

BRIC-A Stock Markets and their Relations with the US stock Market: A Pre & Post Pandemic Analysis

Mr. M. Berchmans¹ Dr. S. Vasanthi Author², Dr. Justin John Stephen³

¹ (Ph.D Scholar - PT), Assistant Professor in Commerce, PG & Research Department of Commerce, St. Joseph's College (Autonomous), Tiruchirappalli-2. (Affiliated to Bharathidasan University, Tiruchhirappalli, Tamil Nadu)

² Research Supervisor & Associate Professor, PG & Research Department of Commerce, Holy Cross College (Autonomous), Tiruchirappalli-2. (Affiliated to Bharathidasan University, Tiruchhirappalli, Tamil Nadu)

³ Assistant Professor Department of Economics St. Xavier's College Palayamkottai

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ABSTRACT

One of the biggest global shocks in recent memory, the COVID-19 epidemic has had a huge effect on financial markets all across the world. This study looks at the dynamic interdependence of the US stock market and the BRIC-A stock markets throughout three different time periods: before, during, and after the pandemic. The findings reveal that this unprecedented crisis altered the nature and extent of stock market linkages. The long-term link between the US and Indian stock markets has not changed, according to the results of the Johansen cointegration test, but the relationships with China and Russia have seen notable alterations. Additionally, the Granger causality test shows that the US stock index had short-term associations with each of the BRIC-A countries prior to the epidemic. But in the aftermath of the pandemic, only the BSE and SSE indices maintain a short-run relationship with the US stock index. These findings highlight the evolving dynamics of global market interconnectedness, during the time of pandemics.

Keywords: Covid - 19, Granger Causality, Co integration analysis, BRIC-A, US stock market,

INTRODUCTION

The COVID-19 pandemic, while catastrophic, is not the only significant event in stock market history. Other major market disruptions have also left lasting impacts. Known as "Black Monday," the 1987 US stock market crisis saw the Dow Jones Industrial Average drop more than 22% in a single day. (Shiller, 1989). The Asian financial crisis of 1997-1998 triggered severe economic downturns in Thailand, Indonesia, South Korea, and beyond (Corsetti et al., 1999). In 1998, Russia's debt default and subsequent financial collapse sent shockwaves through global markets (Mishkin, 1999). The 2008 US subprime mortgage crisis led to the collapse of major financial institutions and a global economic recession (Gorton, 2009). The Eurozone debt crisis of 2009, particularly affecting Greece, Ireland, and Portugal, further highlighted the vulnerabilities in interconnected financial systems (Lane, 2012).

These historical crises underscore the interconnected nature of financial systems and demonstrate how shocks originating in one region can propagate rapidly across the globe. For example, the 2008 subprime mortgage crisis, which began in the United States, spread to Europe and Asia, affecting banking systems and equity markets worldwide (Gorton, 2009). These episodes highlight the fragility of global financial linkages and the potential for systemic risks.

The importance of understanding these markets' interconnections became even more evident during the COVID-19 pandemic. The initial outbreak in China disrupted supply chains, leading to volatility in global stock markets and massive sell-offs (Albulescu, 2021). Subsequent lockdowns and restrictions caused significant economic contractions worldwide, further amplifying market uncertainty and interconnected volatility (Yi et al., 2021). Such disruptions illustrate how global financial networks can magnify localized shocks, making a case for continuous monitoring and analysis of these linkages.

Diversification strategies, as outlined by Markowitz's Portfolio Theory (1952), suggest that spreading investments across uncorrelated assets reduces overall portfolio risk. This approach has been validated in various studies, such

as Hoque (2007), who demonstrated that emerging market diversification can cushion investors from volatility in developed markets.

Increasing globalization and economic liberalization have significantly enhanced the interconnectedness of global markets. Trading blocs like the EU, BRICS, NAFTA, SAARC, and ASEAN further strengthen regional economic ties by reducing trade barriers, harmonizing regulations, and encouraging cooperative economic policies. For instance, BRICS nations, representing major emerging markets, have established frameworks for mutual cooperation in finance and trade, making their markets more responsive to global economic shifts (Aktan et al., 2009).

