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Assessing Global Stock Market Linkages: A Cointegration Analysis of the Indian Stock Market with Selected International Stock Markets

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Abstract

This research paper investigates complex relationships between the Indian stock market and selected international stock markets through an elaborate analysis of their dynamic relationship from 2004 to 2024. The study, focused on Indian stock markets, identifies their global challengers and is supposed to scourge out despondent markets, which by its efforts set down cointegration with the Indian stock exchange, acting as sources of portfolio risk diversification. Furthermore, it investigates the short-run dynamic interconnections of the Indian stock market with those of the US, the UK, China, and Hong Kong, through Granger causality tests.

The analytical research design was used to achieve these objectives. Monthly indices data during 2004-2024 were used for the world's major indices: NIFTY 50 (India), S&P 500 (USA), FTSE (UK), Shanghai Composite (China), and Hang Seng (Hong Kong) to achieve representative stock market indices with convenience sampling. Analytical methods include normality tests, Augmented Dickey-Fuller (ADF) unit root tests, Johansen cointegration, and regression analyses.

The analysis shows that for the selected stock exchanges, Nifty achieved the highest average annual return of 15.058% but with even more extensive volatility as it achieved maximum monthly gains of 26.066% and losses of –26.410%. The US and UK markets have a good deal of correlation (0.76), which indicates much deeper economic synchronism, while the Chinese market seems to operate within the most discrete financial ecosystem since it has the least correlation with the other markets. Granger causality tests indicate a one-way causal relationship between China and India, and a bi-directional cause between the US and UK markets. Regression analysis indicates significant contributions from the UK and Hong Kong markets in explaining returns in the Indian market.

Thus, the study concludes that there are significant interdependencies among selected global stock markets, where the Indian market shows high growth potential and great volatility. It also shows the interaction of complex parameters, which influence market performance, namely, economic, political, and regulatory, and the importance of awareness about these linkages for international investment and risk management.

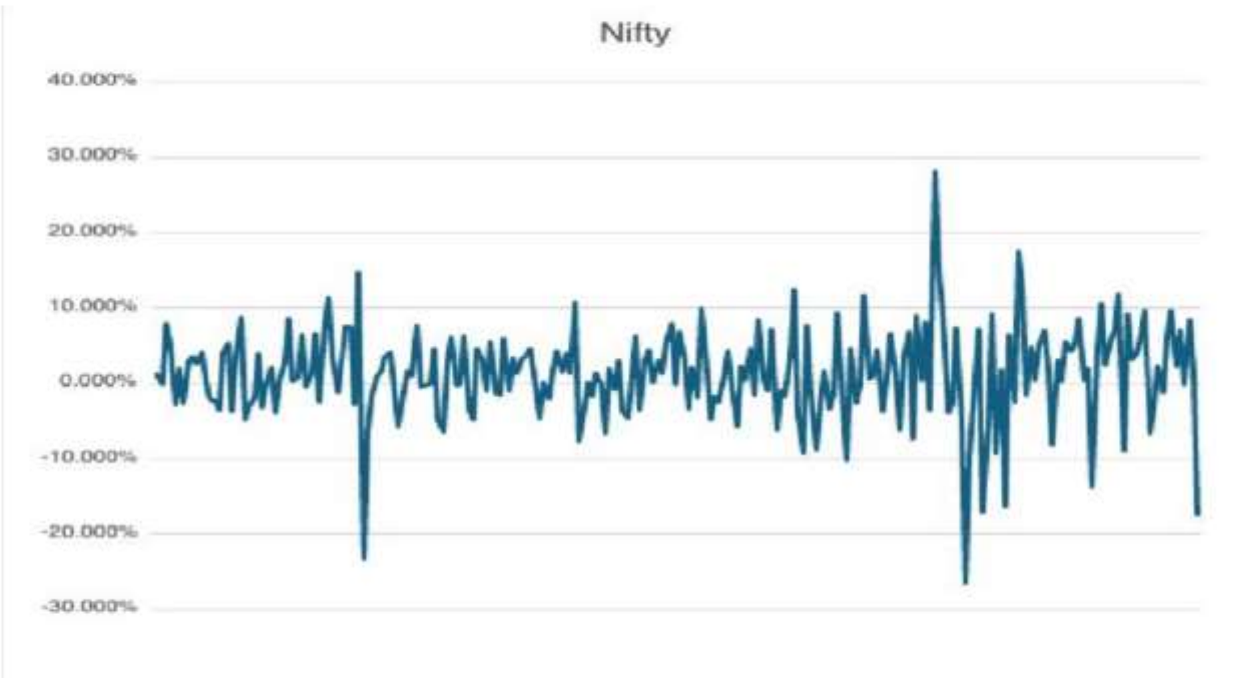
CHAPTER 01: INTRODUCTION

1.1 INTRODUCTION

The evolution of global financial markets constitutes one of the major economic revolutions in human history, a complex about interconnectedness, financial innovation, and economic integration. Stock markets began over 400 years ago with the creation of the first public company, the Dutch East India Company (VOC), in 1602. The VOC revolutionized the raising of capital for business; it was the first popularly held share company that transformed the raising of capital and investment. This pursuit transformed into a long journey to reshape the world economy with new means for accumulating capital, managing risk, and economic growth. As the world economic system became more and more globalized during the 19th and 20th century, stock exchanges arose as a necessary infrastructure to develop international finance.

Stock markets contribute to economic development in at least three ways: Capital Formation Through the sale of company stock to public investors, public companies can raise a significant amount of capital. This capital raised through stock sales can be invested in technology, infrastructure, and company growth. Stock markets offer an alternative to bank loans and traditional capital raising options. The stock market developed by companies issuing shares to the public. Once the company started selling partial ownership in the company, an organized system needed to develop an organized marketplace to buy, sell, and trade these financial instruments. Amsterdam, London and New York became home to some of the first stock exchanges, providing an organized marketplace that established rules and regulations, days and times to trade and a location to trade.

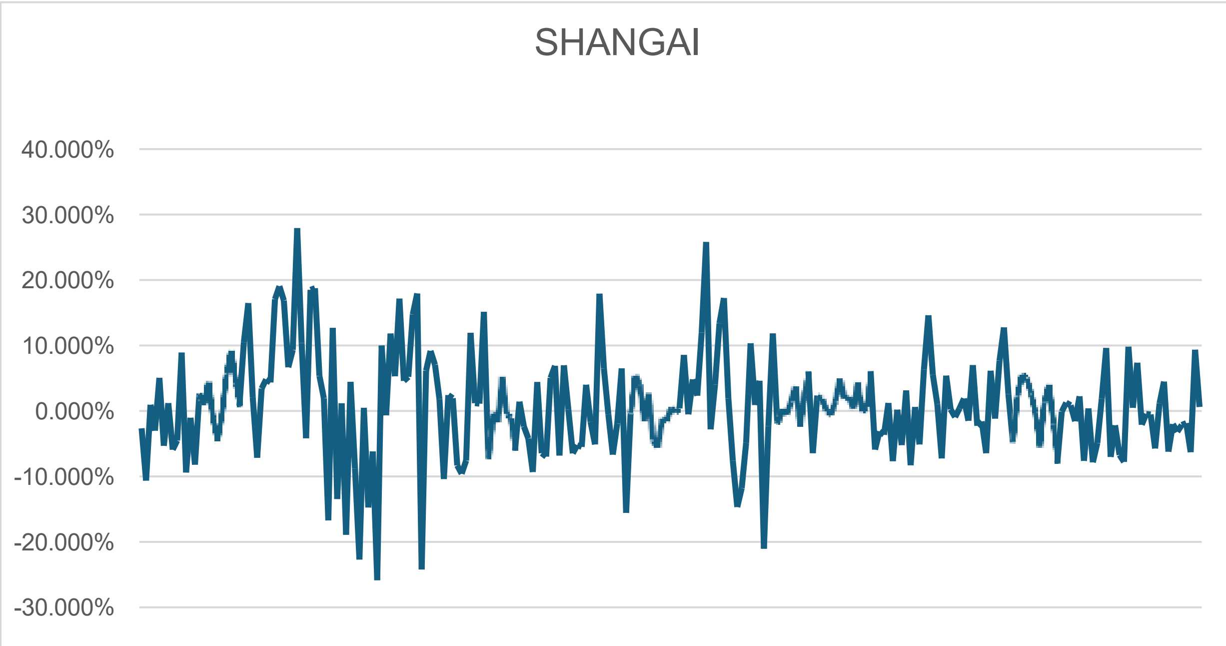
The Indian stock market traces its origins to the British colonial era of the mid-1800s, when organized financial trading on a small scale began in Bombay, which was recognized as a commercial centre. These activities began to pick up speed in the important moment of 1991 when Dr. Manmohan Singh's economic liberalization reforms came to picture. These reforms changed the face of the Indian economy by dismantling restrictions on financial markets in India. The opening of the Securities and Exchange Board of India (SEBI) in 1992 was also a critical moment as it introduced a comprehensive regulatory framework that prioritized transparency, accountability, and investor protection.



