVESPA**	2.75	0.09	Prob.>0.05	Accepted	DLNBOVESP↛DLNMOEX
	DLNJTOPI	5.08	0.02	Prob.<0.05	Rejected	**DLNJTOPI→DLNMOEX**
	DLNSENSEX	1.47	0.22	Prob.>0.05	Accepted	DLNSENSEX↛ DLNMOEX
	DLNSSECI	0.06	0.81	Prob.>0.05	Accepted	DLNSSECI↛ DLNMOEX
	All	11.64	0.02	Prob.>0.05	Accepted	All↛ DLNMOEX
DLNSENSEX	**DLNBOVESPA**	3.39	0.06	Prob.>0.05	Accepted	DLNBOVESPA↛ DLNSENSEX
	DLNJTOPI	6.05	0.01	Prob.<0.05	Rejected	**DLNJTOPI→ DLNSENSEX**
	DLNMOEX	0.00	0.99	Prob.>0.05	Accepted	DLNMOEX↛ DLNSENSEX
	DLNSSECI	0.46	0.49	Prob.>0.05	Accepted	DLNSSECI↛ DLNSENSEX
	All	11.91	0.02	Prob.<0.05	Rejected	**All→ DLNSENSEX**

DV	IV	χ^2	Prob.	Decision Rule	Decision on H_0	Results
DLNSSECI	**DLNBOVESPA**	6.35	0.01	Prob.<0.05	Rejected	**DLNBOVESPA→ DLNSSECI**
	DLNJTOPI	3.59	0.05	Prob.>0.05	Accepted	DLNJTOPI$\nrightarrow$ DLNSSECI
	DLNMOEX	5.61	0.01	Prob.<0.05	Rejected	**DLNMOEX→ DLNSSECI**
	DLNSENSEX	1.91	0.16	Prob.>0.05	Accepted	DLNSENSEX$\nrightarrow$ DLNSSECI
	All	19.78	0.00	Prob.<0.05	Rejected	**All→ DLNSSECI**

Source: Authors' compilation.

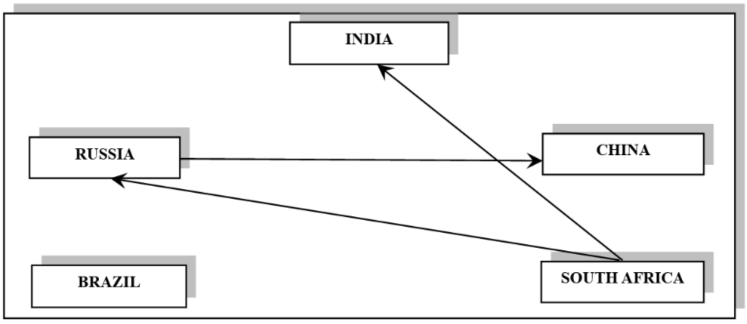

Figure 4: Causality Diagram (Pre-Crisis Period)

The results of the test (Table 4) suggest that stock markets return (first difference of stock indices data) of South African market (DLNJTOPI) Granger cause returns in Russian (DLNMOEX) and Indian market (DLNSENSEX). On the other hand, returns in Chinese stock market (DLNSSECI) is Granger caused by returns of Brazilian (DLNBOVESPA) and Russian market. Stock market returns in India is Granger caused by the remaining four countries in the model. Stock returns of Chinese market is also Granger caused by other four countries.

4.3. Long-Run Relationship and Causality During Covid-19 Global Crisis Period

4.3.1. Long-Run Relationship

All stock indices during the Covid-19 global crisis are I(1) series (Table 3). With a view to exploring the long-run relationship among the stock indices during this period, JJ Cointegration technique is applied. At lag-length 1 (as per HQC) and with the assumption of linear deterministic trend, the results of Trace test indicate 2 cointegrating relationship at 5% level of significance (at no and at most 1 hypothesised CE) (Table 5).

