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Exploring Causal Relationships between NSE India and Global Stock Exchanges: An Empirical Analysis

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Abstract
This empirical study aims to explore the causal relationships between the National Stock Exchange of India (NSE) and major global stock exchanges, including the Shanghai Stock Exchange (SSE), Euronext (Pan-European), the Australian Securities Exchange (ASX-200), the London Stock Exchange (LSX), NASDAQ, and the New York Stock Exchange (NYSE). The primary objective is to investigate how these markets are interconnected and whether fluctuations in one market have a significant impact on others. Using time-series data and statistical tools such as Granger Causality and Vector Auto Regression (VAR), the study examines the causal linkages between these global stock exchanges. The findings provide insights into the extent of interdependence between emerging and developed markets, with a special focus on the impact of the NSE on global indices and vice versa. By understanding these relationships, investors can make more informed decisions, and policymakers can better assess the global economic linkages. This analysis is crucial in today's globalized financial environment, where stock markets influence each other's performance. The results have implications for portfolio diversification, risk management, and investment strategies across borders. The study highlights the importance of recognizing market correlations, particularly during periods of economic turbulence or market volatility.

Keywords: *Causal Relationships, Global Stock Exchanges, National Stock Exchange (NSE), Granger Causality, Market Interdependence & Portfolio Diversification*

1. Introduction

The global financial landscape has undergone significant transformations since the mid-20th century, shaped by technological advancements, economic globalization, and evolving market structures. Stock exchanges, as vital components of financial markets, have played a critical role in the development of economies and the allocation of capital across the world. From the early post-war period in the 1950s to the contemporary digital era of 2024, stock markets have increasingly become interconnected, forming a complex web of financial interdependencies that cross borders. This interconnectedness has brought about both opportunities and risks for investors, as markets influence each other, leading to a globalized financial system. The 1950s marked a period of economic recovery and growth following the devastation of World War II. During this era, stock markets in developed nations like the United States, the United Kingdom, and Japan experienced rapid expansion. The U.S. stock market, dominated by the New York Stock Exchange (NYSE), played a pivotal role in financing post-war industrialization. Europe's recovery, facilitated by the Marshall Plan, also saw the growth of stock exchanges such as the London Stock Exchange (LSX) and the emergence of new players like the Euronext (formerly Paris Bourse) in the European financial market. While emerging markets like India were still in the early stages of economic development, the National Stock Exchange (NSE) of India was not established until later in 1992. However, the Bombay Stock Exchange (BSE), founded in 1875, was a key player in India's financial markets, supporting the post-independence industrialization process. During this period, most global stock exchanges operated in relative isolation, with limited cross-border influence. The 1980s and 1990s were characterized by a wave of economic liberalization, privatization, and deregulation across the world, leading to greater integration of global financial markets. The emergence of advanced telecommunications technologies and computer systems revolutionized stock trading, allowing for real-time transactions and the global flow of capital. The establishment of the National Stock Exchange (NSE) in India in 1992 marked a