NIFTY returns from 2004-2024.

This graph depicts the annual return of NIFTY index in the last 20 years ranging from 2004- 2024. Nifty had an average annual return of around of 15.058% which is highest amongst the selected stock exchanges. The 2004-2024 period represents a complex landscape of economic challenges and opportunities. The Nifty's performance encapsulates broader macroeconomic trends, revealing the Indian market's ability to navigate global economic disruptions while maintaining substantial growth potential. The most significant dips occurred during the 2008 Global Financial Crisis and the 2020 COVID-19 pandemic, with losses ranging between 25- 35%.

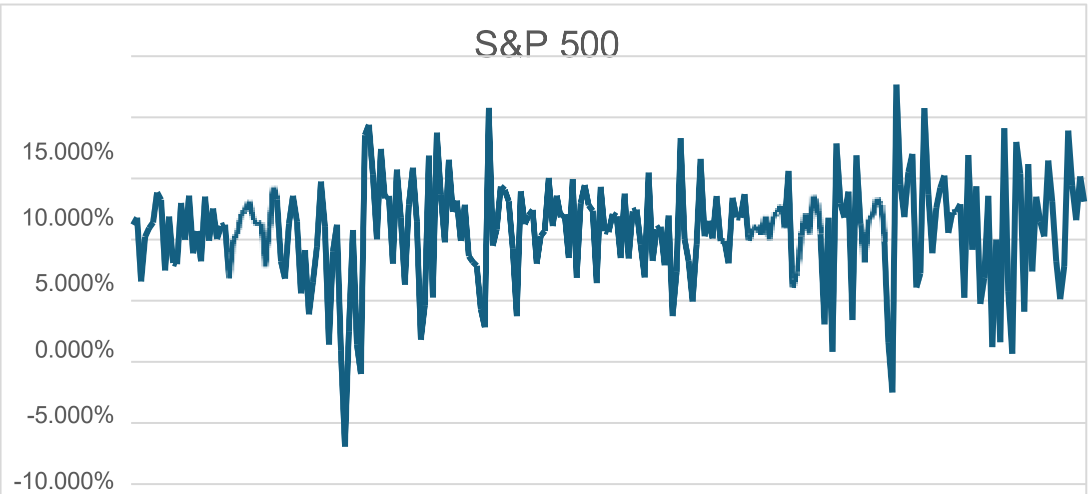
1.2 China (SHANGAI) Returns from 2004-2024



SHANGAI returns from 2004-2024.

The China stock market graph reveals a complicated set of market returns that have incredible volatility and extreme swings between around -30% and +30%. The graph's pattern reveals a market that has frequent, and sometimes intense short-term fluctuations, representing the fast moving, fluid, and often uncontrollable nature of China's economy.

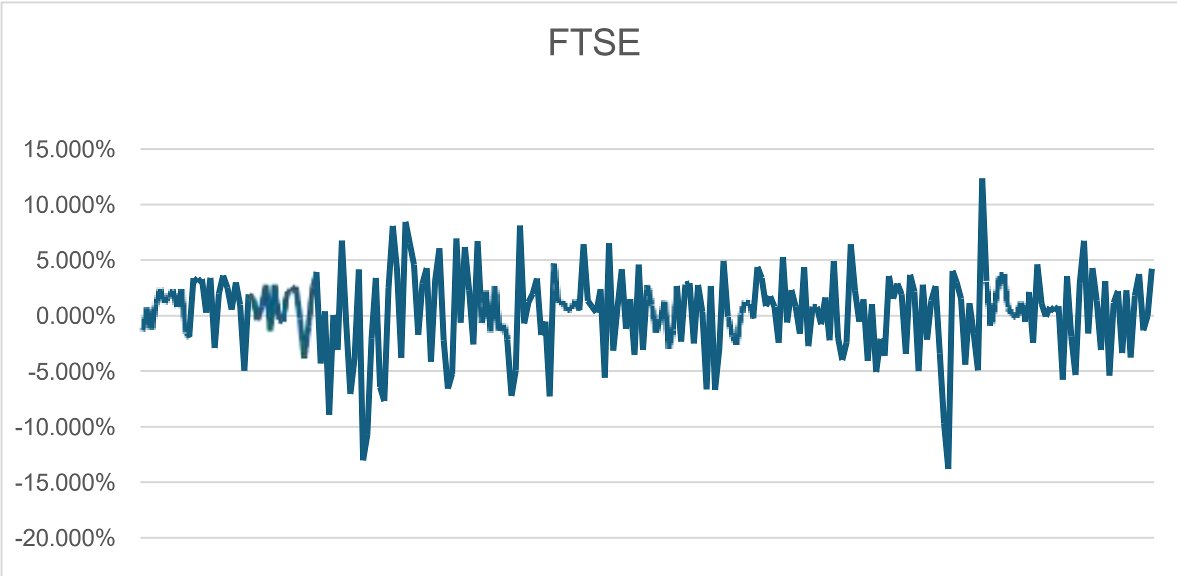
1.3 US S&P 500 Returns from 2004-2024.



S&P 500 returns from 2004-2024.

The graph for S&P 500 indicates less volatility than for Nifty and China markets, with returns usually varying between -20% and 15%. The graph shows a fairly steady path around the zero line, indicative of a calmer environment with less disruptive noise. These measured fluctuations suggest an organized capital market that experiences fluctuations and volatility that are usually consistent with economic activity, indicative of the broader economic resilience and sophisticated regulatory frameworks of the U.S. stock market.