Table 5: Results of Johansen Cointegration Test (Covid-19 Global Crisis Period)

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	0.406	86.917	0.001*	Rejected	34.367	0.044*	Rejected
At most 1	0.325	52.550	0.017*	Rejected	25.997	0.079	Accepted
At most 2	0.174	26.553	0.113	Accepted	12.679	0.482	Accepted
At most 3	0.144	13.874	0.086	Accepted	10.292	0.194	Accepted
At most 4	0.052	3.582	0.058	Accepted	3.582	0.058	Accepted

Note: *Significant at 5% level of significance.
Source: Authors' compilation.

However, Max Eigen-value test indicates only 1 cointegrating relationship at 5% level of significance (at no hypothesised CE). It may be concluded that stock indices are cointegrated during this period. Hence, there exists a long-run relationship among the stock market performances of the BRICS nations during Covid-19 global crisis period.

4.3.2. Long-Run Causality

Since the stock indices are cointegrated, long-run causality among them may be estimated based on the underlying Vector Error Correction Model (VECM), in which the error term from the cointegration equation lagged once is the Error Correction Term (ECT) as follows:

⇒ $\Delta LNBOVESPA_t = a_0 + \lambda_1 \epsilon_{t-1} + \sum_{j=1}^{p} a_{1p}\,\Delta LNBOVESPA_{t-j} + \sum_{j=1}^{p} a_{2p}\,\Delta LNJTOPI_{t-j} + \sum_{j=1}^{p} a_{3p}\,\Delta LNMOEX_{t-j} + \sum_{j=1}^{p} a_{4p}\,\Delta LNSENSEX_{t-j} + \sum_{j=1}^{p} a_{5p}\,\Delta LNSSECI_{t-j} + \mu_t$....(6)

⇒ $\Delta LNJTOPI_t = b_0 + \lambda_2 \epsilon_{t-1} + \sum_{j=1}^{p} b_{1p}\,\Delta LNBOVESPA_{t-j} + \sum_{j=1p}^{p} b_2\,\Delta LNJTOPI_{t-j} + \sum_{j=1}^{p} b_{3p}\,\Delta LNMOEX_{t-j} + \sum_{j=1}^{p} b_{4p}\,\Delta LNSENSEX_{t-j} + \sum_{j=1}^{p} b_{5p}\,\Delta LNSSECI_{t-j} + \mu_t$....(7)

⇒ $\Delta LNMOEX_t = c_0 + \lambda_3 \epsilon_{t-1} + \sum_{j=1}^{p} c_{1p}\,\Delta LNBOVESPA_{t-j} + \sum_{j=1}^{p} c_{2p}\,\Delta LNJTOPI_{t-j} + \sum_{j=1}^{p} c_{3p}\,\Delta LNMOEX_{t-j} + \sum_{j=1}^{p} c_{4p}\,\Delta LNSENSEX_{t-j} + \sum_{j=1}^{p} c_{5p}\,\Delta LNSSECI_{t-j} + \mu_t$....(8)

⇒ $\Delta LNSENSEX_t = d_0 + \lambda_4 \epsilon_{t-1} + \sum_{j=1}^{p} d_{1p}\,\Delta LNBOVESPA_{t-j} + \sum_{j=1}^{p} d_{2p}\,\Delta LNJTOPI_{t-j} + \sum_{j=1}^{p} d_{3p}\,\Delta LNMOEX_{t-j} + \sum_{j=1}^{p} d_{4p}\,\Delta LNSENSEX_{t-j} + \sum_{j=1}^{p} d_5\,\Delta LNSSECI_{t-j} + \mu_t$....(9)

⇒ $\Delta LNSSECI_t = e_0 + \lambda_5 \epsilon_{t-1} + \sum_{j=1}^{p} e_{1p}\,\Delta LNBOVESPA_{t-j} + \sum_{j=1}^{p} e_{2p}\,\Delta LNJTOPI_{t-j} + \sum_{j=1}^{p} e_{3p}\,\Delta LNMOEX_{t-j} + \sum_{j=1}^{p} e_{p4}\,\Delta LNSENSEX_{t-j} + \sum_{j=1}^{p} e_{5p}\,\Delta LNSSECI_{t-j} + \mu_t$....(10)

