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Analyzing interconnections between national stock exchange India and global markets using data analytics

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ABSTRACT

Financial networks have become increasingly complex and interconnected in the global economy. In this context, the use of data analytics has emerged as a valuable tool for understanding and analyzing the relationships between different financial markets. This paper presents a study using Pearson and partial correlation analysis to explore the interconnections between the National Stock Exchange India (NSEI) and global stock markets. The analysis aims to provide insights into the dynamics and patterns or cross-markets interactions and to identify potential opportunities for investment and risk management that to considering the world's 43 major indices based on imports and exports. The historical data from 1st January 2008 to 30th June 2022 was obtained from the public domain. In this study, a Python framework was developed to investigate Pearson and partial correlation-based networks in financial markets. The results showed that these two types of networks are significantly different from each other. Furthermore, the study discovered that the NSEI is closely connected to the Singapore market and is integrated with other markets. These findings emphasize the complexities to financial market relationships and have important implications for investors and policymakers.

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1. INTRODUCTION

In today's era of global economic integration, exploring National Stock Exchange Indias (NSEI's) ties to global markets reveals valuable insights for strategic investments. Understanding these interconnections and their impact on India's economy is vital. Data analytics provides powerful tools to uncover hidden patterns and transmission mechanisms between these markets. There are several examples of correlation, the most famous being October 1987, where the crash had spillover effects across the world [1]. In another study, it was found that contagion was transmitted to other financial markets [2]. The auto-regressive conditional heteroskedasticity (ARCH) method analyzed daily stock prices in major U.S., Japan, and UK markets, revealing contagion effects among them [3]. A correlation was detected in daytime and overnight returns between Tokyo and New York markets [4]. The U.S. and UK market correlation depends on the discount rate of stocks [5]. The Japan and US market are correlated [6]. Asian markets (Malaysia, Philippines, Indonesia, Singapore, and Thailand) except Indonesia are connected [7], [8]. The financial market correlation structure was studied using the minimum spanning tree (MST) [9], [10]. The correlation-based network offers a visual representation of extracted data and multivariate time series, enabling the observation of market trends, particularly during crises [11]. Japanese and Asian markets are integrated, and Malaysia, New Zealand, Australia, Hong Kong, and Singapore are highly integrated with the Japanese market [12]. In subsequent studies, MST was expanded by incorporating a planar maximally-filtered graph (PMFG) [13]. Pearson's MST and PMFG were utilized, revealing that the French stock market emerged as the most significant node in both MST and PMFG analyses [14], [15]. A Pearson-MST constructed with 53 stock markets from 1997 to 2006 revealed a trend of increasing compactness in the network [16]. The Pearson correlation-based network was applied to various financial markets [17]–[22]. Partial correlation-based network or dependency network filters the complex result, with other correlation-based networks [23]–[25]. The spillover effect has been illustrated [26]–[28]. The literature suggests that stock markets in different countries behave synchronously and has a contagion spillover effects due to international trade and the rapid dissemination of information. However, limited research is available on the NSEI, and there are challenges involved in analyzing the association with other stock markets, including cultural differences, regulatory compliance, economic fluctuations, political instability, and competition.

This paper systematically contributes to the understanding of correlation and dynamics among 43 stock exchanges based on import and export goods. To analyze these correlations, MSE-Pearson and MST-partial correlation are used, focusing on the NSEI. The study considers three distinct time regions, allowing for a comprehensive examination of the stock markets under different temporal conditions. This consideration adds further depth and accuracy to the analysis. Additionally, it investigates causality tests to explore relationships between the markets. Furthermore, the study examines volatility and stationarity using the augmented dickey-fuller (ADF) test. The remainder of this paper is organized as follows. In method section, data pre-processing are introduced, and the proposed techniques is delineated. Result and discussion section explicates correlation, heat map, HT, MST, volatility and causality. The last section devoted to conclusion.

2. METHOD

This study examines the correlation between NSEI and global markets using Pearson's and partial correlation analysis. Historical stock market data from January 1st, 2008, to June 30th, 2022, is collected, including significant events like the 2008 financial crisis and COVID-19 pandemic. The system architecture as shown in Figure 1 involves data collection, preprocessing, and descriptive statistics, followed by visualizing the correlation using Pearson's and partial correlation-based MST for world stock markets.