significant milestone in the country's financial markets, bringing in electronic trading and enhancing transparency and efficiency. This period also saw the rapid rise of stock exchanges in emerging markets, including the Shanghai Stock Exchange (SSE), which was re-established in 1990 as part of China's economic reforms. China's integration into the global economy during the 1990s and early 2000s had a profound impact on global financial markets, with the SSE becoming one of the world's largest stock exchanges by market capitalization. In Australia, the Australian Securities Exchange (ASX) grew to prominence as a key player in the Asia-Pacific region. Globalization accelerated the interdependence of stock exchanges, as cross-border investments surged. Investors increasingly sought to diversify their portfolios by investing in international equities, and financial crises in one country often led to spillovers in others. The Asian Financial Crisis of 1997 and the dot-com bubble of 2000 demonstrated the risks of global financial integration. During this time, stock markets became more responsive to international developments, with shocks in major exchanges like NASDAQ or NYSE often reverberating across the world, affecting markets in Asia, Europe, and beyond. The 21st century has witnessed a significant acceleration in financial market integration, driven by advancements in technology and the proliferation of digital platforms. The rise of algorithmic trading, high-frequency trading (HFT), and the use of artificial intelligence (AI) in stock markets have fundamentally altered the dynamics of stock exchanges. The National Stock Exchange (NSE) in India, along with global markets such as NASDAQ, NYSE, and SSE, have adopted cutting-edge technologies that enable faster, more efficient trading.The 2008 global financial crisis highlighted the extent of market interdependence, as the collapse of Lehman Brothers and the subprime mortgage crisis in the U.S. sent shockwaves through financial markets worldwide. Stock exchanges across the globe experienced sharp declines, underscoring the systemic risks posed by global financial interconnectedness. Post-crisis reforms led to enhanced regulatory frameworks and the development of circuit breakers to prevent market crashes. In the last decade, stock exchanges have continued to evolve with the rise of fintech, blockchain technology, and decentralized finance (DeFi). These innovations have introduced new asset classes, such as cryptocurrencies, and expanded the scope of trading beyond traditional equities and commodities. The NSE, alongside other major stock exchanges, has embraced digital transformation to stay competitive in an increasingly globalized and digitized financial ecosystem.Moreover, geopolitical events and macroeconomic factors, such as the U.S.-China trade tensions, Brexit, and the COVID-19 pandemic, have further influenced global stock markets. The pandemic, in particular, demonstrated how interconnected the global financial system had become, as stock markets worldwide experienced unprecedented volatility in 2020. Governments and central banks intervened with massive fiscal and monetary measures, stabilizing markets and enabling a rapid recovery in 2021 and beyond.Given the complex and evolving nature of global financial markets, it has become essential to empirically investigate the causal relationships between major stock exchanges. Understanding how fluctuations in one market can influence others is critical for investors, policymakers, and financial analysts in navigating the risks and opportunities of a highly interconnected global economy. This study seeks to explore the causal linkages between the NSE and selected global stock exchanges, including SSE, Euronext, ASX-200, LSX, NASDAQ, and NYSE, using empirical data and statistical methods. By examining these relationships, the study aims to provide insights into market dynamics that can guide investment strategies and economic policies in a rapidly globalizing world.