Here, ϵ_{t-1} is the ECT which can be written as $LNBOVESPA_{t-1} + \beta_0 + \beta_1 LNJTOPI_{t-1} + \beta_2 LNMOEX_{t-1} + \beta_3 LNSENSEX_{t-1} + \beta_4 LNSSECI_{t-1}$; and λ_i is the ECT coefficient, which measures the speed of an exogenous shock. This can be adjusted back to the equilibrium. If $\lambda_i<0$ and significant at 5% level of significance, the endogenous variable and other regressor variables have long-run causality flowing from the latter to the former. Here, the cointegrating relationship among the stock indices during Covid-19 global crisis period may be represented as follows:

⇒ LNBOVESPA(-1)=-0.856262125271*LNJTOPI(-1)+0.991349525471*LNMOEX(-1)+ 0.951804268637*LNSENSEX(-1) + 3.13235263005*LNSSECI(-1) - 22.1136791016 .... (11)

⇒ ECT=LNBOVESPA(-1)+0.856262125271*LNJTOPI(-1)-0.991349525471*LNMOEX(-1)- 0.951804268637*LNSENSEX(-1)-3.13235263005*LNSSECI(-1)+22.1136791016…….. (12)

VECM estimates give equations considering five stock indices individually as endogenous variables:

⇒ D(LNBOVESPA)=C(1)*ECT+C(2)*D(LNBOVESPA(-1))+ C(3)*D(LNJTOPI(-1)) + C(4)*D(LNMOEX(-1)) + C(5)*D(LNSENSEX(-1)) + C(6)*D(LNSSECI(-1)) + C(7)...............(13)

⇒ D(LNJTOPI)= C(8)*ECT+ C(9)*D(LNBOVESPA(-1)) + C(10)*D(LNJTOPI(-1)) + C(11)*D(LNMOEX(-1)) + C(12)*D(LNSENSEX(-1)) + C(13)*D(LNSSECI(-1)) + C(14)................(14)

⇒ D(LNMOEX)=C(15)*ECT+C(16)*D(LNBOVESPA(-1))+C(17)*D(LNJTOPI(-1)) + C(18)*D(LNMOEX(-1)) + C(19)*D(LNSENSEX(-1)) + C(20)*D(LNSSECI(-1)) + C(21)................(15)

⇒ D(LNSENSEX)=C(22)*ECT+C(23)*D(LNBOVESPA(-1))+C(24)*D(LNJTOPI(-1))+ C(25)*D(LNMOEX(-1)) + C(26)*D(LNSENSEX(-1)) + C(27)*D(LNSSECI(-1)) + C(28)................(16)

⇒ D(LNSSECI)=C(29)*ECT+C(30)*D(LNBOVESPA(-1))+C(31)*D(LNJTOPI(-1)) + C(32)*D(LNMOEX(-1)) + C(33)*D(LNSENSEX(-1)) + C(34)*D(LNSSECI(-1)) + C(35)...............(17)

In Eqn. (13) to (17), coefficients of ECTs [C(1); C(8); C(15); C(22); and C(29)] measure the speed of adjustment of any deviation from the long-run equilibrium back to the equilibrium through partial short-run dynamic adjustments. In order to test the H_0 of no long-run causality of one stock index with the remaining four indices, the significance of the coefficients at 5% level is estimated using OLS procedure. If the coefficient is negative and significant (Prob.<0.05), the endogenous stock index is caused by the other four indices in the long-run. The estimated values of the coefficient, t-statistic and probability values are shown in the following table.

Table 6: Statistical Significance of ECT Coefficients

Equation	Coefficient	Estimate	Decision	t-statistic	Prob.	Decision Rule	Decision
13	**C(1)**	-0.305	Estimate<0	3.213	0.001	Prob.<0.05	Rejected
14	**C(8)**	-0.211	Estimate<0	4.095	0.001	Prob.<0.05	Rejected
15	**C(15)**	-0.248	Estimate<0	5.529	0.000	Prob.<0.05	Rejected
16	**C(22)**	-0.221	Estimate<0	3.609	0.001	Prob.<0.05	Rejected
17	**C(29)**	-0.082	Estimate<0	3.547	0.001	Prob.<0.05	Rejected

Source: Authors' compilation.

The coefficients of the ECTs are all significant at 5% level of significance, and they are all negative. Hence, each stock index during the Covid-19 global crisis is caused by the remaining 4 stock indices in the long-run.