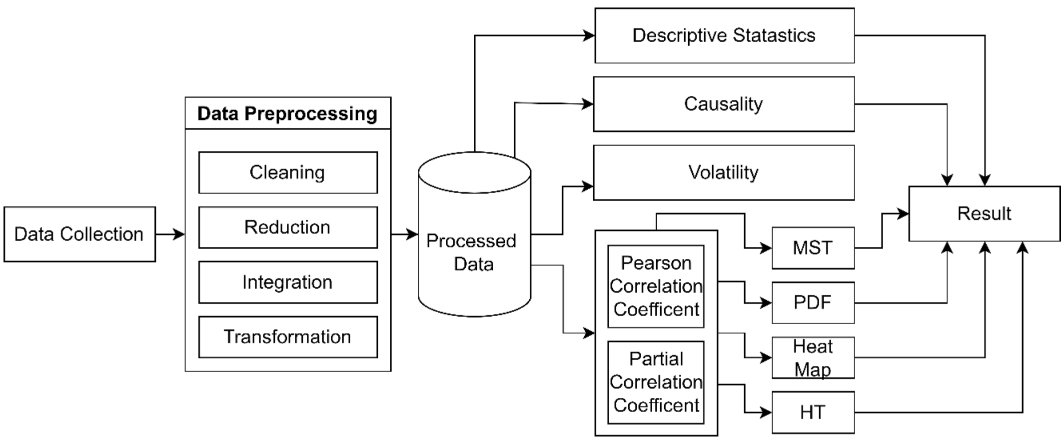


Figure 1. System architecture

Table 1 illustrated the list of exchanges with alpha-3 code for regions and other relevant information. Finally, A software framework was developed to test the relation with Python 3.8 and libraries such as NumPy, pandas, matplotlib, and seaborn. The hardware configuration included an i5 processor, 16 GB RAM, 2 GB graphics card, and a 1 TB SSD.

2.1. Pearson's correlation

The Pearson correlation assesses the correlation between two numerical variables and quantifies the extent to which the variables align with each other. The correlation result is always within the range of -1 to 1. A correlation closer to 1 indicates a positive linear relationship, while a correlation closer to -1 indicates a negative linear relationship. In (1) defines the Pearson correlation coefficient (r).

$$r = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2}\sqrt{\sum_i (y_i - \bar{y})^2}} \quad (1)$$

where, $x_i, = x\ value\ y_i = y\ value, \bar{x}\ = x\ mean\ and\ \bar{y} = y\ mean.$

The resulting value of (1) is saved in a square matrix with dimensions of 43x43, signifying the involvement of 43 stock markets. In (2) displays the set of Pearson's correlation (C) in matrix form.

$$C = \begin{bmatrix} C_{i,j} & \cdots & C_{iN} \\ \vdots & \ddots & \vdots \\ C_{Nj} & \cdots & C_{NN} \end{bmatrix} \quad (2)$$

Where, i, j =0,1,2,3…. N.