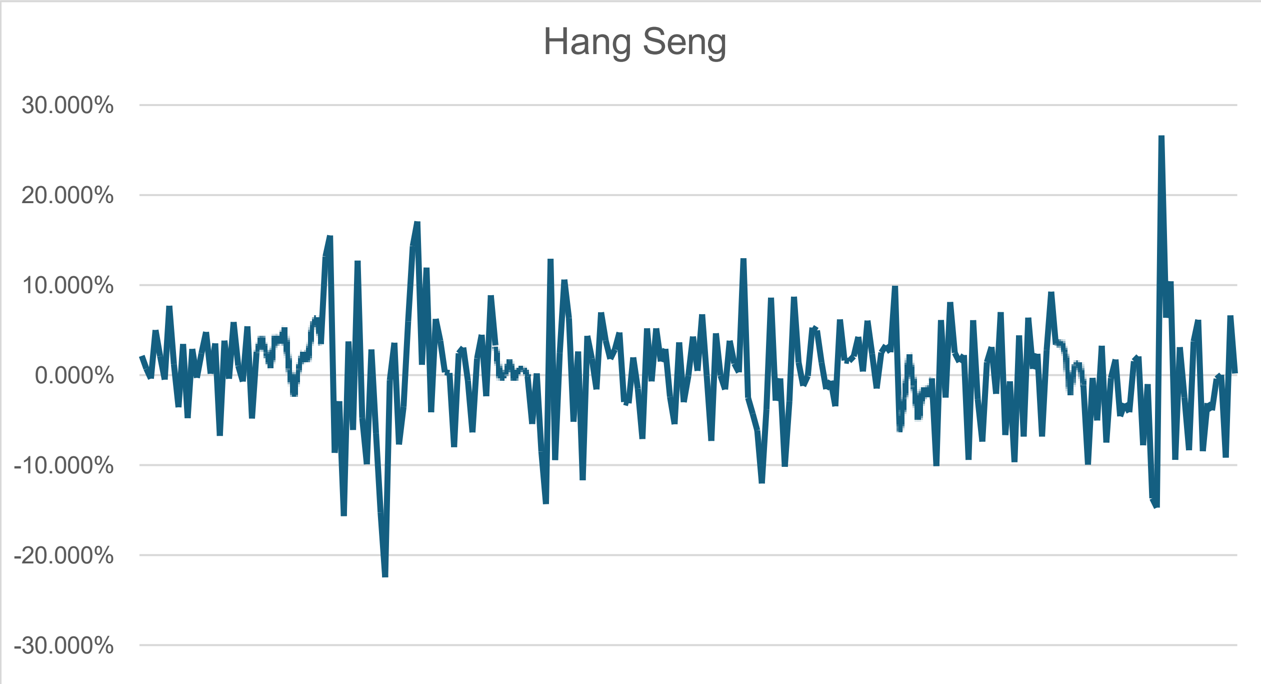
1.4 UK FTSE Returns from 2004-2024.



FTSE returns from 2004-2024.

The FTSE exhibits market returns that follow a pattern that is quite similar to that of the S&P 500, with the majority of returns showing fluctuations in a primary range of -20% and +15%. The graph also shows that the majority of the fluctuations remain relatively consistent, oscillating around the zero line. This indicates that a stable market environment is present relatively consistently which we would find in older and developed European financial markets. These variations in the FTSE were no rapid changes that one would find in an emerging market, so the measurement of controlled volatility likely reflects the well-developed economic structure of the United Kingdom and regulated economy, as well as market regulations governing the London Stock Exchange market.

1.5 Hong Kong Heng Seng Returns from 2004-2024.



Hang Seng Returns from 2004-2024.

The Hang Seng chart reflects a more volatile market pattern when compared to Western markets, as returns swing across -30% and +30%, which are much more extreme swings expected as a consequence of an emerging market. Furthermore, the chart suggests a market that is acutely sensitive to changes in politics, regulation, and the economy in the Asia-Pacific region.

CHAPTER 02: REVIEW OF LITERATURE

2.1 LITERATURE REVIEW

The integration of global stock markets has been one of the focal points in this paper, particularly in understanding the interconnectedness between emerging markets like India and developed economies. This literature review takes findings from various studies that explore the cointegration, correlation, and spillover effects between the Indian stock market and major global indices, such as the S&P 500 (USA), FTSE 100 (UK), Nikkei 225 (Japan), Hang Seng (Hong Kong), and Shanghai Composite (China). The review also highlights the impact of significant global events, such as the COVID-19 pandemic, on market integration.

Financial Integration and Cointegration:

In *(Agarwal et al., 2005)* the long-term equilibrium relationships and short-run dynamic interlinkages between the Indian stock market (BSE 200) and major global markets (S&P 500, FTSE 100, and Nikkei 225) from 1991 to 2003 was investigated. Using fractional cointegration approaches, the paper had found evidence of long-run integration but noted limitations, such as the exclusion of post-2005 financial policy changes and geopolitical factors. The authors emphasized the need for future research to explore how novel dynamics, such as technological advancements and global crises, influence India's financial linkages.

Similarly *(Marisetty, 2024)* analysed the cointegration and correlation among NSE Nifty (India), S&P 500, FTSE 100, Hang Seng, and Nikkei 225 from 2008 to 2023. The study employed econometric techniques, including the Johansen Cointegration Test and Vector Error Correction Model (VECM), revealing strong positive correlations and long-run cointegration between NSE Nifty and major global indices. However, the study did not address short-term volatility spillovers or the role of regional financial policies, suggesting future research incorporate macroeconomic variables like inflation and interest rates. Global macroeconomic factors were mentioned, but the study did not include the influence of regional financial policies or institutional investors in shaping these interconnections.

Spillover Effects and Interconnectedness:

(Agarwal et al., 2024) explored spillover effects and interdependencies among the stock markets of the US, China, Germany, Japan, and India using the DCC-GARCH model and Diebold-Yilmaz method. The study identified the US and Germany as net transmitters of volatility, while China, Japan, and India were net receivers. Despite its comprehensive methodology, the study overlooked the role of high-frequency trading (HFT) and algorithmic trading in intensifying spillover effects, indicating a need for broader research scope.

Impact of Financial Liberalization:

(Deo & Arun Prakash, 2017) examined the long-run correlation between the Indian stock market (NSE Nifty) and major global indices from 2006 to 2015. Using Johansen cointegration and Granger causality tests, the study found strong long-run relationships but highlighted the absence of sectoral linkages and short-term volatility spillovers in the analysis. The researchers recommended incorporating Foreign Direct Investment (FDI) and Foreign Institutional Investment (FII) as dependent variables in future studies to better understand market integration.

(Kumar Chattopadhyay et al., n.d.) studied the integration of the Indian stock market with developed markets (USA, UK, Japan, and Hong Kong) over a 15-year period (2008–2023). The research revealed one-way causality from developed markets to India, excluding Japan, suggesting that the Indian stock market is not fully integrated with global markets. The study also emphasized the need to examine the impact of financial policy changes and geopolitical events, such as COVID-19, on market integration.

Regional and Global Market Integration:

(Tripathi & Sethi, 2010) measured the degree of integration between the Indian stock market and four major global markets (USA, UK, Japan, and China). The study found that India is more integrated with the US market than with Japan, the UK, or China. However, the analysis did not consider sectoral linkages or short-term volatility spillovers, which could provide deeper insights into market dynamics.

(Panda, 2015) investigated the dynamic interdependencies between the Indian stock market and markets in the US, UK, Japan, Singapore, Hong Kong, Malaysia, South Korea, Taiwan, and China from 2001 to 2008. The study identified a cointegration relationship between India and the US but noted time-varying relationships with other Asian markets. The research highlighted the need to account for post-2008 developments, such as financial crises and technological advancements, in future studies.

Integration with Global and Regional Markets:

(Raj & Dhal, 2008) examined the relationship between the Indian stock market and major global markets, including the USA, UK, and Japan, as well as regional markets such as Singapore and Hong Kong. Using multivariate cointegration models, correlation analysis, and Vector Error Correction Models (VECM), the study found evidence of cointegration between the Indian market and global markets, particularly with the USA and UK. The results indicated that India is more closely tied to international markets than to regional ones, highlighting the transformative role of financial globalization. However, the study acknowledged a limitation; it did not account for developments post-2008, such as the global financial crisis and subsequent policy changes, which could have significantly

influenced financial integration.

BRIC Market Integration:

(Dasgupta, 2014) analysed the integration and dynamic linkages between the Indian stock market and other BRIC markets (Brazil, Russia, and China). The study found positive correlations among BRIC markets, with bidirectional Granger causality between India and Brazil. However, long-run cointegration was absent, except between India and Brazil. The research emphasized India's influence on BRIC markets and suggested further exploration of sectoral integration and investor sentiment.

CHAPTER 03: RESEARCH METHODOLOGY

Objectives:

- To identify the countries and indexing influencing the Indian Stock market
- To identify markets not cointegrated with Indian stock exchange to invest to ensure portfolio risk diversification.
- To analyse short term dynamic interactions between Indian, US, UK, China, Hong- Kong stock markets using Granger causality tests.