4.3.3. Short-Run Causality

Short-run causality among the stock indices is estimated using Block Exogeneity Wald test on level data. However, here the underlying model is VECM.

Table 7: Results of VEC Granger Causality Test (Covid-19 Global Crisis Period)

Dependent Variable	Independent Variables	Chi-Square	Prob.	Decision Rule	Decision on H_0	Results
DLNBOVESPA	**DLNJTOPI**	1.469	0.22	Prob.>0.05	Accepted	DLNJTOPI ↛ DLNBOVESPA
	DLNMOEX	2.428	0.12	Prob.>0.05	Accepted	DLNMOEX↛ DLNBOVESPA
	DLNSENSEX	0.921	0.34	Prob.>0.05	Accepted	DLNSENSEX ↛ DLNBOVESPA
	DLNSSECI	4.889	0.03	Prob.<0.05	Rejected	**DLNSSECI→ DLNBOVESPA**
	All	7.991	0.09	Prob.>0.05	Accepted	All↛ DLNBOVESPA
DLNJTOPI	**DLNBOVESPA**	0.594	0.44	Prob.>0.05	Accepted	DLNBOVESPA ↛ DLNJTOPI
	DLNMOEX	15.661	0.00	Prob.<0.05	Rejected	**DLNMOEX→ DLNJTOPI**
	DLNSENSEX	10.934	0.00	Prob.<0.05	Rejected	**DLNSENSEX→ DLNJTOPI**
	DLNSSECI	10.574	0.00	Prob.<0.05	Rejected	**DLNSSECI→ DLNJTOPI**
	All	34.891	0.00	Prob.<0.05	Rejected	**All→ DLNJTOPI**
DLNMOEX	**DLNBOVESPA**	0.181	0.67	Prob.>0.05	Accepted	DLNBOVESP↛ DLNMOEX
	DLNJTOPI	9.608	0.00	Prob.<0.05	Rejected	**DLNJTOPI→D LNMOEX**
	DLNSENSEX	6.672	0.00	Prob.<0.05	Rejected	**DLNSENSEX→ DLNMOEX**
	DLNSSECI	12.548	0.00	Prob.<0.05	Rejected	**DLNSSECI→ DLNMOEX**
	All	26.828	0.00	Prob.<0.05	Rejected	**All→**

Dependent Variable	Independent Variables	Chi-Square	Prob.	Decision Rule	Decision on H_0	Results
						DLNMOEX
DLNSENSEX	**DLNBOVESPA**	0.804	0.36	Prob.>0.05	Accepted	DLNBOVESPA ↛ DLNSENSEX
	DLNJTOPI	4.614	0.03	Prob.<0.05	Rejected	**DLNJTOPI→ DLNSENSEX**
	DLNMOEX	6.791	0.01	Prob.<0.05	Rejected	**DLNMOEX→ DLNSENSEX**
	DLNSSECI	8.878	0.00	Prob.<0.05	Rejected	**DLNSSECI→ DLNSENSEX**
	All	18.961	0.00	Prob.<0.05	Rejected	**All→ DLNSENSEX**
DLNSSECI	**DLNBOVESPA**	0.001	0.98	Prob.>0.05	Accepted	DLNBOVESPA ↛ DLNSSECI
	DLNJTOPI	0.304	0.58	Prob.>0.05	Accepted	DLNJTOPI↛ DLNSSECI
	DLNMOEX	3.425	0.06	Prob.>0.05	Accepted	DLNMOEX↛ DLNSSECI
	DLNSENSEX	5.048	0.02	Prob.<0.05	Rejected	**DLNSENSEX→ DLNSSECI**
	All	9.286	0.05	Prob.>0.05	Accepted	All↛ DLNSSECI

Source: Authors' compilation.