Table 1. List of stock exchange

ID	Region (country)	Code	Stock exchange	Index	UTC	Continent	Type
1	Canada	CAN	Toronto	TXI S&P 500	-5.00	North America	Developed
2	United States	USA	New York	DJ	-5.00	North America	Developed
3	France	FRA	France	FR40	-3.00	Europe	Developed
4	Argentina	ARG	Buenos Aires	S&P 500	-3.00	South America	Frontier
5	United Kingdom	GBR	London	FTSE100	0.00	Europe	Developed
6	Belgium	BEL	Brussels	BE20	1.00	Europe	Developed
7	Germany	DEU	Frankfurt	DAX	1.00	Europe	Developed
8	Italy	ITA	Italy	IT40	1.00	Europe	Developed
9	Netherlands	NLD	Netherland	NL25	1.00	Europe	Developed
10	Nigeria	NGA	Nigeria	NSE30	1.00	Africa	Frontier
11	Spain	ESP	Madrid	IBEX35	1.00	Europe	Developed
12	Switzerland	CHE	SIX Swiss	SMI	1.00	Europe	Developed
13	Egypt	EGY	Egyptian*	ETF	2.00	Asia	Emerging
14	Russia	RUS	Moscow (MOEX)	IMOEX	2.00	Asia	Emerging
15	South Africa	ZAF	Johannesburg	All share	2.00	Africa	Emerging
16	Israel	ISR	Tel Aviv	TA-125	2.00	Asia	Developed
17	Iraq	IRQ	Iraq	ISX60	3.00	Asia	Frontier
18	Qatar	QAT	Doha	All share	3.00	Asia	Frontier
19	Saudi Arabia	SAU	Tadawul	TASI	3.00	Asia	Emerging
20	Turkey	TUR	Borsa	BIST-100	3.00	Asia	Emerging
21	Bahrain	BHR	Bahrain Bourse	All Share	3.00	Asia	Emerging
22	Abu Dhabi	AED	Abu Dhabi	ADX General	3.00	Asia	Emerging
23	Oman	OMN	Muscat	MSM30	3.00	Asia	Frontier
24	Kuwait	KWT	Kuwait	All Share	3.00	Asia	Emerging
25	Brazil	BRA	B3	BOVESPA	4.00	SA	Emerging
26	UAE	ARE	United Arab Emirates	ADX General	4.00	Asia	Emerging
27	Sri Lanka	LKA	Colombo	All Share Price	5.30	Asia	Frontier
28	India	IND	National	NIFTY50	5.30	Asia	Emerging
29	Nepal	NPL	Nepal	NEPSE	5.45	Asia	Frontier
30	Bangladesh	BGD	Dhaka	DSE30	6.00	Asia	Frontier
31	Mexico	MEX	Mexican Balsa	IPC	6.00	NA	Emerging
32	Thailand	THA	Thailand	SETI	7.00	Asia	Emerging
33	Vietnam	VNM	Ho Chi Minh	VN	7.00	Asia	Frontier
34	China	CHN	Shenzhen	SSI	8.00	Asia	Emerging
35	Hong Kong	HKG	Hong Kong	SHI	8.00	Asia	Developed
36	Indonesia	IDN	Indonesia	Jakarta Composite	8.00	Asia	Emerging
37	Malaysia	MYS	Bursa Malaysia	KLCI	8.00	Asia	Emerging
38	Singapore	SGP	Singapore	STI	8.00	Asia	Developed
39	Taiwan	TWN	Taiwan	TAIEX	8.00	Asia	Emerging
40	Japan	JPN	Japan	NIKKEI225	9.00	Asia	Developed
41	South Korea	KOR	Korea	KOSPI	9.00	Asia	Emerging
42	Australia	AUS	Australian	ASX All Ordinaries	10.00	Australia	Developed
43	New Zealand	NZD	New Zealand	NZX 50	13.00	Australia	Developed

2.2. Partial correlation

The partial correlation coefficient (C') measures the degree of association without controlling variable. It is calculated using the matrix inversion method as shown in (3):

$$C' = C^{-1} = \begin{bmatrix} C'_{ij} & \cdots & C'_{iN} \\ \vdots & \ddots & \vdots \\ C'_{Nj} & \cdots & C'_{NN} \end{bmatrix} \quad (3)$$

in (4) is used to calculate the partial correlation coefficient between any two stock exchanges:

$$C^*_{ij} = -\frac{C'_{ij}}{\sqrt{C'_{ii}C'_{jj}}} \quad (4)$$

where, C_{ij}= correlation between stock exchange. Thus, the partial correlation matrix is defined using (5).

$$C^* = \begin{bmatrix} C^*_{ij} & \cdots & C^*_{iN} \\ \vdots & \ddots & \vdots \\ C^*_{Nj} & \cdots & C^*_{NN} \end{bmatrix} \quad (5)$$

The correlation matrix is a symmetrical matrix that exhibits the linear connection between two stock markets, with the correlation coefficient representing the elements of the matrix. By using (6), the correlation matrix is transformed into a distance matrix, which consists of D and D*:

$$d_{ij} = \sqrt{2(1 - C_{ij})} \text{ or } d^*_{ij} = \sqrt{2(1 - C^*_{ij})} \quad (6)$$

the value of d_{ij} or d^*_{ij} range from 0 to 2, adhering to the Euclidean distance axioms: i) d_{ij} = 0 if i=j; ii) d_{ij} = d_{ji}; and iii) $d_{ij} \leq d_{ik} + d^2_{kj}$.