3.1 : Research Methodology:

This study employs an analytical approach to investigate cointegration relationships among major global stock indices and their influence on the Indian stock market from 2004 to 2024.

a. Method of Sampling: The study utilizes convenience sampling methodology to select representative stock market indices from global exchanges.
b. Sample technique: Non-probability convenience sampling was used to strategically select indices that represent key global financial markets.
c. Sample Size: The sample comprises monthly index data for five major indices spanning 2004-2024:

Number	Index	Market Represented
1	**NIFTY 50**	**India**
2	**S&P 500**	**United states**
3	**FTSE**	**United Kingdom**
4	**Shanghai**	**China**
5	**Hang Seng**	**Hong Kong**

d. Analytical Methods

The research employs the following statistical methodologies:

1. Normality Test
2. Augmented Dickey-Fuller (ADF) Unit Root Test
3. Johansen Cointegration Test

Regression Analysis

3.2 : Research Limitations:

1. The study is restricted to five major global indices (NIFTY, S&P 500, FTSE, Shanghai Composite, Hang Seng), excluding other influential markets.

2. Only monthly data from 2004-2024 is analysed, potentially missing intraday volatility and short-term spillovers.
3. The methodology relies on linear cointegration tests (Johansen) which may not capture nonlinear relationships during crises.
4. Structural breaks from major events (2008 crisis, COVID-19 pandemic) may affect data stationarity results.
5. The analysis excludes macroeconomic factors and geopolitical events that could influence market integration.
6. Data consistency assumptions are made despite varying index calculation methodologies across countries.

CHAPTER 04: DATA ANALYSIS AND INTERPRETATION

4.1 Performance of the selected stock exchanges:

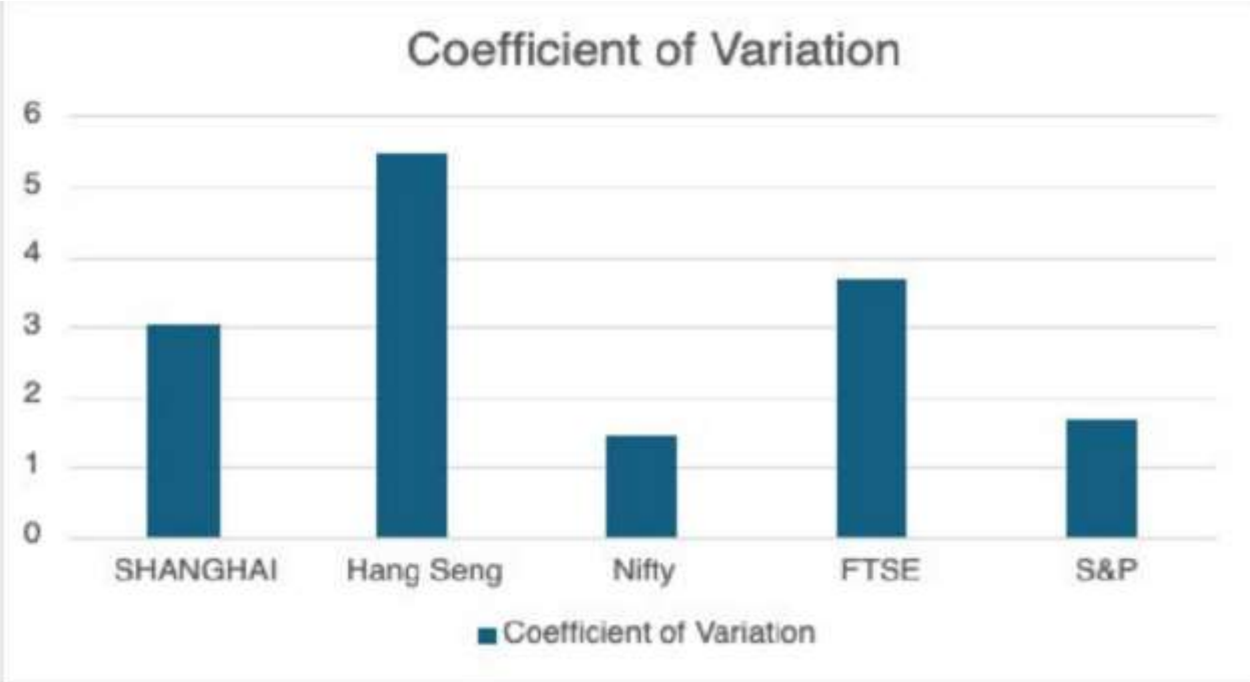
	Shanghai	Hang Seng	Nifty	FTSE	S&P
Average Monthly Data	**0.757%**	**0.322%**	**1.255%**	**0.293%**	**0.738%**
Average Annum Data	**9.086%**	**3.867%**	**15.058%**	**3.519%**	**8.851%**
Maximum Monthly Data	**27.929%**	**26.624%**	**28.066%**	**12.352%**	**12.684%**
Minimum Monthly Data	**-25.851%**	**-22.466%**	**-26.410%**	**-13.808%**	**-16.942%**
Std deviation monthly	**7.984%**	**6.094%**	**6.233%**	**3.730%**	**4.319%**
Std Deviation annum	**27.657%**	**21.111%**	**21.591%**	**12.922%**	**14.963%**
Coefficient of Variation	**3.043941691**	**5.458803481**	**1.433841345**	**3.671636303**	**1.690484923**
Ranking	**3**	**5**	**1**	**4**	**2**

The statistical measures of standard deviation and coefficient of variation are very insightful in understanding the behaviour of the market. The Nifty's annual standard deviation of 21.591% suggests a moderate degree of volatility, implying a market that gives large returns with a relatively contained risk profile. By comparison, Shanghai Composite has the highest yearly standard deviation of 27.657%, which testifies to the more volatile and unstable nature of the Chinese market fuelled by governmental interference, aggressive economic changes, and intricate rule books.

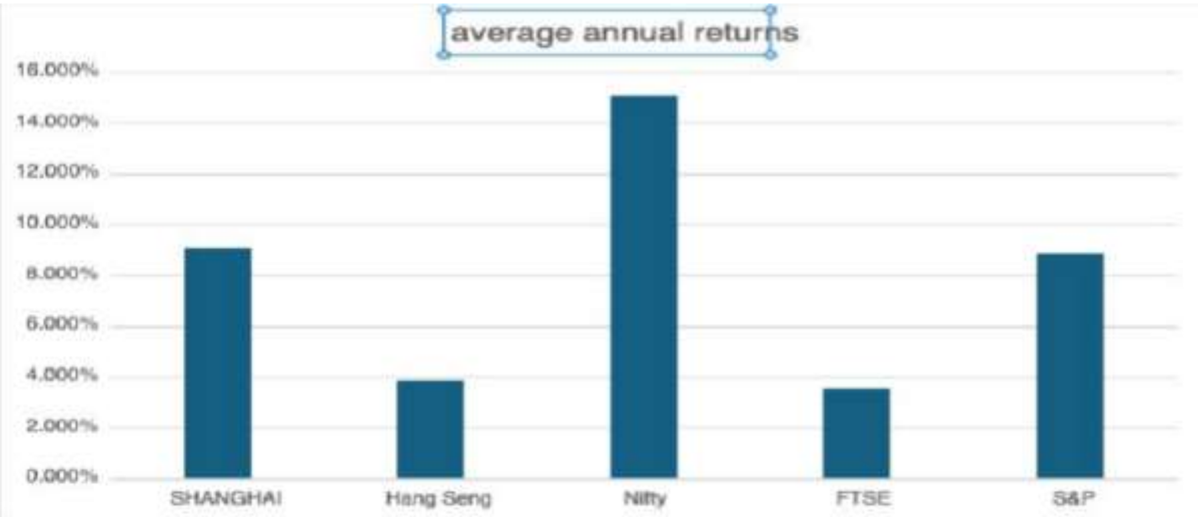
The coefficient of variation comes out as a pivotal measure in interpreting risk-adjusted performance. The extremely low coefficient of variation of the Nifty at 1.43 indicates a superb efficiency in return delivery against volatility. This measure implies that for each unit of risk taken, the Indian market offers a more stable and predictable return than other indices. The S&P 500 also tracks closely at 1.69 coefficient of variation, pointing to its own solid and steady performance typical of developed, regulated markets.