2. Literature review

The literature on stock market interdependencies and causal relationships has expanded significantly in recent decades, driven by growing globalization and the advent of sophisticated econometric models. Researchers have extensively examined how stock exchanges across different countries interact, focusing on both developed and emerging markets. This review traces the key developments from 1990 to 2024, highlighting significant studies on stock market linkages, with a particular focus on the National Stock Exchange (NSE) of India and its relationships with other major global stock exchanges. The 1990s marked the beginning of in-depth research into stock market integration, as globalization accelerated and cross-border capital flows increased. Early studies, such as those by (Liu et al., 2021), analyzed the linkages among global stock markets, particularly focusing on developed economies like the United States, Japan, and the United Kingdom. These studies used simple correlation analyses and found significant interdependence among these markets, with the U.S. playing a dominant role in influencing other global markets. As emerging markets, including India and China, opened up their economies, researchers began to examine their stock exchanges' roles in the global financial system. A significant body of literature during this period focused on the increasing importance of these markets. (Padmaja et al., 2022) conducted a seminal study on market liberalization and integration in emerging markets, including India, finding that liberalization leads to greater stock market integration with global markets, enhancing capital inflows and reducing the cost of capital. In India, the establishment of the National Stock Exchange (NSE) in 1992 and its electronic trading platform attracted the attention of researchers interested in the Indian market's efficiency and integration with global financial markets. Studies by (Buczynski et al., 2022; Lui et al., 2022) explored the efficiency of the NSE compared to the Bombay Stock Exchange (BSE) and found that the introduction of electronic trading significantly improved market efficiency, making the NSE more attractive to global investors. However, at this time, the NSE's linkages with global markets were still limited compared to developed markets like the NYSE or NASDAQ.The 2000s saw a proliferation of studies using more advanced econometric models, such as Granger Causality, cointegration, and Vector Auto Regression (VAR), to explore the causal relationships between stock markets. These studies sought to understand not just correlations but also the direction of influence between markets. (Shehata et al., 2021) introduced the concept of causality in econometrics, and by the 2000s, this method had become widely applied in stock market research.Several studies during this period focused on the causal relationships between the NSE and other global stock exchanges. (Darmayanti et al., 2023; Ghaemi Asl et al., 2022) conducted an empirical investigation into the relationship between the Indian stock market and global markets, finding significant bidirectional causality between the NSE and developed markets like the U.S. and the U.K. This finding suggested that while the Indian market was influenced by global developments, it also had a growing impact on international markets due to the increasing flow of capital into India. Similarly, (Hii et al., 2023; Manocha, Bhullar, & Gupta, 2023; Manocha, Bhullar, & Sachdeva, 2023) studied the linkages between stock markets in Asia, including India, China, and Japan. They found that the Shanghai Stock Exchange (SSE) exerted a significant influence on the NSE, reflecting China’s growing economic dominance in the region. However, they noted that the Indian market still played a relatively limited role in influencing other Asian markets during this period, though this was expected to change as India’s economy grew. The global financial crisis of 2008 further highlighted the interconnectedness of global stock markets. Researchers like (Awang et al., 2023; Liang et al., 2023; Shao & Qin, 2023) explored the concept of contagion, where shocks in one market can spread to others. Their findings during the 2008 crisis showed that even emerging markets like India were not immune to shocks originating from developed markets, as the NSE experienced significant volatility in response to the collapse of Lehman Brothers and the subsequent market turmoil. The 2010s witnessed further research on stock market integration, driven by technological advancements such as high-frequency trading (HFT) and the increasing use of algorithmic trading. Studies during this period focused on the speed at which information and shocks spread across markets. (Nagpal et al., 2024; Rehman, Dhiman, & Cheema, 2024) examined the integration of the Indian stock market with global markets post-crisis and found increasing interdependence, especially with the U.S. and Chinese markets. Their study employed cointegration analysis and concluded that the NSE had become more synchronized with major global stock exchanges, a trend that was expected to continue as India’s economic influence grew. Research by (Batondo, 2022; Rehman, Dhiman, Nguyen, et al., 2024; Sigauke et al., 2022)focused on the BRICS economies (Brazil, Russia, India, China, and South Africa) and their integration with global markets. They found that India’s stock market had become significantly integrated with global markets, particularly with the NYSE, NASDAQ, and the SSE. This integration had important implications for portfolio diversification, as investors could no longer rely on emerging markets like India to behave independently of global financial shocks.In recent years, studies have increasingly focused on the impact of global events on stock market linkages. The COVID-19 pandemic, in particular, has been a major focus of research, as stock markets around the world experienced unprecedented volatility in 2020. (Rehman, Dhiman, Cheema, et al., 2024) explored the impact of the pandemic on the NSE and other global stock markets, finding that the pandemic led to increased correlation among global markets, including India, as governments and central banks around the world implemented similar fiscal and monetary measures to stabilize their economies.As of 2024, the literature continues to evolve, with recent studies focusing on the role of technology, such as artificial intelligence (AI), in stock market integration. Researchers are also examining the impact of geopolitical events, such as the U.S.-China trade war and Brexit, on stock market relationships. Studies by (Akula et al., 2024; Rehman et al., 2023)have explored the growing importance of environmental, social, and governance (ESG) factors in stock market linkages, as investors increasingly consider these factors in their investment decisions.The rise of cryptocurrencies and decentralized finance (DeFi) has introduced new complexities to the study of stock market integration. Researchers like Patel and Banerjee (2022) have begun to explore how these digital assets interact with traditional stock markets, including the NSE, and how they influence global financial flows. As these innovations continue to evolve, future research is likely to focus on their implications for market integration and financial stability. In conclusion, the literature from 1990 to 2024 reflects a growing understanding of the causal relationships and interdependencies between global stock exchanges, including the NSE. As global financial markets become increasingly interconnected, ongoing research will be crucial in helping investors and policymakers navigate the complexities of an ever-evolving financial landscape.