2.3. Kruskals' algorithm

Kruskal's algorithm [29] is a greedy method to identify the minimum spanning tree of a graph that encompasses all the vertices of the graph with the lowest possible total edge weight among all spanning trees. The algorithm can generate a forest that works as a disconnected component and performs better in sparse graphs. After forming the tree, in (7) is utilized to group similar nodes using k-means clustering:

$$J(V) = \sum_{i=1}^{c} \sum_{j=1}^{c_i} \left(\left|\left|x_i - v_i\right|\right|\right)^2 \quad (7)$$

where, J(V)=objective function, c=No. clusters, c_i=No. of data points in the i^{th} node, x_i=case i and finally v_i is centroid for cluster J. further, the algorithm divides the tree into smaller clusters, and this division can be visualized through the dendrogram.

2.4. Augmented dickey-fuller

The ADF test is used to determine whether a time series is stationary or non-stationary. It is an extension of the Dickey-Fuller test, which tests for a unit root in a time series and it is defined using (8):

$$\Delta y_t = \rho y_{t-1} + \sum\left(\delta_j * \Delta y_{t-1}\right) + \varepsilon_t \quad (8)$$

where, $\sum\left(\delta_j * \Delta y_{t-1}\right) + \varepsilon_t$=summation of lagged difference, Δy_t=difference between time series, ε_t =error.

2.5. Granger causality

A causality test is performed to determine causality between two variables, but establishing causality can be challenging, and correlation does not imply causation. In (9) and (10) are used to calculate causality:

$$X_1(t) = \sum_{j=1}^{p} A_{11,j} X(t-j) + \sum_{j=1}^{p} A_{12,j} X_2(t-j) + E_1(t) \quad (9)$$

$$X_2(t) = \sum_{j=1}^{p} A_{21,j} X(t-j) + \sum_{j=1}^{p} A_{22,j} X_2(t-j) + E_2(t) \quad (10)$$

where, p=max. Lagged observations, A=correlation matrix, $X_1(t)$, $X_2(t)$, E_1 and E_2 are residuals for each time series.

2.6. Volatility

Volatility is the rate at which the price of a stock increases or decreases over a particular period. The volatility is calculated using (11):

$$V = \sqrt{(\sum(\mathrm{R_i} - \mathrm{R_{avg}})^2)/(\mathrm{N}-1)} \quad (11)$$

where, $\mathrm{R_i}$=i[th] return, $\mathrm{R_{avg}}$=Average return, N=No. of trading days.

3. RESULTS AND DISCUSSION

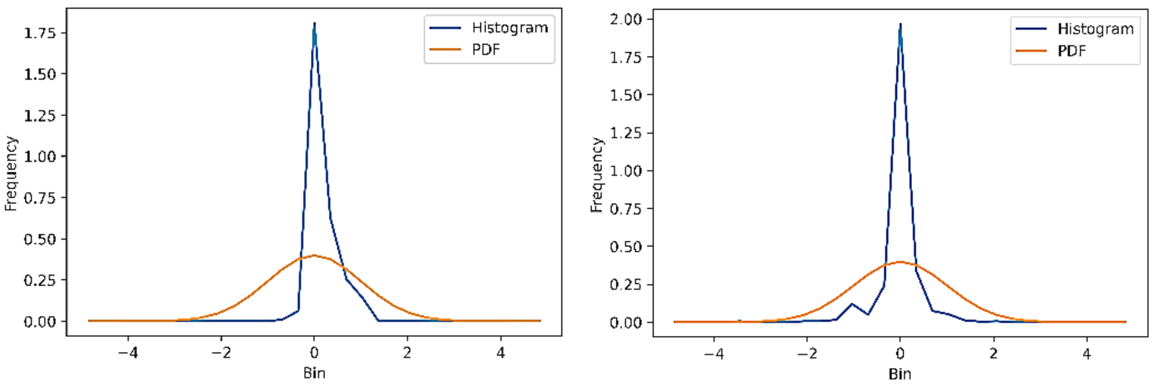
3.1. Statistics of Pearson's and partial correlation