By contrast, Hang Seng shows the maximum coefficient of variation at 5.45, indicating a less efficient market with more volatility against returns. This mirrors the consistent geopolitical tensions, economic uncertainty, and structural problems being encountered by the Hong Kong market. The FTSE and Shanghai indices also show higher coefficients, which indicate the multifaceted interaction of economic, political, and regulatory forces that affect market performance.

The comparison of maximum gains and losses among these five stock market indexes paints an interesting picture of worldwide financial activity. India's Nifty index shows the most extreme price fluctuations with maximum monthly gains of 28.066% and losses of -26.410%. Comparatively, the S&P index for the United States shows relatively moderate volatility with maximum monthly gains of 12.684% and losses of -16.942%. This relative calm is a testament to the maturity of the U.S. financial system, supported by strong regulatory systems, diversified economic sectors, and advanced financial intermediaries. New markets such as India and China exhibit more volatility, due to their dynamic economic changes, whereas mature markets such as the United States and United Kingdom exhibit more cautious reactions to global economic stimuli.



The Coefficient of Variation is a normalized measure of dispersion that enables us to compare the volatility of various datasets in relation to their average annual return. It is computed by dividing the standard deviation by the average annual return and is.A higher CV reflects higher variability in relation to the mean which is undesirable as it implies higher volatility. In the chosen stock exchanges data, Nifty has the lowest coefficient of variation of approximately 1.48, showing the most stable performance out of these indices with the lowest relative price variations.



Average Annual Returns of the selected stock exchanges.

A comparative review of global stock market indices from 2004 to 2024 presents a story of economic performance and promise. The Nifty index is the top performer, clocking in awe- inspiring average annual returns of around 15%, comfortably outperforming various chosen global indices. Such breathtaking performance is a result of India's healthy economic growth, highlighted by a young and vibrant population, liberal economic reforms, and rising global economic integration.

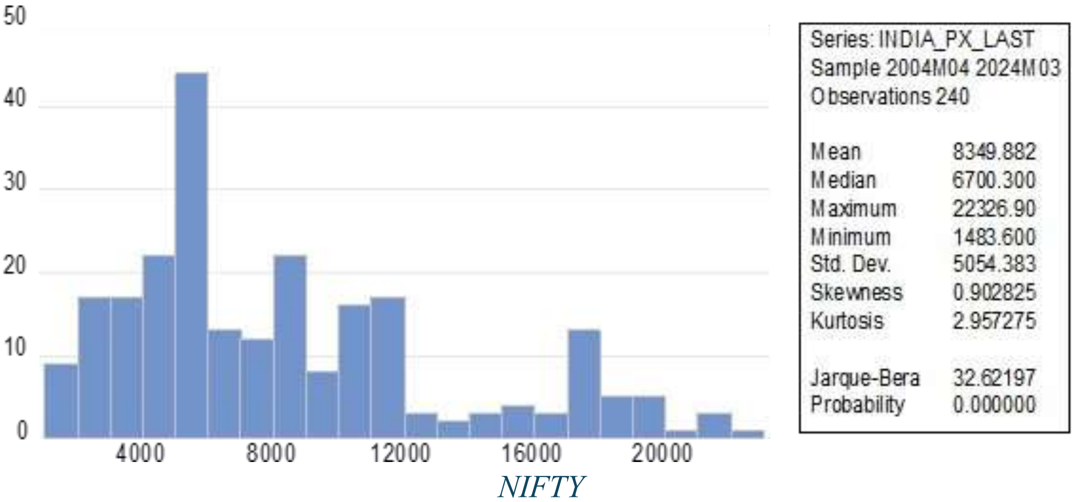
By comparison, the S&P 500 shows consistent robustness, creating approximately 9% average yearly returns. Such performance mirrors United States technological advancements, business resiliency, and sustained global economic leadership. The Shanghai Composite index shows moderate performance, averaging around 9%, reflective of China's continuing economic development and the multifaceted interplay between government-controlled market intervention and technological sector growth.

The FTSE and Hang Seng indices offer more restrained return profiles of about 3-4% returns per year. These are lower returns, and they trace their origins to distinct regional challenges: geopolitical uncertainties in Hong Kong, Brexit-induced uncertainty in the United Kingdom, and the wider structural economic problems that these markets experience. The differing performance reflects the fundamental importance of national economic strategies, regulatory settings, sector compositions, and international economic linkages.

4.2 NORMALITY DATA

Null Hypothesis(H0): The selected stock exchanges data is normally distributed.

Alternative Hypothesis(H1): The selected stock exchanges data is not normally distributed.



NIFTY

The histogram of Nifty Index returns over the time period of 2004 and 2024 provides insight into the market action since it has a rather complicated distribution that is far from classical normal expectations of distribution. In the histogram, we can see, at first glance, that return distributions are clearly asymmetrical. We see that return data points are concentrated in clustered amounts around the middle ranges, but there are also several clear outliers toward the right end of the distribution. Even from this graphical presentation we can immediately suggest there is a deviation from an ideal bell curve we would normally see for normally distributed data.

4.3 Normality test

	NIFTY	S&P 500	FTSE	Hang Seng	SHANGHAI
Mean	8349.882	2193.735	6305.93	21825.18	3138.141
Median	6700.3	1878.145	6384.275	22032.91	3246.42
Maximum	22326.9	5254.35	7952.62	32887.27	5688.54
Minimum	1483.6	735.09	3838.09	11942.96	855.95
St. Deviation	5054.383	1132.26	954.4612	4538.176	1143.846
Skewness	0.902825	0.907101	-0.402608	-0.163109	-0.226207
Kutosis	2.957275	2.647085	2.37952	2.528807	2.548689
Jarque Bera	32.62197	34.15876	10.33369	3.284417	4.083604
prob	0	0	0.005703	0.193552	0.129795
sum	2003972	526496.4	1513423	5238044	753153.9

After going through the probabilities in the above table, we find that $p<0.05$ for NIFTY, S&P500 and FTSE. Hence, we fail to reject null hypothesis concluding that the data for these selected exchanges are not normally distributed.

Similarly, we find that $p>0.05$ for Hand Seng and Shanghai. Therefore, we reject null hypothesis and conclude the data for these selected stock exchanges are normally distributed.

Jarque-Bera Test

The Jarque Bera test quantifies the difference between the skewness and kurtosis of our data and the skewness and kurtosis of a perfectly normal distribution and helps us understand the deviation from normality. Higher the value of the Jarque Bera statistic, greater the deviation from normality.

After analysing the above table, we find that the Jarque Bera statistic for NIFTY (32.62197) and S&P500 (34.15876) are very high implying a substantial deviation from expected skewness and kurtosis of a normal distribution signalling strong evidence against normality.

The Jarque Bera statistic for FTSE (10.3369) is relatively high, though it is significantly lower than NIFTY and S&P500. This indicates that the skewness or kurtosis, or both are deviating from what a normal distribution and skewness, and kurtosis is.

Hang Seng (3.284417) and Shanghai (4.083604) have much lower Jarque Bera statistics compared to the other three indices. These lower values indicates that the skewness and kurtosis of these datasets are closer to those of a normal distribution. These value are still above 0 meaning there is some deviation. However, it is significantly low compared to the other 3 indices.