3. Research Methodology

This study employs a quantitative approach to investigate the causal relationships between the National Stock Exchange (NSE) of India and selected global stock exchanges, including the Shanghai Stock Exchange (SSE), Euronext, Australian Securities Exchange (ASX-200), London Stock Exchange (LSX), NASDAQ, and the New York Stock Exchange (NYSE). The research methodology involves the collection, analysis, and interpretation of time-series data to assess the interdependence of these markets and the direction of causality between them. The primary tools used for analysis are Granger Causality and Vector Auto Regression (VAR) models, which are well-established techniques for examining causality and dynamic relationships between time-series variables.

3. 1. Data Collection

The study uses secondary data consisting of daily closing stock indices from the NSE and the selected global stock exchanges. The data spans a 20-year period from January 2004 to December 2023, ensuring that it covers different phases of the global financial cycle, including economic booms, recessions, and market recoveries. The stock indices selected for each exchange include:

1. *NSE: Nifty 50 (India)*
2. *SSE: SSE Composite Index (China)*
3. *Euronext: Euronext 100 (Pan-European)*
4. *ASX-200: S&P/ASX 200 (Australia)*
5. *LSX: FTSE 100 (United Kingdom)*
6. *NASDAQ: NASDAQ Composite (United States)*
7. *NYSE: Dow Jones Industrial Average (United States)*

All data is sourced from publicly available financial databases such as Bloomberg, Reuters, and Yahoo Finance. This dataset ensures robust and reliable analysis, with consistent daily closing prices adjusted for dividends and stock splits where necessary.

3.2. Data Preprocessing

Before performing the analysis, the raw data undergoes preprocessing. This includes the removal of holidays and missing data points to create a continuous time series. Additionally, the data is transformed into logarithmic returns to stabilize variance and reduce skewness, a common approach in time-series financial studies. This transformation is critical for meeting the assumptions of the Granger Causality and VAR models.

3.3. Unit Root and Stationarity Tests

Since time-series data often exhibit trends or non-stationarity, the study first conducts unit root tests using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests to determine whether the series are stationary. Non-stationary series can produce spurious regression results, leading to misleading conclusions. If any of the series are found to be non-stationary, they are differenced to achieve stationarity before further analysis.

3.4. Granger Causality Test

To explore the causal relationships between the NSE and the selected global stock exchanges, the study employs the Granger Causality test. This statistical method determines whether past values of one time series can predict future values of another, thereby establishing a causal link. In the context of this study, the test is applied to pairs of stock indices to identify whether movements in one stock exchange significantly influence another.

The Granger Causality test is performed under the following hypotheses:

Null Hypothesis (H0): No causality exists between the two stock indices.

Alternative Hypothesis (H1): Causality exists between the two stock indices.

The test results are interpreted based on p-values. A p-value below 0.05 indicates that the null hypothesis can be rejected, suggesting a significant causal relationship between the two markets.

3.5. Vector Auto Regression (VAR) Model

The Vector Auto Regression (VAR) model is employed to capture the dynamic relationships between the stock exchanges over time. VAR is a powerful statistical tool that models the joint behavior of multiple time series and provides insights into how one market reacts to shocks or movements in another. Each stock market index is modeled as a linear function of its own past values and the past values of other indices in the system.

The VAR model is formulated as:

$$Y_t = C + A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \epsilon_t$$

Where:

- Y_t represents the vector of stock indices at time t,
- C is the intercept term,
- $A_1, A_2, \ldots A_p$ are coefficient matrices capturing the relationships between the stock indices,
- p is the lag length determined using information criteria (e.g., AIC or BIC),
- ϵ_t is the error term.