This study examines whether the relationships between the US stock market and the BRIC-A countries—Brazil, Russia, India, China, and Argentina—were stable prior to, during, and during the following period of pandemic. The inclusion of Argentina alongside the BRIC nations is justified by its status as an emerging market with high growth potential and its significant influence in Latin American geopolitics and economics (Hoque, 2007). Despite the importance of these markets, comparative empirical research on their interactions, particularly in the context of the pandemic, is still limited (Yi et al., 2021).

Markowitz's Portfolio Theory (1952) underscores the importance of diversification in reducing investment risk. Diversification benefits are maximized when the correlations between markets are low or negative. However, high correlations among global markets, especially during crises, can reduce these benefits (Singh & Tripathi, 2016). For investors looking to successfully diversify their portfolios and for policymakers hoping to stabilize financial systems during upheavals, it is imperative that they comprehend these interconnections. The interdependencies and connections between international stock markets have been the subject of numerous research, which have provided insightful information on how developed and

emerging markets behave. These studies show how market interdependence is changing and offer a basis for comprehending how the COVID-19 pandemic has affected international financial institutions.

Husain & Saidi (2000) and Ali et al. (2011) found that emerging markets tend to have weaker linkages with developed markets compared to the strong interconnections observed among developed markets. This finding underscores the notion that emerging markets can sometimes offer diversification benefits for global investors due to their relative isolation from developed markets. However, increasing globalization and liberalization have started to blur these distinctions.

On the other hand, Morales & Andreosso-O'Callaghan (2012) came to the conclusion that Asian markets are not greatly impacted by the US stock market. This suggests that during periods of regional financial stability, Asian markets may demonstrate a degree of independence. However, other research such as Wong et al. (2004) shows that since the 1987 stock market meltdown, the interconnectedness between developed and emerging markets has grown considerably. This trend points to the growing importance of globalization and the integration of financial markets facilitated by advancements in information technology and communication systems.

Expanding on these themes, Aktan et al. (2009) highlighted the substantial influence of the US on BRIC-A markets, with Russia and Brazil showing the highest levels of integration. This implies that during financial disruptions originating in the US, markets like Russia and Brazil are particularly vulnerable to contagion effects. However, the extent of this influence can vary, as noted by Ali et al. (2011), who reported that while Pakistan's stock market did not show significant co-movement with developed markets such as the US, UK, and Taiwan, Co-integration with regional markets such as China, India, Indonesia, and Japan was evident. This highlights the role of geographic and economic proximity in shaping market interdependencies.

The dynamic nature of these linkages was further explored by Maher et al. (2017), who documented the changing relationships among South Asian stock markets, indicating that regional economic policies and crises can alter market behaviors. This knowledge was expanded by Mishra et al. (2020), who demonstrated that the COVID-19 epidemic had a more detrimental effect on Indian markets than structural adjustments like demonetization and the introduction of the Goods and Services Tax (GST). This finding suggests that global crises can have disproportionately severe impacts on emerging markets compared to localized economic reforms.

During the pandemic, Bhattacharjee & Das (2020) and Yi et al. (2021) observed increased dependence among global

markets. Their findings illustrate how a global health crisis like COVID-19 can synchronize market behaviors across regions, diminishing the diversification benefits that investors typically seek in emerging markets.

OBJECTIVES

To examine the pattern of correlation between the Indian, Russian, and Brazilian stock markets

To investigate the long-term relationship between the stock indices of the BRIC-A countries and the US stock index, as well as the US and China (BRIC-A) countries before and after the pandemic

To analyse the short-term correlation between the US stock index and the stock indexes of the BRIC countries

METHODS

For the duration of the study, the daily closing index values of the US and BRICA countries' main indices were taken, i.e. 1st April 2013 to 31st June 2023. In order for the period of the study to be of 10 years, the data begins from April 2013 and to stay updated, the period goes up to June 2023. Table 1 provides the details of the nations and the indices selected.