4.4 CORRELATION

Returns

	INDIA	CHINA	HK	UK	US
INDIA	1.00				
CHINA	0.31	1.00			
HK	0.58	0.56	1.00		
UK	0.60	0.27	0.60	1.00	
US	0.60	0.33	0.57	0.76	1.00

The five global financial markets' return correlation matrix shows a dense web of market interdependencies, with complex relationships that go beyond mere linearity. The most striking observation is the high correlation between the US and UK markets, where the correlation coefficient is 0.76, showing a profound economic synchronism potentially underpinned by shared economic institutions, similar regulatory regimes, and highly integrated financial systems.

Medium levels of correlations among Indian, Hong Kong, and UK financial markets (0.58 and 0.60) indicate strong linkages between these markets with an influence spanning over geographical lines. The linkage can be justified based on a list of critical drivers. First, financial market globalization has increased investment sentiment and the investment pattern across international investors. Second, both markets have corresponding levels of economic development, and these influence similarities in economic development, which partly explains the correlation between the two markets. That the correlations across countries are of moderate magnitude signifies that these markets experience similar cycles of economic advancement, have corresponding economic similarities, and are hit by similar sets of global economic conditions. Third, the comparable globalization of both capital markets also explains the third factor of linkages between different markets. The Chinese market is a relatively isolated financial system as indicated by the lowest correlation with any other markets. Its ties with the UK (0.27) and US (0.33) markets are much weaker compared to the other ties of this research, illustrating China's special economic features. These peculiarity features, like state-controlled economic systems, significant market regulatory systems, and capital-market systems including state dominance structure6 specific to the western financial systems and structures, are factors contributing to China's lower correlations with foreign (western) average correlations. These correlations can pose great global diversification opportunities for foreign investors as they strive to reduce their portfolio risk through economic and geographic divergence.

4.5 STATIONERY DATA SERIES TEST:

STATIONERY DATA FOR LEVEL=0. (at significance level 95%)				
Countries	**T-STAT**	**P Value**	**Hypothesis**	**Conclusion**
NIFTY	**1.474**	**0.992**	**Null Hypothesis (H0): The data is non stationery.**	**NIFTY 50 is non stationery.**
S&P 500	**1.364**	**0.9989**	**Null Hypothesis (H0): The data is non stationery.**	**S$P 500 is non stationery.**
FTSE	**1.952**	**0.3078**	**Null Hypothesis (H0): The data is non stationery.**	**FTSE is non stationery.**

SHANGHAI	**2.151**	**0.225**	**Null Hypothesis (H0): The data is non stationery.**	**SHANGAI is non stationery.**
Hang Seng	**2.645**	**0.0854**	**Null Hypothesis (H0): The data is non stationery.**	**Hang Seng is non stationery.**

Ensuring that the data is Stationary is a prerequisite for the model as it shows whether the mean, variance, autocorrelation remain constant over time or not. It reflects the validity of statistical inferences including unit root tests (e.g., Augmented Dickey-Fuller test). It also simplifies the interpretation of relationships between variables, allowing for comparison across different time periods.

Hypothesis Testing for Stationarity:

Null Hypothesis (H0): The stock market data for the selected indices (NIFTY 50, S&P 500, FTSE, Shanghai Composite, and Hang Seng) is non-stationary.

Alternative Hypothesis (H1): The stock market data for the selected indices (NIFTY 50, S&P 500, FTSE, Shanghai Composite, and Hang Seng) is stationary.

The stationarity test reveals that all examined stock market indices demonstrate non-stationary properties, indicating significant variability in their statistical characteristics over time. This finding underscores the importance of applying appropriate transformation techniques, such as converting the monthly data to returns calculations in order to proceed with further testing.

STATIONERY DATA FOR LEVEL=1. (at significance level 95%)				
Countries	**T-STAT**	**P Value**	**Hypothesis**	**Conclusion**
NIFTY	**15.334**	**0**	**Null Hypothesis (H0): The data is non stationery.**	**NIFTY 50 is stationery.**
S&P 500	**16.847**	**0**	**Null Hypothesis (H0): The data is non stationery.**	**S$P 500 is stationery.**
FTSE	**16.35**	**0**	**Null Hypothesis (H0): The data is non stationery.**	**FTSE is stationery.**

SHANGHAI	**14.244**	**0**	**Null Hypothesis (H0): The data is non stationery.**	**SHANGAI is stationery.**
Hang Seng	**15.433**	**0**	**Null Hypothesis (H0): The data is non stationery.**	**Hang Seng is stationery.**

Hypothesis Testing for Stationarity:
Null Hypothesis (H0): The data of all indices is non-stationary.
Alternative Hypothesis (H1): The data in all indices is stationary.
At a 95% significance level, the p-values for all indices are 0, which is significantly less than the alpha value of 0.05. Therefore, we reject the null hypothesis of non-stationarity for all indices. This indicates that the first difference of each index is stationary.
We have converted the data at a difference level of 1, using the returns for standardization as well as testing compatibility.
As we can see with the level 0, (i.e. raw data), all indices fail to reject the null hypothesis of non-stationarity, while at level 1 (first differences or returns), the series become stationary.
Which justifies our use of returns for subsequent analysis The establishment of stationarity all the Indices (NIFTY 50, S&P 500, FTSE, SHANGHAI, and Hang Seng), shows that all indices are integrated of order one(1) , signifies that while the original level data exhibited non-stationarity, the first difference of each index achieved stationarity. This transformation is essential as it allows us to employ time series models that rely on the assumption of stationarity, such as cointegration analysis, which is done for understanding the dynamic relationships and long-run equilibrium among these markets.

4.6 Pairwise Granger Casualty Test

Null Hypothesis:,	Obs	F-Statistic	Prob
R_CHINA does not Granger Cause R_INDIA	237	5.01504	0.0074
R_INDIA does not Granger Cause R_CHINA		0.58141	0.5599
R_HK does not Granger Cause R_INDIA	237	1.80153	0.1673
R_INDIA does not Granger Cause R_HK		0.26081	0.7706
R_UK does not Granger Cause R_INDIA	237	0.04952	0.9517
R_INDIA does not Granger Cause R_UK		0.80271	0.4494
R_US does not Granger Cause R_INDIA	237	0.19485	0.8231
R_INDIA does not Granger Cause R_US		0.62338	0.537
R_HK does not Granger Cause R_CHINA	237	0.07789	0.9251
R_CHINA does not Granger Cause R_HK		2.41533	0.0916
R_UK does not Granger Cause R_CHINA	237	0.0055	0.9945
R_CHINA does not Granger Cause R_UK		2.67419	0.0711
R_US does not Granger Cause R_CHINA	237	0.84611	0.4304
R_CHINA does not Granger Cause R_US		2.29578	0.103
R_UK does not Granger Cause R_HK	237	0.05911	0.9426
R_HK does not Granger Cause R_UK		1.33144	0.2661
R_US does not Granger Cause R_HK	237	0.20351	0.816
R_HK does not Granger Cause R_US		1.69776	0.1854
R_US does not Granger Cause R_UK	237	4.21103	0.016
R_UK does not Granger Cause R_US		0.02258	0.9777

Hypothesis testing :

Null Hypothesis(H0): One time series does not affect the other time series.

Alternative Hypothesis(H1): One time series does affect the other time series.

Key Statistically Significant Relationships

Relationship between Indian and Chinese Markets: The strongest statistically significant relationship exists between the Indian and Chinese markets; where R_CHINA Granger Causes R_INDIA has a p-value of 0.0074. This implies a one-way causal relationship in which returns in the Chinese market lead to information that informs the returns of the Indian market. The F- statistic of 5.01504 implies statistical significance at the 95% confidence level.

Relationship between UK and US Markets: There seems to be a significant bidirectional causal relationship between the UK and US markets, where the US Granger causes UK returns at p-value of 0.0160. This suggests that historical US returns offer predictive power to the future direction of the UK returns; based on the fundamental economic interlinkage of the UK and US markets.