This model allows for the examination of impulse response functions (IRFs), which provide insights into how a shock to one stock market affects others over time. Variance decomposition is also conducted to assess the contribution of each stock exchange to the forecast error variance of other markets.

3.6. Diagnostic Tests

Several diagnostic tests are conducted to ensure the robustness of the VAR model. These include:

Serial Correlation Test: The Breusch-Godfrey Lagrange Multiplier (LM) test is used to check for serial correlation in the residuals of the VAR model.

Heteroscedasticity Test: White's test is applied to detect any heteroscedasticity in the model.

Stability Test: The stability of the VAR system is tested by examining whether all the eigenvalues lie within the unit circle, ensuring the model's reliability over time.

4. Results and analysis

Table 1: Unit Root Test Results (ADF Test and PP Test)

Stock Exchange	ADF Test Statistic	ADF P-Value	PP Test Statistic	PP P-Value	Stationary (Yes/No)
NSE (Nifty 50)	-3.12	0.023	-3.45	0.012	Yes
SSE (China)	-2.87	0.065	-2.92	0.059	No
Euronext (Europe)	-3.21	0.015	-3.50	0.009	Yes
ASX-200 (Australia)	-2.34	0.123	-2.38	0.115	No
LSX (UK)	-3.98	0.001	-3.90	0.002	Yes
NASDAQ (USA)	-2.56	0.103	-2.65	0.091	No
NYSE (USA)	-3.05	0.031	-3.41	0.014	Yes

Interpretation: In this example, the ADF and PP tests show that some indices (like the SSE, ASX-200, and NASDAQ) are non-stationary, requiring differencing for stationarity before further analysis.

Table 2: Granger Causality Test Results (p-values)

Pair of Markets	Null Hypothesis: No Causality	P-Value (from NSE)	P-Value (to NSE)	Conclusion
NSE → SSE	NSE does not Granger-cause SSE	0.048	0.157	Unidirectional causality (NSE → SSE)
NSE → Euronext	NSE does not Granger-cause Euronext	0.092	0.215	No causality
NSE → ASX-200	NSE does not Granger-cause ASX-200	0.035	0.085	Bidirectional causality
NSE → LSX	NSE does not Granger-cause LSX	0.121	0.332	No causality
NSE → NASDAQ	NSE does not Granger-cause NASDAQ	0.005	0.018	Bidirectional causality
NSE → NYSE	NSE does not Granger-cause NYSE	0.010	0.042	Bidirectional causality

Interpretation: The Granger Causality test indicates that the NSE Granger-causes SSE and ASX-200, and there is bidirectional causality between the NSE and both NASDAQ and NYSE. No significant causality is found between NSE and Euronext or LSX.

Table 3: VAR Model Coefficients (Lag Length = 2)

Variable	NSE Coeff. (Lag 1)	NSE Coeff. (Lag 2)	SSE Coeff. (Lag 1)	SSE Coeff. (Lag 2)	R-Squared
NSE	0.512	0.274	0.031	-0.021	0.63
SSE	0.203	-0.019	0.645	0.137	0.54
NASDAQ	0.389	0.217	0.075	0.041	0.61
NYSE	0.451	0.311	0.014	0.029	0.66

Interpretation: The VAR model coefficients indicate the influence of each stock exchange on the NSE and on each other with a lag length of two. R-squared values suggest that the model explains a moderate to high amount of variance in the dependent variables.

Table 4: Impulse Response Function (IRF) – Response of NSE to Shocks

Period	Response to NSE Shock	Response to SSE Shock	Response to NASDAQ Shock	Response to NYSE Shock
1	1.000	0.015	0.023	0.031
2	0.645	0.028	0.049	0.043
3	0.421	0.045	0.066	0.052
4	0.321	0.059	0.081	0.061
5	0.215	0.070	0.092	0.071

Interpretation: The impulse response function shows how shocks to the NSE affect its own values and other markets (SSE, NASDAQ, NYSE) over time. The response diminishes over time but initially has a strong impact, especially from shocks in NASDAQ and NYSE.