Table 2: BRIC-A Countries and their selected indices

S.No	Country	Index selected
1)Brazil		BOVESPA
2)Russia		RTSI
3)India		SENSEX
4)China		SSE
5)Argentina		S & P Merval
6)US		S&P500

The daily closing prices have been taken from the investing.com and the BSE's official webpage. Returns have been computed daily for the purpose of calculating inter-linkages based on the daily closing prices. The logarithmic technique is used to calculate the return.

$$r_t (\text{Return}) = (\log p_t - \log p_{t-1}) * 100$$

where r_t = Market return at the period t

p_t = Price index at day t

p_{t-1} = Price index at day $t-1$

While analyzing the inter-linkages of the stock markets, different stock exchange holidays on different days, led to the missing data on some stock exchanges on some days. By simply entering the price from the previous day, the Occam's razor method was used to solve this issue (Jeon, B. N. et al., 1990). This method's justification is that since the closed stock market doesn't produce any information, the value from the previous day is carried over to the next.

The pandemic period:

Although many research have varied definitions of the pandemic period (Chopra & Mehta, 2022), the following definition is used for the sake of this study.

In December 2019, China reported the first instances of the new coronavirus, which quickly spread to other nations worldwide. On January 30, 2020, the WHO designated the outbreak as a Public Health Emergency of International Concern (PHEIC), and on March 11, 2020, it was classified as a pandemic. The Civil Aviation Ministry of Indian Government on March 8th 2022 announced that regular overseas flights would resume from March 27 2022 amid a decline in coronavirus cases. Therefore the pandemic period is taken as a period between 11 March 2020 to 8 March 2022.

Therefore the study period is divided into 3 time zones

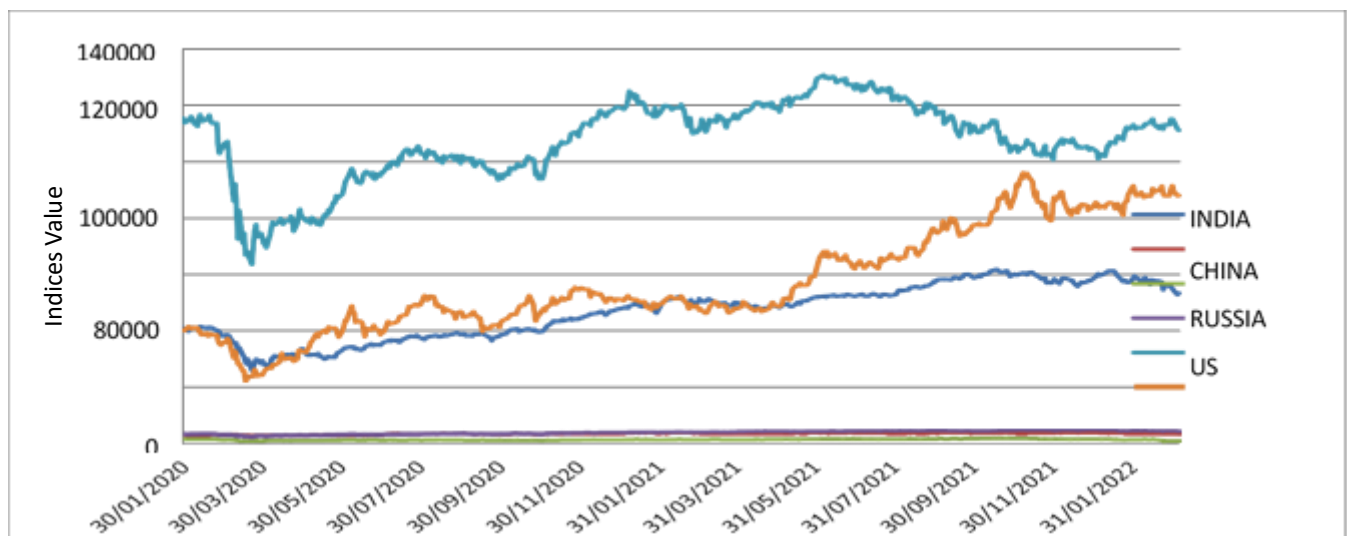
1. Pre Pandemic	: 1 st October 2013	to 29 th January 2020	(1784)
2. Pandemic	: 30 th January 2020	to 8 th March 2022	(549)
3. Post Pandemic	: 9 th March 2022	to 30 th September 2023	(343)