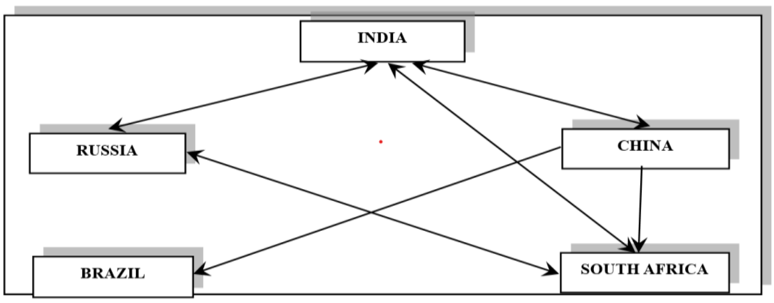

Figure 5: Causality Diagram (Crisis Period)

The results suggest that there exists a bidirectional causality between the stock indices of Russia and South Africa; India and South Africa; India and Russia; and India and China, and unidirectional causality between the stock indices of China and Brazil; China and South Africa; and China and Russia flowing from China to the other countries. Stock markets in South Africa, Russia and India separately are Granger caused by the remaining four countries.

4.4. Long-Run Relationship and Causality During Post-Covid-19 Global Crisis Period

4.4.1. Long-Run Relationship

During the post-Covid-19 global crisis period, LNBOVESPA, LNMOEX, LNJTOPI and LNSENSEX are I(1) series, while LNSSECI is an I(0) series. Since the stock market indices are integrated of different orders, long run relationships among the stock indices may be estimated with level data using ARDL technique, which is less restrictive to the order of integration:

$$\Rightarrow \Delta LNBOVESPA_t = a_0 + \sum_{i=1}^{n} a_{1i}\,\Delta LNBOVESPA_{t-i} + \sum_{i=0}^{n} a_{2i}\,\Delta LNJTOPI_{t-i} + \sum_{i=0}^{n} a_{3i}\,\Delta LNMOEX_{t-i} + \sum_{i=0}^{n} a_{4i}\,\Delta LNSENSEX_{t-i} + \sum_{i=0}^{n} a_{5i}\,\Delta LNSSECI_{t-i} + a_6 LNBOVESPA_{t-1} + a_7 LNJTOPI_{t-1} + a_8 LNMOEX_{t-1} + a_9 LNSENSEX_{t-1} + a_{10} LNSSECI_{t-1} + \mu_t \,..\ (1)$$

⇒ $\Delta LNJTOPI_t=b_0+\sum_{i=1}^{n} b_{1i}\,\Delta LNJTOPI_{t-i}+\sum_{i=0}^{n} b_{2i}\,\Delta LNBOVESPA_{t-i}+\sum_{i=0}^{n} b_{3i}\,\Delta LNMOEX_{t-i}+\sum_{i=0}^{n} b_{4i}\,\Delta LNSENSEX_{t-i}+\sum_{i=0}^{n} b_{5i}\,\Delta LNSSECI_{t-i}+b_6LNBOVESPA_{t-1}+b_7LNJTOPI_{t-1}+b_8LNMOEX_{t-1}+b_9LNSENSEX_{t-1}+b_{10}LNSSECI_{t-1}+\mu_t$...(2)

⇒ $\Delta LNMOEX_t=c_0+\sum_{i=1}^{n} c_{1i}\,\Delta LNMOEX_{t-i}+\sum_{i=0}^{n} c_{2i}\,\Delta LNJTOPI_{t-i}+\sum_{i=0}^{n} c_{3i}\,\Delta LNBOVESPA_{t-i}+\sum_{i=0}^{n} c_{4i}\,\Delta LNSENSEX_{t-i}+\sum_{i=0}^{n} c_{5i}\,\Delta LNSSECI_{t-i}+c_6LNBOVESPA_{t-1}+c_7LNJTOPI_{t-1}+c_8LNMOEX_{t-1}+c_9LNSENSEX_{t-1}+cLNSSECI_{t-1}+\mu_t$....(3)

⇒ $\Delta LNSENSEX_t=d_0+\sum_{i=1}^{n} d_{1i}\,\Delta LNSENSEX_{t-i}+\sum_{i=0}^{n} d_{2i}\,\Delta LNJTOPI_{t-i}+\sum_{i=0}^{n} d_{3i}\,\Delta LNMOEX_{t-i}+\sum_{i=0}^{n} d_{4i}\,\Delta LNBOVESPA_{t-i}+\sum_{i=0}^{n} d_{5i}\,\Delta LNSSECI_{t-i}+d_6LNBOVESPA_{t-1}+d_7LNJTOPI_{t-1}+d_8LNMOEX_{t-1}+d_9LNSENSEX_{t-1}+d_{10}LNSSECI_{t-1}+\mu_t$....(4)