Prior to analyzing Pearson and partial correlation MST, the data underwent preprocessing and augmented dickey test to determine whether the time series is stationary or not. The results showed that Spain, Switzerland, Iraq, Turkey, Abu Dubai, Brazil, and Vietnam are stationary, while all other countries are non-stationary. Table 2 shows the descriptive statistics of Pearson and partial correlation coefficients. Pearson has a higher mean compared to partial correlation, with maximum value in Pearson and minimum in partial correlation. The standard deviation of both measures is similar, with Pearson and partial correlation having right and left skewed distributions, respectively. Kurtosis greater than 3 indicates heavy tails and riskier investments. The normality of the data is tested using the Jarque-Bera test.

Table 2. Descriptive statistics

Parameter	Pearson correlation	Partial correlation
Mean	0.2010	0.1550
Maximum	1.0000	0.6243
Minimum	-0.05635	-1.0000
Standard deviation	0.2440	0.2762
Skewness	1.1155	-1.2815
Kurtosis	3.7561	8.2583
Jarque-Bera	9.9431	61.3104
Observation	2590	2590

Figure 2 illustrated the probability density function, with the horizontal axis representing the center of each bin, and the vertical-axis representing the frequency of samples. Figures 2(a) and (b) depict the probability density function (PDF) of N(N-1)/2 in Pearson correlation $\{\mathrm{C_{i,j}},\ i<j\}$ and partial correlation coefficient $\{\mathrm{C_{i,j}}*,\ i<j\}$ respectively. The PDF exhibits a skewed or positively skewed distribution with a prominent positive value at the center. The positively skewed indicate that the mode will be less than mean and median. Similarly, the median is close to first and third quartile and mean will be greater than median and mode. This suggests that most of the data points are clustered around this value, while the other values are relatively less frequent.

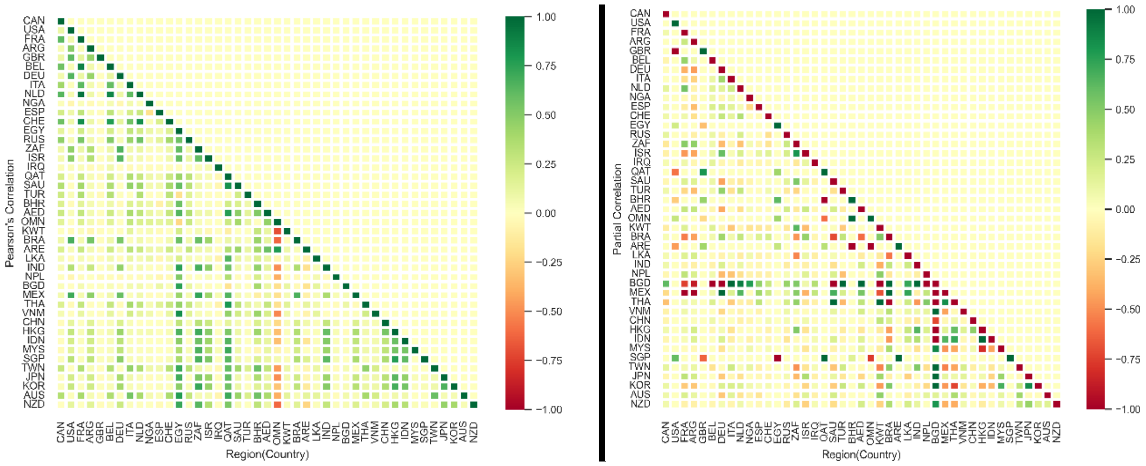


(a) (b)

Figure 2. Comparison of PDF results between (a) Pearson's correlation coefficient and (b) partial correlation coefficient

3.2. Heat map analysis

Heat map analysis is a graphical representation of data that uses color-coding to show the relationship between different variables. Figure 3 illustrated the correlation between the stock markets and NSEI, with the vertical axis representing the correlation and the horizontal axis indicating the names of countries. The darker shades in Figures 3(a) and (b) represent a higher correlation, while the diagonals are darker green because they indicate self-correlation. It is clearly observed that NSEI has connections with Asian and South American markets, as well as developed markets.