DISCUSSION

The epidemic period's graphical depiction shows notable volatility in the Indian, Argentinean, and Brazilian stock markets. The stock indices of China, Russia, and the United States, on the other hand, showed comparatively little volatility throughout this time. The data indicate that within two months of the initial pandemic lockdowns, the markets experiencing the highest volatility—Brazil's BOVESPA, Argentina's S&P Merval, and India's Sensex—hit their lowest points. The recovery times varied significantly among these markets. India's Sensex took approximately 10 months to return to pre-pandemic levels, while Argentina's S&P Merval rebounded in just 5 months. Brazil's BOVESPA experienced the longest recovery period, taking

15.5 months to regain its pre-pandemic status. This variation in recovery times reflects differences in economic resilience, government responses, and market dynamics during and after the pandemic.

Figure 1: BRIC-A Nations stock indices movement during the pandemic Period



The diagram, highlights significant volatility across several economies. Notably, the stock indices of Brazil, Argentina, and India experienced pronounced fluctuations in this time period.

In Brazil, the BOVESPA index showed sharp declines and frequent swings as the country's economy grappled with the health crisis, political uncertainty, and structural weaknesses exacerbated by the pandemic. Similarly, Argentina's S&P Merval index exhibited substantial volatility, driven by pre-existing economic fragilities, such as high inflation, currency depreciation, and debt issues, which were further intensified by the economic fallout. The SENSEX, also displayed significant turbulence, with investors reacting to strict lockdowns, disruptions in supply chains, and uncertainty surrounding the recovery of key sectors like manufacturing and services.

(iii) Correlation Analysis

The following tables present the cross-correlation matrices for the pre-pandemic, pandemic, and post-pandemic periods. To mitigate fluctuations, the log-transformed values of the indices were used for analysis. This approach helps smooth out data volatility and allows for more accurate comparisons of percentage changes.

The pre-pandemic correlations likely reflect stable market relationships, while during the pandemic, increased market uncertainty may have led to stronger correlations as global markets reacted similarly to the crisis. In the post-pandemic period, the correlations may indicate a return

to previous patterns or the formation of new relationships, shaped by recovery policies and market adjustments. This analysis highlights the shifting interconnections among global stock markets during different phases of the pandemic.

Table 2: Correlation among Indices (Pre pandemic Period)

	BRAZIL	RUSSIA	INDIA	CHINA	ARGENTINA	US
BRAZIL	1.000					
RUSSIA	0.602*	1.000				
INDIA	0.907*	0.303*	1.000			
CHINA	0.036	-0.439*	0.246*	1.000		
ARGENTINA	0.927*	0.380*	0.938*	0.194*	1.000	
US	0.934*	0.398*	0.971*	0.218*	0.963*	1.000

* Significant at 0.05

During the pre-pandemic period, a positive correlation exists among all the countries, except for China and Russia, which show a negative correlation. Both China and Russia have a weak positive correlation with the US. India, on the other hand, exhibits a strong positive correlation with the US, Brazil, and Argentina, while its correlation with Russia and China is mild but positive. This indicates that, before the pandemic, India's stock market movements were more aligned with the US and Latin American markets, while China and Russia exhibited more independent trends.

Table 3: Correlation among Indices (pandemic Period)

	BRAZIL	RUSSIA	INDIA	CHINA	ARGENTINA	US
BRAZIL	1.000					
RUSSIA	0.668*	1.000				
INDIA	0.692*	0.802*	1.000			
CHINA	0.751*	0.672*	0.855*	1.000		
ARGENTINA	0.462*	0.652*	0.902*	0.721*	1.000	
US	0.703*	0.796*	0.973*	0.863*	0.902*	1.000

* Significant at 0.05

During the pandemic period, all countries exhibit positive correlations, with no negative correlations observed, and all values are significant at the 5% level. This indicates that the stock markets moved in unison, experiencing simultaneous declines during the initial shock of the pandemic and recovering together as conditions improved. The strong positive correlations suggest a high degree of synchronization in global market behavior. In particular, India and Argentina show a strong positive correlation with the United States, reflecting similar market responses to the pandemic-induced volatility and subsequent recovery.