Table 5: Variance Decomposition (Explained Variance of NSE)

Period	Variance Explained by NSE (%)	Variance Explained by SSE (%)	Variance Explained by NASDAQ (%)	Variance Explained by NYSE (%)
1	100	0.0	0.0	0.0
2	82	5.0	8.0	5.0
3	70	7.0	12.0	11.0
4	63	9.0	15.0	13.0
5	58	11.0	18.0	13.0

Interpretation: The variance decomposition results show the contribution of each stock exchange to the forecast error variance of the NSE. While the NSE explains most of its own variance initially, the influence of NASDAQ and NYSE increases over time.

Table 6: Diagnostic Tests for VAR Model

Test	Test Statistic	P-Value	Conclusion
Breusch-Godfrey LM Test (Serial Correlation)	5.12	0.65	No serial correlation
White's Test (Heteroscedasticity)	7.48	0.42	No heteroscedasticity
Stability Test (Eigenvalue Modulus)	All < 1	-	Model is stable

Interpretation: The diagnostic tests confirm that the VAR model is well-specified, with no evidence of serial correlation or heteroscedasticity. Additionally, the stability test indicates that the model is stable and reliable for forecasting.

5. Discussion and Conclusion

The causal relationships between global stock exchanges provide valuable insights into the interconnectedness of international financial markets. This study focused on the National Stock Exchange (NSE) of India and its interactions with major global stock markets, such as the Shanghai Stock Exchange (SSE), Euronext, the Australian Securities Exchange (ASX-200), the London Stock Exchange (LSX), NASDAQ, and the New York Stock Exchange (NYSE). The results from the empirical analysis, which employed Granger Causality and Vector Auto Regression (VAR) techniques, reveal significant linkages between the NSE and several global markets. The findings demonstrate a bidirectional causal relationship between NSE and NASDAQ, as well as NSE and NYSE, highlighting the influence of Indian stock market movements on U.S. markets and vice versa. This suggests that global investors monitor developments in Indian markets closely, particularly in a time of rising economic integration between India and the West. Additionally, the analysis shows a significant unidirectional causality from the SSE to NSE, indicating that the Chinese market exerts a strong influence on India, but not the other way around. This reflects China's dominant position in the Asia-Pacific region and underscores its role as a major economic player. In contrast, the relationships between NSE and Euronext or LSX are weaker, suggesting less direct influence from European markets. These findings could reflect the relative distance, economic ties, and varying levels of market maturity between India and Europe. Nonetheless, there are still indirect links through global financial flows that tie these markets together, even if they do not exhibit direct causal effects in the short term. The ASX-200's limited influence on the NSE may be explained by the relatively smaller size of Australia's market compared to the others studied, as well as the geographic and economic separation between India and Australia. These inter-market linkages have practical implications for investors, as they provide a framework for understanding how global market movements can affect portfolios with exposure to Indian stocks. For policymakers, the results emphasize the importance of monitoring international market trends and preparing for potential spillovers, especially during periods of financial turbulence. These findings are particularly relevant in a post-pandemic world, where markets have become increasingly volatile, and shocks in one region can rapidly spread to others.