Connection between the China/Hong Kong Market: There appears to be a statistically marginal relationship between the Hong Kong and China markets where p-value for China did not Granger cause Hong Kong was 0.0916. This would indicate that there is a weak causal connection which could be anticipated from geographic proximity as well as the economic integration of the two areas

REGRESSION ANALYSIS:

Dependent Variable: INDIA				
Method: Least Squares				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob**
UK	0.652562	0.102441	6.370106	0
HK	0.348741	0.073047	4.774197	0
CHINA	0.009238	0.04636	0.199272	0.8422
C	0.009348	0.003061	3.054283	0.0025
R-squared	0.436576		Mean dependent var	0.012561
Adjusted R-squared	0.429383		S.D. dependent var	0.062196
S.E. of regression	0.046983		Akaike info criterion	-3.261479
Sum squared resid	0.518733		Schwarz criterion	-3.203296
Log likelihood	393.7468		Hannan-Quinn criter.	-3.238033
F-statistic	60.69756		Durbin-Watson stat	2.032787
Prob(F-statistic)	0			

HYPOTHESIS

Null Hypothesis(H0): There is no significant impact of other selected exchanges on NIFTY . **Alternative Hypothesis(H1):** There is significant impact of other selected exchanges on NIFTY .

The results confirm the alternative hypothesis and reveal high statistical contributions of the UK and Hong Kong markets in the explanation of Indian market returns. The highest contribution comes from the UK market with a coefficient of 0.65262 (p = 0.0000), meaning that a unit change in the returns of the UK market is related to a 0.65262 unit change in the Indian market.

The Hong Kong market also reveals significant influence with a coefficient of 0.348741 (p = 0.0000) that contributes to the evidence for interdependencies of these financial markets. The adjusted R-squared of the model of 0.42983 implies that roughly 43% of the variation in the Indian market returns is explained by the chosen international markets, indicating that interdependencies in financial markets are more intricate than simplistic assumptions. The Chinese market coefficient was not statistically significant (p = 0.8422) and once more, this could suggest the fine nuances of the ways in which markets may interact and therefore the value of judicious variable selection within multivariate research in finance. These results contribute not only to our knowledge of international financial market interdependencies, but also provide insight for cross-border investment and risk management strategies.

REGRESSION ANALYSIS:

Dependent Variable: INDIA				
Method: Least Squares				
Variable	Coefficient	Std. Error	t-Statistic	Prob
US	0.563523	0.085842	6.564651	0
HK	0.383223	0.069382	5.523386	0
CHINA	-0.023579	0.045924	-0.513428	0.6081
C	0.007295	0.003084	2.365133	0.0188
R-squared	0.441674		Mean dependent var	0.012561
Adjusted R-squared	0.434547		S.D. dependent var	0.062196
S.E. of regression	0.04677		Akaike info criterion	-3.270569
Sum squared resid	0.513039		Schwarz criterion	-3.212386
Log likelihood	394.833		Hannan-Quinn criter.	-3.247123
F-statistic	61.96709		Durbin-Watson stat	2.071119
Prob(F-statistic)	0			

HYPOTHESIS

Null Hypothesis(H0): There is no significant impact of other selected exchanges on NIFTY . **Alternative Hypothesis(H1):** There is significant impact of other selected exchanges on NIFTY .

Empirical evidence provides strong evidence against the null hypothesis, finding statistically significant influences of the US and Hong Kong markets to explain Indian market returns. The US market has the greatest influence, with a coefficient of 0.63523 (p = 0.0000), which means that an increase in US market returns by 1 unit is related to an increase in Indian market returns of 0.63523 units, holding everything else constant. The Indian market also has a large association with Hong Kong market returns, with the coefficient being 0.38023 (p = 0.0000). These findings further support the interdependence of financial markets. The adjusted R-squared of the model at 0.434547 suggests that almost 43.45% of variation in Indian market returns is explained by the international markets researched. This suggests that, in complicated ways, markets are interdependent even across the world. The coefficient of the Chinese market indicates a weak statistical significance (p = 0.6181) and illustrates the subtleties involved with the interaction of markets, and more the significance instead, of establishing the right variables in a multivariate financial analysis.

The constant term is also statistically significant (p = 0.0188), indicating that there can be trend factors and other systematic drivers of market returns beyond the international markets analyzed and accounted for. These findings in relation to the importance of variables not only enrich literature and knowledge in areas concerning international financial markets but have implications concerning cross-border investments within a portfolio balancing strategy, risk handling procedures, and guide interests regarding global financial integration.

4.7 Johansen Cointegration Test:

Unrestricted Cointegration Rank Test (TRACE)				
Hypothesized No.of CE(S)	Eigenvalue	Trace Statistic	Critical Value	Prob
NONE *	0.296244	231.806	69.81889	0
At Most 1 *	0.205582	149.5961	47.85613	0
At Most 2 *	0.154167	95.74205	29.79707	0
At Most 3 *	0.130063	56.56265	15.49471	0
At Most 4 *	0.097319	23.95827	3.841465	0
Trace test 5 cointegrating equations at the 0.05 level				
denotes rejection of the hypothesis at level 0.05.				

Unrestricted Cointegration Rank Test (MAXIMUM EIGENVALUE)				
Hypothesized No.of CE(S)	Eigenvalue	Trace Statistic	Critical Value	Prob
NONE *	0.296244	82.20987	33.87687	0
At Most 1 *	0.205582	53.85404	27.58434	0
At Most 2 *	0.154167	39.17941	21.13162	0.0001
At Most 3 *	0.130063	32.60438	14.2646	0
At Most 4 *	0.097319	23.95827	3.841465	0
Maximum -Eigenvalue test 5 cointegrating equations at the 0.05 level				
denotes rejection of the hypothesis at level 0.05.				

The hypotheses tested are: 1: H_0: $r = 0$ (No cointegrating equations)
H_1: $r \geq 1$
2: H_0: $r \leq 1$ (At most 1 cointegrating equation) H_1: $r \geq 2$
3: H_0: $r \leq 2$ (At most 2 cointegrating equations) H_1: $r \geq 3$
4: H_0: $r \leq 3$ (At most 3 cointegrating equations) H_1: $r \geq 4$
5: H_0: $r \leq 4$ (At most 4 cointegrating equations) H_1: $r = 5$ (Since there are 5 variables)

Trace Test: The Trace Statistic for each null hypothesis is greater than the corresponding 0.05 Critical Value, and the associated p-values are all 0.0000. This leads to the rejection of the null hypothesis at each step. Consequently, the Trace test indicates 5 cointegrating equations at the 0.05 significance level.

Maximum Eigenvalue Test: Similarly, the Max-Eigen Statistic for each null hypothesis was greater than the 0.05 Critical Value, with p-values less than 0.05 (except for "At most 2" which is 0.0001). This also leads to the rejection of the null hypothesis at each step. The Maximum Eigenvalue test also indicates 5 cointegrating equations at the 0.05 significance level.

Both tests consistently suggest the presence of 5 cointegrating relationships among the returns of the five stock market indices. This implies that there is a strong long-term equilibrium relationship between these markets. Even though short-term fluctuations may occur, these indices tend to move together in the long run.

CHAPTER 05: CONCLUSION AND FINDINGS

5.1 Summary of Key Findings

This research takes a deep dive into the intricate connections between the Indian stock market and four key global markets—the United States, the United Kingdom, China, and Hong Kong—spanning a 20-year period from 2004 to 2024. By using a range of robust statistical methods, including correlation coefficients, regression analysis, Granger causality tests, and Johansen cointegration, this study has uncovered several important insights into how global financial markets are intertwined, with a special emphasis on the role of the Indian market within the broader financial landscape.