⇒ $\Delta LNSSECI_t=e_0+\sum_{i=1}^{n} e_{1i}\,\Delta LNSSECI_{t-i}+\sum_{i=0}^{n} e_{2i}\,\Delta LNJTOPI_{t-i}+\sum_{i=0}^{n} e_{3i}\,\Delta LNMOEX_{t-i}+\sum_{i=0}^{n} e_{4i}\,\Delta LNSENSEX_{t-i}+\sum_{i=0}^{n} e_{5i}\,\Delta LNBOVESPA_{t-i}+e_6LNBOVESPA_{t-1}+e_7LNJTOPI_{t-1}+e_8LNMOEX_{t-1}+e_9LNSENSEX_{t-1}+e_{10}LNSSECI_{t-1}+\mu_t$..(5)

The Bounds test under ARDL technique is based on the following hypothesis, considering LNSENSEX as the DV and others as dynamic regressors. H_0: $d_6=d_7....=d_{10}=0$; against H_1: $d_6\neq d_7....\neq d_{10}\neq 0$. The asymptotic distribution of the F-statistic is non-standard. There are sets of critical values at a given significance level. While one set assumes that the variables are I(0), the other assumes that they are I(1). If the computed F-statistic exceeds the upper bound critical value [I(1)], H_0 of no cointegration cannot be accepted. However, if the computed F-statistic is less than the lower bound critical value [I(0)], H_0 of no cointegration is accepted. If F-statistic falls between these two bounds, the result is inconclusive. The appropriate lag length as per AIC, SBC, and HQC criteria is as follows: 1. The results of ARDL Bound test with LNSENSEX as the DV and other stock indices as dynamic regressors with lag 1 is shown in Table 8.

Table 8: Results of ARDL Bounds Test

F Statistics	Significance Level	I(0) Bound	I(1) Bound	Decision Rule	Decision on H_0
1.538147	10%	2.2	3.09	F-Stat<I(0) Bound	Accepted
1.538147	5%	2.56	3.49	F-Stat<I(0) Bound	Accepted
1.538147	2.5%	2.88	3.87	F-Stat<I(0) Bound	Accepted
1.538147	1%	3.29	4.37	F-Stat<I(0) Bound	Accepted

Source: Authors' compilation.

Since the value of F-statistics is lower than the critical value of I(0) bound at difference levels of significance, there is no long-run relationship among the stock market indices during post-Covid-19 global crisis period.

4.4.2. Short-Run Causality

Since stock indices during this period are integrated of different orders, short-run causality among them may be estimated using Pair-wise Granger causality (F) test considering all the data at their first difference. In Eqn. (1) to (5), Granger causality between BOVESPA and JTOPI can be tested based on the following hypothesis: H_0: $b_{11} = b_{12} = ...\ b_{1p} = 0$ against H_1: $b_{11}\neq b_{12}\neq ...\neq b_{1p}\neq 0$ (it may be applied in all the other pairs). The test statistic (F) = $(RSS_R - RSS_{UR})*(n-k)/RSS_{UR}*m$ Where, RSS_R is the Residual Sum of Square (RSS) of the regression where one variable is regressed against the lagged value of same variable; RSS_{UR} is the RSS of the regression of the same variable regressed against the lagged value of same variable and other variables. At (n-k) df and 5% level of significance, if Prob.<0.05, H_0 of non-causality cannot be accepted and vice versa. If both the variables Granger cause one another, it is called bi-directional causality. If any one of the variables Granger causes the other, it is called unidirectional causality.