Table 4: Correlation among Indices (Post pandemic Period)

	BRAZIL	RUSSIA	INDIA	CHINA	ARGENTINA	US
BRAZIL	1.000					
RUSSIA	-0.281*	1.000				
INDIA	0.625*	-0.423*	1.000			
CHINA	-0.350*	0.054	-0.110*	1.000		
ARGENTINA	0.457*	-0.348*	0.843*	0.018	1.000	
US	0.602*	-0.349*	0.576*	0.172*	0.577*	1.000

* Correlation is significant at 0.05

During the post pandemic period almost all the countries have negative correlation with one or more countries. Russia's indices have a negative correlation with 4 other countries. India has negative correlation with Russia and China. India, Brazil and Argentina have a strong relationship with the US.

(iv) Unit Root Test Results

Ensuring the data are stationary at the same level is crucial for figuring out the long-term link between the data series. This is because using non-stationary data in time-series analysis can lead to misleading and incorrect results (Dickey & Fuller, 1979). Non-stationary data contain trends, and statistical models applied to such data may produce spurious relationships that do not reflect the true underlying dynamics. To verify the stationarity of the data, the Augmented Dickey- Fuller (ADF) test developed by Dickey and Fuller (Dickey & Fuller, 1979) and Phillips-Perron (PP) tests are used to verify the stationarity of the data.

Table 5: Unit Root Test

Index	Different periods at level							
	Total Period		Pre pandemic Period		Pandemic Period		Post Pandemic Period	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP
BRAZIL	-1.050	-1.163	0.477	0.733	-1.356	-1.656	-2.141	-2.264
RUSSIA	-2.476	-2.625	-1.094	-1.128	-1.225	-1.356	-2.746	-2.711
INDIA	-0.035	-0.050	-0.921	-0.885	-0.734	-0.779	-1.221	-1.326
CHINA	-2.808	-2.866*	-2.263	-2.178	-1.886	-1.876	-3.018*	-2.963*
ARGENA	7.931	5.307	-0.726**	-0.764**	-0.240	-0.282	0.649	0.751
US	-0.870	-0.828	-0.377	-0.299	-0.991	-1.002	-2.007	-2.007

Table 6: Unit Root Test

Index	Different Periods at 1 st difference							
	Total Period		Pre pandemic Period		Pandemic Period		Post Pandemic Period	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP
BRAZIL	-56.603*	-56.327*	-42.318*	-42.479*	-28.701*	-28.136*	-18.740*	-18.692*

RUSSIA	-51.887*	-51.938*	-39.430*	-39.421*	-25.958*	-25.824*	-16.829*	-16.784*
INDIA	-21.318*	-50.292*	-38.433*	-38.394*	-23.754*	-23.782*	-19.448*	-19.463*
CHINA	-48.257*	-48.287*	-18.601*	-37.642*	-23.126*	-23.127*	-20.951*	-21.141*
ARGEN	-8.174*	-39.779*	-45.870*	-45.811*	-22.147*	-22.132*	-15.134*	-15.378*
US	-15.814*	-56.460	-40.938*	-41.002*	-6.792*	-28.463*	-20.149*	-20.154*

*Significant at 1%; **Significant at 5%;

According to the return series' unit root test results, every stock index is stationary. Only the Chinese and Argentinean indices at the 5% significance level reject the null hypothesis of non-stationarity at the level form. The level form does not allow for the rejection of the null hypothesis of non-stationarity for the remaining indices. However, when the tests are applied to the first-differenced series, Ho of non-stationarity is rejected for all the indices. Therefore, the return series are integrated of order 1 (I(1)), meaning they achieve stationarity after being differenced once.

(vi) The result of Co-integration Test

This test is being employed to investigate whether the stock markets of BRIC-A nations are co-integrated with the stock market of the United States. Co-integration refers to a statistical relationship where, although individual time series may deviate from each other in the short term, they exhibit a long-run equilibrium relationship and tend to move together over time due to a shared underlying stochastic trend (Johansen, 1988). The presence of co-integration implies that the indices are linked in such a way that deviations from equilibrium are temporary and eventually corrected.