5.2 Performance Analysis and Market Characteristics

The comparative performance analysis showed that the NIFTY 50 index has really stood out, boasting an impressive average annual return of 15.058%, which is the highest among all the indices we looked at. This stellar performance leaves other major indices in the dust, with the Shanghai Composite at 9.086% and the S&P 500 at 8.851%, trailing quite a bit behind. Meanwhile, the FTSE and Hang Seng had more modest returns, coming in at 3.519% and 3.867%, respectively. This remarkable outperformance can be linked to India's strong economic fundamentals, its demographic advantages, liberalization policies, and growing integration into the global economy. However, it’s important to note that while India’s returns are impressive, they come with a fair amount of volatility. The NIFTY has seen some significant monthly swings, with maximum gains reaching 28.066% and maximum losses hitting 26.410%. The annual standard deviation of 21.591% really highlights this volatility. Despite these ups and downs, the NIFTY has shown the best risk-adjusted performance among all the indices we analysed, with the lowest coefficient of variation at 1.43. This indicates that investors can expect better returns for the level of risk they take on in the Indian market compared to others in the sample. The differences in maturity between emerging and developed markets are clear when you look at the volatility patterns. Emerging markets like India and China tend to have more dramatic price movements, reflecting their rapid economic changes, while developed markets such as the US and UK respond more steadily to global economic shifts, showcasing their established financial systems and strong regulatory frameworks.

5.3 Correlation Analysis

The correlation analysis revealed complex interdependencies among the five markets, with varying degrees of market synchronization. The strongest correlation was observed between the US and UK markets (0.76), indicating profound economic synchronism underpinned by shared economic institutions, similar regulatory regimes, and highly integrated financial systems. These markets tend to respond similarly to global economic events, reflecting their deep historical ties and compatible market structures.

The Indian market demonstrated moderate positive correlations with the US (0.60), UK (0.60), and Hong Kong (0.58) markets, suggesting significant but not overwhelming linkages. These relationships indicate that while the Indian market is increasingly integrated into the global financial system, it still maintains a degree of independence that could be valuable from a portfolio diversification perspective.

Interestingly, the Chinese market showed the weakest correlations with other markets, especially with the UK (0.27) and US (0.33), which demonstrates China's rather isolated financial system. This seclusion is a result of China's unique economic features such as state- run market mechanisms, distinctive regulatory environments, and capital market structures that are fundamentally different from

Western financial markets. Such lower correlations offer valuable diversification potential for global investors who wish to lower portfolio risk through economic and geographical divergence.

5.4 Granger Causality Analysis

The Granger causality tests revealed several significant directional relationships among the markets. A notable unidirectional causality was identified from China to India (p-value: 0.0074), indicating that historical returns in the Chinese market have predictive power for future movements in the Indian market. This finding suggests that developments in the Chinese economy and financial markets precede and influence the Indian market, highlighting the growing economic interconnectedness between Asia's two largest economies.

The UK and US markets were found to have a strong bidirectional causality, indicating that these two economies are closely integrated and mutually influencing. Such a relationship shows the strong cross-border investments, shared market participants, and synchronized economic cycles between these two major developed economies.

The relationship between Hong Kong and China showed a marginally significant causal effect, which aligns with expectations given their geographic proximity and economic integration. However, the relatively weak statistical significance suggests that despite their close ties, these markets maintain distinct characteristics and respond to different sets of factors beyond their shared economic connections.

5.5 Regression Analysis Findings

The regression analysis produced a number of quantitative evidence on the impact of global markets on the returns of Indian markets. The models explained around 43% of the variance in NIFTY returns, showing significant yet not overwhelming international influence. This result strengthens the idea that global factors are indeed dominant in the Indian market but domestic variables as well as idiosyncratic ones still largely drive movements in the market.

Among the international markets, the UK and US exhibited the strongest influence on Indian market returns. The UK market demonstrated a coefficient of 0.65262 (p-value: 0.0000), indicating that a one-unit change in UK market returns corresponds to approximately a 0.65- unit change in Indian market returns, holding other factors constant. Similarly, the US market showed a coefficient of 0.63523 (p-value: 0.0000), highlighting its substantial impact on Indian market dynamics.

Hong Kong market also had strong impacts on Indian returns with coefficients of 0.348741 and 0.38023 in the two equations, emphasizing the significance of regional Asian market linkages as well as with Western financial centres. The influence could possibly be due to Hong Kong's function as an important financial hub channelling international capital inflows into Asian markets, including India.

Curiously, statistically insignificant coefficients were found in both models for the Chinese market, even though it has a strong Granger causality with India. The seeming contradiction implies that Chinese market movement might be leading and potentially predict Indian market movement, but its strength of influence is tempered by other variables and is less overt than that of markets such as the UK, US, and Hong Kong.

5.6 Cointegration Analysis

The Johansen cointegration test provided compelling evidence of long-term equilibrium relationships across all five markets. Both the Trace test and Maximum Eigenvalue test consistently pointed to the existence of five cointegrating equations at the 0.05 significance level. This suggests that even though there may be short-term fluctuations and varying levels of correlation, these markets ultimately share common long-term trends and tend to move toward equilibrium.

The complete cointegration among all markets carries important implications for portfolio diversification strategies. It indicates that while there might be short-term benefits to diversification, these advantages tend to fade over longer investment periods as the markets converge. This finding challenges the traditional belief that geographic diversification is a reliable long-term risk reduction strategy and underscores the necessity for more advanced methods to achieve true portfolio diversification in our increasingly interconnected global financial landscape.

LIMITATIONS

5.7 Methodological Limitations

This study points out a few methodological limitations worth considering. First off, relying on monthly data might miss out on capturing the short-term volatility spillovers and those intraday market interactions that could really shed light on market relationships. It would be beneficial for future research to use higher-frequency data to dig into these short-term dynamics. Secondly, while the linear modelling techniques used here are statistically sound, they might not fully reflect the nonlinear relationships that often pop up in financial markets, especially during times of crisis. Exploring advanced nonlinear methods like threshold cointegration, regime-switching models, or even machine learning approaches could reveal more intricate interdependencies. Lastly, the sample period includes several significant economic events, such as the 2008 Global Financial Crisis and the COVID-19 pandemic, which might have changed how market relationships function. Future studies could benefit from using structural break tests and time-varying parameter models to see how these market linkages shift across different economic conditions.

5.8 Scope Limitations

The study zeroed in on five key stock market indices, intentionally leaving out other significant markets that could impact global financial dynamics. Looking ahead, future research could broaden its horizons to include more emerging markets, especially from Latin America and Africa, to paint a fuller picture of global market integration. Moreover, the analysis concentrated solely on broad market indices, which might overlook important sector-specific variations in international market connections. By diving into sector-specific analyses, we could uncover more detailed patterns of integration that are crucial for tailored investment strategies and focused economic policies. Additionally, the research didn't take into account macroeconomic variables or policy factors that could shed light on the market relationships observed. Future studies could benefit from incorporating macroeconomic data, monetary policy indicators, and measures of institutional quality to gain a deeper understanding of what drives market interdependencies.

5.9 Future Research Directions

This study opens up several exciting paths for future research. For starters, looking into how geopolitical events and trade relationships shape market connections could shed light on the non-economic factors that drive financial integration. This might involve examining how trade disputes, political alliances, and diplomatic tensions influence market correlations and cointegration patterns.

Next, broadening the analysis to encompass fixed income markets, currency markets, and commodity markets would give us a more comprehensive understanding of financial market integration beyond just equities. Each of these asset classes might show unique integration patterns that either complement or counterbalance what we see in equity markets.

Additionally, delving into the role of institutional investors, especially regarding cross-border investment flows, could clarify the mechanisms behind the market linkages we've observed. By analysing foreign portfolio investment data alongside market movements, we could uncover how capital flows transmit shocks across borders and contribute to market synchronization.

Lastly, investigating the effects of technological advancements in trading systems— particularly the rise of algorithmic and high-frequency trading—could reveal how these changes are reshaping the speed and nature of international market connections. The growing automation in trading might be speeding up information transmission across markets and potentially strengthening short-term correlations.

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