Table 9: Results of Pair-wise Granger Causality Test

Null Hypothesis (H_0)	F-Statistic	Prob.	Decision Rule	Decision on H_0	Results
DLNJTOPI does not Granger Cause DLNBOVESPA	3.51154	0.0652	Prob.>0.05	Accepted	DLNJTOPI↛ DLNBOVESPA
DLNBOVESPA does not Granger Cause DLNJTOPI	0.64420	0.4249	Prob.>0.05	Accepted	DLNBOVESPA↛ DLNJTOPI
DLNMOEX does not Granger Cause DLNBOVESPA	0.21421	0.6449	Prob.>0.05	Accepted	DLNMOEX↛ DLNBOVESPA
DLNBOVESPA does not Granger Cause DLNMOEX	0.00698	0.9337	Prob.>0.05	Accepted	DLNBOVESPA↛ DLNMOEX
DLNSENSEX does not Granger Cause DLNBOVESPA	4.62633	0.0350	Prob.<0.05	Rejected	**DLNSENSEX →DLNBOVESPA**
DLNBOVESPA does not Granger Cause DLNSENSEX	6.50161	0.0130	Prob.<0.05	Rejected	**DLNBOVESPA →DLNSENSEX**
DLNSSECI does not Granger Cause DLNBOVESPA	0.18397	0.6693	Prob.>0.05	Accepted	DLNSSECI ↛ DLNBOVESPA
DLNBOVESPA does not Granger Cause DLNSSECI	0.57150	0.4522	Prob.>0.05	Accepted	DLNBOVESPA↛ DLNSSECI
DLNMOEX does not Granger Cause DLNJTOPI	0.67447	0.4143	Prob.>0.05	Accepted	DLNMOEX ↛ DLNJTOPI
DLNJTOPI does not Granger Cause DLNMOEX	0.10381	0.7483	Prob.>0.05	Accepted	DLNJTOPI↛ DLNMOEX
DLNSENSEX does not Granger Cause DLNJTOPI	1.10415	0.2970	Prob.>0.05	Accepted	DLNSENSEX↛ DLNJTOPI
DLNJTOPI does not Granger Cause DLNSENSEX	1.22918	0.2714	Prob.>0.05	Accepted	DLNJTOPI↛ DLNSENSEX
DLNSSECI does not Granger Cause DLNJTOPI	3.42636	0.0684	Prob.>0.05	Accepted	DLNSSECI↛ DLNJTOPI
DLNJTOPI does not Granger Cause DLNSSECI	0.00044	0.9834	Prob.>0.05	Accepted	DLNJTOPI↛ DLNSSECI
DLNSENSEX does not Granger Cause DLNMOEX	0.53529	0.4669	Prob.>0.05	Accepted	DLNSENSEX↛ DLNMOEX
DLNMOEX does not Granger Cause DLNSENSEX	0.11231	0.7386	Prob.>0.05	Accepted	DLNMOEX↛ DLNSENSEX
DLNSSECI does not Granger Cause DLNMOEX	0.40959	0.5243	Prob.>0.05	Accepted	DLNSSECI↛ DLNMOEX
DLNMOEX does not Granger Cause DLNSSECI	0.07936	0.7790	Prob.>0.05	Accepted	DLNMOEX↛ DLNSSECI
DLNSSECI does not Granger Cause DLNSENSEX	0.01474	0.9037	Prob.>0.05	Accepted	DLNSSECI↛ DLNSENSEX
DLNSENSEX does not Granger Cause DLNSSECI	1.10904	0.2960	Prob.>0.05	Accepted	DLNSENSEX↛ DLNSSECI

Source: Authors' compilation.

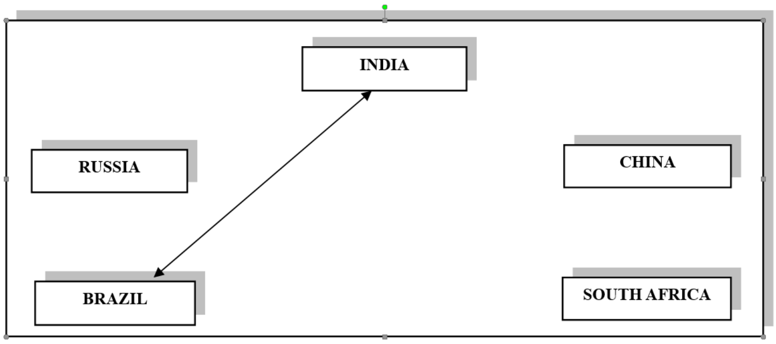

Figure 6: Causality Diagram (Post-Crisis Period)

At lag 1, results of Granger causality test suggest that bidirectional causality exists only between the stock marks returns of Brazil and India. However, there is no causal relationship among the stock market returns of any other countries during this period.