Table 7: Co integration Test Results Total Period

Indices	Eigenvalue	Trace Statistic	Prob.	Cointegrated
US - Brazil	0.003110	9.273246	0.3407	No
US - Russia	0.003499	10.62289	0.2358	No
US - India	0.005206	15.08479	0.0501*	Yes
US - China	0.002695	7.854993	0.4810	No
US - Argentina	0.001236	4.523478	0.8571	No

Table 8: Co integration Test Results Pre Pandemic Period

Indices	Eigenvalue	Trace Statistic	Prob.	Cointegrated
US - Brazil	0.008004	13.42125	0.1002	No
US - Russia	0.005138	8.794853	0.3847	No
US - India	0.009184	16.46935	0.0356*	Yes
US - China	0.002885	4.912391	0.8181	No
US - Argentina	0.005873	11.31592	0.1928	No

Table 9: Co integration Test Results Pandemic Period

Indices	Eigenvalue	Trace Statistic	Prob.	Cointegrated
US - Brazil	0.008676	6.455628	0.6416	No
US - Russia	0.002781	1.985527	0.9952	No

US - India	0.035198	21.13492	0.0063*	Yes
US - China	0.027514	16.56943	0.0343*	Yes
US - Argentina	0.007141	4.579543	0.8517	No

Table 10: Co integration Test Results Post Pandemic Period

Indices	Eigenvalue	Trace Statistic	Prob.	Cointegrated
US - Brazil	0.015615	10.20756	0.2651	No
US - Russia	0.027312	15.18810	0.0501*	Yes
US - India	0.012243	16.997493	0.0439*	Yes
US - China	0.018977	11.39387	0.1884	No
US - Argentina	0.015621	6.355648	0.6535	No

The eigenvalue and trace statistic for the US and Indian stock indexes were computed for the whole study period and compared to the critical values at the 5% significance level. The null hypothesis of no co-integration was rejected in this instance since the eigenvalue and the trace statistic were both found to be below the critical values. This finding suggests that the US and Indian stock indices have a substantial long-term link. This suggests that there is close integration between the US and Indian financial markets, as evidenced by the long-term co- movement of respective stock indices.

However, when examining with that of US stock market and other countries during different time periods, the results showed some variation. Specifically, during the pandemic period, the stock indices of the US and China are co-integrated, indicating a long-run relationship between these two markets during this specific period. This co-integration was not observed during the other time zones analyzed, suggesting the possibility that the epidemic momentarily changed the connections between the stock markets of the US and China.

Similarly, it was discovered that the US and Russia indices were co-integrated in the post- pandemic time zone. Earlier periods did not detect this association. It implies that the US and Russian capital markets became more integrated after the pandemic, something that had not been the case before.

In summary, the findings from this test during the three time zones show that the pandemic significantly affected the BRIC-A nations' interdependencies with the US stock market. According to the test results, the pandemic significantly changed the long-term dynamics of the linkages between the US stock market and the stock markets of other nations.

(v) The result of Granger Causality Test

This test is employed to assess whether one time series can predict another within a bivariate VAR model, identifying short-term relationships between stock indices. In this analysis, the data is made stationary by taking the first difference, which is necessary for valid causal inference.

The findings show that, at the 5% significance level, Brazil demonstrated unidirectional causation over the US stock market during the pre-pandemic period. On the other hand, the US stock market showed unidirectional causality over the Chinese, Argentinean, Indian, and Russian stock indices, indicating that shifts in US stock prices caused shifts in their respective stock indices.

During the pandemic period, the analysis found that the US stock market exerted unidirectional causality over Russia and China, meaning changes in US stock prices influenced the stock indices of these countries. However, a bidirectional relationship was found between the US and India, indicating that during the pandemic, changes in US

stock prices led to changes in Indian stock prices and vice versa.

The findings indicate that the US stock market had a unidirectional causation over the Chinese and Indian stock indices in the post-pandemic period, suggesting that shifts in US stock prices continued to affect stock prices in these two nations. Nevertheless, throughout this time, no bidirectional causality was detected.