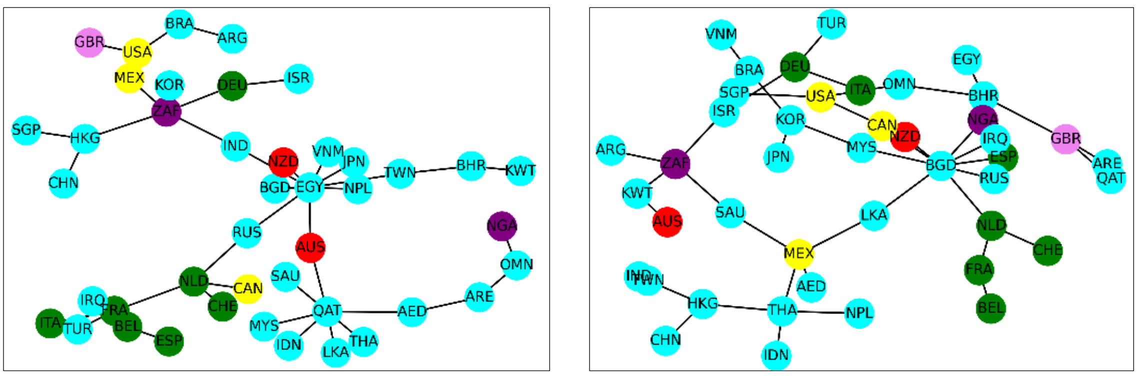


(a) (b)

Figure 3. Comparison of heatmap graphs between (a) Pearson's correlation coefficient and (b) partial correlation coefficient

3.3. MST-Pearson and MST-partial

In the MST, each node corresponds to a stock market in a continent. The nodes are colored based on their corresponding continent, with Australia as red, North America as yellow, South America as violet, Europe as green, Africa as purple, and Asia as blue. The edges represent the associations between the stock exchanges, and the correlation between them depends on the distance between the connected nodes. Figure 4 portrays a minimum spanning tree derived from both Pearson's and partial correlation coefficients. In Figure 4(a), it vividly depicts the linkage of NSEI with markets from Asia, South America, and other developed regions. Simultaneously, Figure 4(b) reveals a close relationship between the NSEI and Asian markets, particularly Hong Kong, Singapore, and other countries in the region.

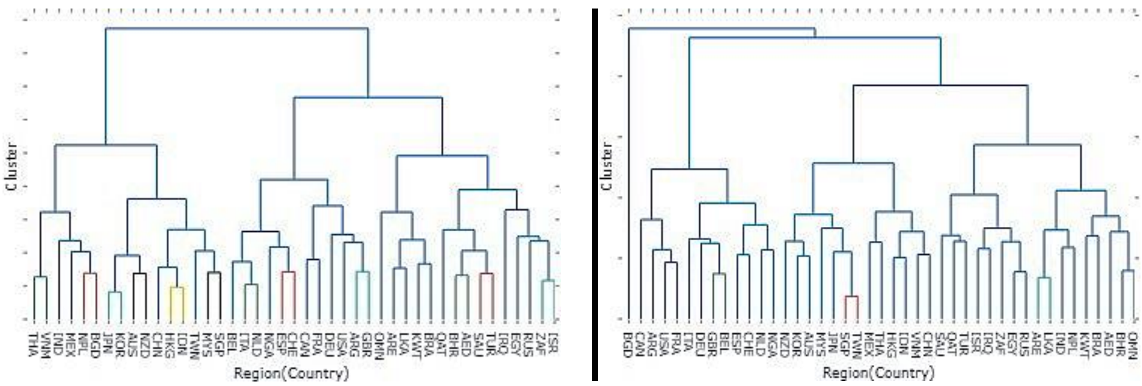


(a) (b)

Figure 4. Comparison of minimum spanning trees based on (a) Pearson's correlation coefficient and (b) partial correlation coefficient

3.4. HT-Pearson and HT-partial

Figure 5 represents Hierarchical trees, with vertical-axis as the correlation coefficient and the horizontal-axis as the countries. Figure 5(a) illustrated Asian market cluster comprising 14 countries (excluding Mexico), a European cluster comprising 12 countries (excluding Nigeria and the US), and a third cluster consisting of the Middle East, some Asian countries, and South Africa. These three clusters show significant associations among themselves. In Figure 5(b), three major clusters are depicted. The first cluster consists of Europe (excluding Bangladesh), the US, and Nigeria. The second cluster consists of the Asian market (excluding New Zealand, Australia, and Mexico). The third cluster is primarily composed of the Middle East, with India.