5. Conclusion

During the pre-crisis period, BRICS stock markets were not cointegrated. However, despite their Geo-political and economic diversity, stock markets of BRICS nations were integrated in the long-run by the sighting of the black swan due to Covid-19 and its ensuing economic shutdown, which continued in the post-Covid-19 transition phase as well. During February to June 2020, stock markets have gone into an acute recession and such adverse market sentiments in all the countries might have resulted in their cointegration. However, the studies Bhardwaj, Sharma, and Mavi (2022) and Mishra and Mishra (2022) showed that the BRICS stock markets were not integrated during the Covid-19 pandemic. The results in their studies differed, perhaps due to a different study period. However, Rout and Das (2024) had observed an increased association among the BRICS stocks during the crisis. Volatility spill-over effect had also been observed in G7 bloc due to the integration of their markets (Yosef, 2020). Just prior to the crisis, South African stock market Granger caused the Russian and Indian stock markets, while the Russian stock market Granger caused the Chinese stock market. However, during the crisis period, a robust causal relationship has been observed among all the stock markets, possibly due to their coordinated actions towards prevention and treatment of Covid-19 and providing a favourable condition for the supply of equipment. Specifically, bi-directional causality was observed between the stock markets of Russia and South Africa; India and South Africa; India and Russia; and India and China. Furthermore, during the crisis period, the Chinese stock market Granger caused Brazilian, South African and Russian stock markets. However, the moment Covid-19 entered a transition phase, all the aforesaid causal relationships ceased to exist. Only the stock markets of India and Brazil were connected through a bi-directional causal relationship.

Prior to the Covid-19 led economic crisis, the BRICS stock markets were not cointegrated. It allowed the Foreign Portfolio Investors (FPIs) to manage their portfolio risk by diversifying their investments among the BRICS stock markets. However, due to short term causal interactions among the stock markets of India, China, Russia and South Africa, the investors were required to adjust their diversification strategies. Since the Brazilian stock market was out of such causal interaction, FPIs could have focussed on this market to build a resilient portfolio. During the crisis, the stock markets of the BRICS bloc were interconnected over the long term. It did not allow the FPIs to diversify their investors in this bloc. Furthermore, the existence of causal relationships among all the countries also creates a possibility of volatility spill-over. Hence, creating a resilient portfolio based on the stocks of these markets was almost impossible. The situation continued in the transition phase as well. However, during this phase, only Indian and Brazilian stock markets were causing one another, allowing FPIs to form a resilient portfolio by focusing on the remaining three markets. Truly speaking, stock market integration and causality among two or more nations are the results of their economic cooperation stemming from multilateral trade agreements and other strategic ties. Policymakers of a particular country have a significant influence on such cooperation. Keeping in view the results, Indian policymakers may usually encourage India's economic ties with other member countries in the BRICS bloc and allow Indian investors to diversify their portfolio by investing in the other BRICS stock markets. But they should be cautious about any adversities in the South African market. However, whenever there is a crisis that can cause global economic turbulence, Indian policymakers should curb all economic ties with other member nations to avoid any spill-over effect and investors are advised to withdraw their investments from those markets during times of crisis. Liu, et al. (2020) and Helidoro, et al. (2020) also came up with the same conclusions in their respective studies. The status quo should be maintained even in the transition era.

The limitations of the study as identified by the authors, are as follows:

(a) Taking into account a limited time frame (October 2019 to October 2020) during which the stock markets of nearly all of the member countries experienced a severe decline as a result of global economic downturns, the current study attempted to determine the long-term integration and short-term causality among the stock markets of BRICS countries; however, taking into account a longer study period might have yielded a more trustworthy result.

(b) The study has considered five notable stock indices from the five member nations. While the authors have referred a few literature where these indices have been used to measure the stock market movements, the authors have used judgement sampling in initially selecting these indices, which is a limitation of the current study.

(c) The study has considered only BRICS bloc for drawing its conclusions. A similar analysis on other economic blocs (e.g. OECD, G7) and its comparison with the findings of this study may be considered in future research.

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