Table 11: Pair wise Granger Causality Test Results - Pre Pandemic Period

Null Hypothesis	F statistics	Prob.
US does not Granger Cause Brazil	1.4630.231	
Brazil does not Granger Cause US	3.1860.042**	
US does not Granger Cause Russia	22.9202.E-10*	
Russia does not Granger Cause US	0.4150.659	
US does not Granger Cause India	46.2873.E-20*	
India does not Granger Cause US	2.6920.0680	
US does not Granger Cause China	19.2595.E-09*	
China does not Granger Cause US	0.6810.505	
US does not Granger Cause Argentina	3.1570.0428**	
Argentina does not Granger Cause US	9.8530.605	

Table 12: Pair wise Granger Causality Test Results -Pandemic Period

Null Hypothesis	F statistics	Prob.
US does not Granger Cause Brazil	1.345	0.261
Brazil does not Granger Cause US	0.834	0.434
US does not Granger Cause Russia	13.277	2.E-06*
Russia does not Granger Cause US	0.782	0.457
US does not Granger Cause India	36.414	1.E-15*
India does not Granger Cause US	5.313	0.005*
US does not Granger Cause China	10.087	5.E-05*
China does not Granger Cause US	0.237	0.788
US does not Granger Cause Argentina	1.083	0.339
Argentina does not Granger Cause US	0.165	0.847

Table 13: Pair wise Granger Causality Test Results- Post Pandemic Period

Null Hypothesis	F statistics	Prob.
US does not Granger Cause Brazil	0.635	0.530
Brazil does not Granger Cause US	0.575	0.563
US does not Granger Cause Russia	0.476	0.621
Russia does not Granger Cause US	1.784	0.169
US does not Granger Cause India	37.533	1.E-15*
India does not Granger Cause US	0.261	0.770
US does not Granger Cause China	7.420	0.001*
China does not Granger Cause US	1.466	0.232
US does not Granger Cause Argentina	0.181	0.833
Argentina does not Granger Cause US	1.404	0.246

Table 14: Granger Causality Results – A summary

US and	Total Period	Pre Pandemic	Pandemic	Post Pandemic
Brazil	No	Brazil \square US**	No	No
Russia	US \square Russia*	US \square Russia*	US \square Russia*	No
India	US \square India*	US \square India*	US \square India*	US \square India*
China	US \square China*	US \square China*	US \square China*	US \square China*
Argentina	No	US \square Argentina**	No	No

* significant at 1%, **significant at 5%

→ signifies unidirectional causality, \rightleftarrows signifies bidirectional causality

Based on the above tables, there is unidirectional causality between China and India over the three time periods. This suggests that any shift in the US stock market has an impact on the values of Chinese and Indian stocks. There is evidence of a bidirectional causal relationship between the US and India throughout the epidemic period, suggesting that both nations' stock values have experienced Granger effects. This indicates that there is a short-term short term relationship among the indices of US & India and US & China.

CONCLUSION:

While couple of studies have explored the co-integration and causal effects within common trading blocs such as ASEAN and SAARC, the effect of the COVID-19 pandemic on these linkages has received very little attention. By investigating whether the pandemic has changed the relationships between the stock indices of the BRIC-A countries and the US stock market, which leads the world market, this study seeks to close that gap.

The findings of this study indicate that the pandemic has indeed altered the financial interlinkages among the BRIC-A nations' stock indices in relation to the US stock index. In particular, the US and Indian stock markets have a steady long-term association over the course of the three time zones according to the Johansen co-integration test. This suggests that the pandemic did not disrupt the established co-integration between the US and India, indicating a stable financial relationship. Conversely, a co-integration between the US and China's stock indices was found only during the pandemic period, with no such relationship before or after the pandemic. Similarly, the US and Russia's stock indices exhibited co-integration only in the post- pandemic period, a relationship that did not exist during either the pre-pandemic or pandemic periods.

These conclusions are further supported by the Granger causality test results. The US stock index showed a short-run unidirectional causation with the stock indices of all BRIC-A countries prior to the pandemic, indicating that shifts in the US stock market caused changes in these countries' stock indices. However, in the post-pandemic period, the causal relationship was limited to India and China, indicating a narrowing of the influence of the US stock market. Furthermore, Brazil exhibited unidirectional causality over the US stock market in the pre-pandemic period, a relationship that did not persist during the pandemic or post-pandemic periods.

These results highlight how global disruptions like COVID-19 affect how interconnected global financial markets are, and they imply that the pandemic has brought forth new market dynamics, especially in relation to China and Russia's contacts with the US stock market.

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