(a) (b)

Figure 5. Hierarchical trees for (a) Pearson’s correlation coefficient and (b) partial correlation coefficient

3.5. Volatility

Figure 6 displays the volatility levels of various stock exchanges, with volatility referring to the amount of uncertainty in a security's value. Higher volatility means a security's value is spread over a larger range. Malaysia, Singapore, and the UK show lower volatility levels compared to India.

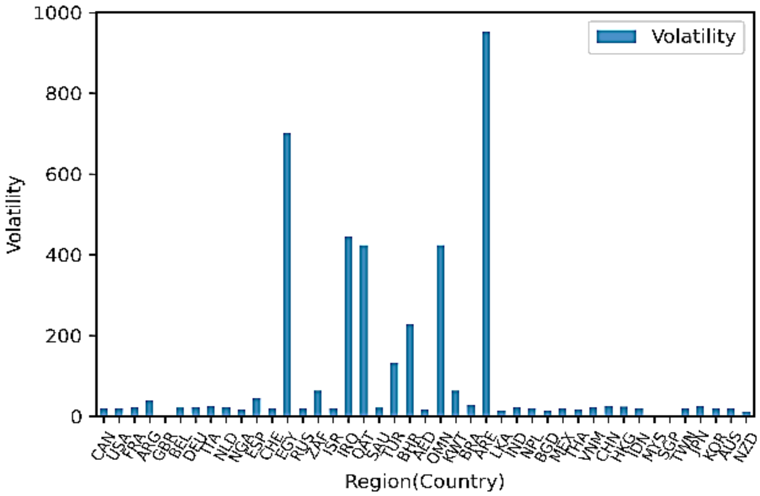


Figure 6. Volatility of stock exchanges

3.6. Granger causality

This test served as a valuable tool in exploring the connection between the two series, providing valuable insights into the dynamics of the financial markets studied. The findings, presented in Table 3, reveal a strong and significant association between the NSEI and markets in Singapore, Indonesia, and Hong Kong, as well as other developed markets, with a significance level of 0.05. The results highlight the interdependence of the NSEI and the identified markets.

Table 3. Top three regions (countries)

Sr. No	Region	Chi–Square	p-Value	Sample
1.	Singapore	30.5694	0.0000	3073
2.	Indonesia	4.9116	0.0419	2982
3.	Hong Kong	17.2556	0.0041	3012

4. CONCLUSION

This study uses data analytics to explore the relationships between the NSEI and global stock markets, aiming to provide insights into cross-market interactions and potential opportunities for investment and risk management. Historical data from 2008 to 2022 was used, and a Python framework was developed to investigate Pearson and partial correlation-based networks in financial markets. The analysis compared the descriptive statistics of Pearson and partial correlation coefficients, with Pearson showing a higher mean and maximum value, and both measures exhibiting right and left-skewed distributions, respectively. The Jarque-Bera test was used to test for normality. The probability density function in Pearson and partial correlation coefficients exhibited a positively skewed distribution, with the data points clustered around the center. The heatmap and correlation matrices showed that NSEI had significant linkages with Asian and South American markets, as well as other developed markets. The HT-Pearson correlation matrix formed three significant clusters, while the HT-partial correlation matrix yielded three major clusters. The Granger causality test revealed that NSEI was significantly associated with markets in Singapore, Indonesia, and Hong Kong, as well as other developed markets. Finally, the study showed that Malaysia, Singapore, and the UK had lower volatility levels compared to India. Our work has some limitations like we have not consider the impact of oil, gold prices and rate of interest to the respective countries.

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