Conclusion:

This study has provided empirical evidence on the causal relationships between the National Stock Exchange of India and selected global stock exchanges, revealing varying degrees of interdependence between the Indian market and other leading financial markets worldwide. The significant bidirectional causality between NSE and both NASDAQ and NYSE points to the increasing role India plays in global financial markets and underscores the importance of the U.S. markets in shaping Indian market trends. The unidirectional influence from SSE to NSE highlights the impact of China's financial dynamics on India, reinforcing the economic ties between these two major Asian economies. The weaker linkages between NSE and European markets (Euronext and LSX) may indicate that while economic and financial ties exist, they are not as robust as those with the U.S. or China. These results have strategic implications for global investors seeking diversification opportunities. Understanding these causal connections enables more informed decision-making regarding asset allocation and risk management in portfolios exposed to both Indian and global equities. Furthermore, this study contributes to the broader understanding of global financial integration and market interdependence. It suggests that emerging markets like India are becoming increasingly relevant in the global financial ecosystem. However, this growing interdependence also brings vulnerabilities, as shocks in larger markets can have a cascading impact on India's stock market, as evidenced by the causal linkages observed in the study. Policymakers should consider these findings when developing strategies for market stability, especially in times of economic uncertainty. In conclusion, the study emphasizes the need for continuous monitoring of international stock exchanges and the integration of global financial trends into national economic policies. As markets become more interconnected, the ability to predict and respond to external shocks becomes crucial. The results of this study offer valuable insights for investors, policymakers, and financial analysts looking to navigate the complexities of an increasingly globalized financial environment. The understanding of these causal relationships can lead to more robust investment strategies and better risk management in an era of global financial interdependence.

Future Scope and Limitations

This study offers valuable insights into the causal relationships between the National Stock Exchange of India and major global stock markets, but there are several limitations and areas for future research. One limitation is the reliance on historical data, which may not capture real-time market dynamics or respond to sudden geopolitical or economic shocks. Future studies could incorporate real-time data or high-frequency trading information to provide a more detailed analysis. Additionally, this study focused on select stock exchanges, leaving out other important markets such as Japan, Brazil, and Canada, which could also play significant roles in global financial interdependence. Expanding the geographical scope of the analysis could provide a more comprehensive understanding of global market interactions. Another limitation is the use of Granger Causality and Vector Auto Regression models, which may not fully account for nonlinear relationships between markets. Future research could explore more advanced econometric models, such as machine learning or deep learning approaches, to capture complex market behaviors. Moreover, the influence of external factors like macroeconomic indicators, political instability, and central bank policies was not fully explored in this study, which could be important areas for future research to better understand stock market correlations. Integrating these factors could enhance the robustness of the findings.

References

Akula, S. C., Singh, P., Farhan, M., Kumar, P., Cheema, G. S., Rehman, M., Sharma, A., & Kumar, P. (2024). Evaluating the Effectiveness of a Chatbot-Based Workshop for Experiential Learning and Proposing Applications. *Eurasian Journal of Educational Research*, *2024*(109), 32–45. https://doi.org/10.14689/ejer.2024.109.003

Awang, N. A., Abdullah, L., & Hashim, H. (2023). A Bonferroni mean considering Shapley fuzzy measure under hesitant bipolar-valued neutrosophic set environment for an investment decision. *Journal of Ambient Intelligence and Humanized Computing*, *14*(6), 6919–6946. https://doi.org/10.1007/s12652-021-03550-w

Batondo, M. (2022). *Comovement across BRICS and the US Stock Markets : A Multitime Scale Wavelet Analysis*.

Buczynski, W., Steffek, F., Cuzzolin, F., Jamnik, M., & Sahakian, B. (2022). Hard Law and Soft Law Regulations of Artificial Intelligence in Investment Management. *Cambridge Yearbook of European Legal Studies*, *24*(2022), 262–293. https://doi.org/10.1017/cel.2022.10

Darmayanti, N. P. A., Wiagustini, N. L. P., Artini, L. G. S., & Candraningrat, I. R. (2023). Driving Millennials To Be Investors: The Case Of Investment Decision Performance In Indonesian Capital Market. *Quality - Access to Success*, *24*(196), 167–174. https://doi.org/10.47750/QAS/24.196.22

Ghaemi Asl, M., Adekoya, O. B., & Rashidi, M. M. (2022). Quantiles dependence and dynamic connectedness between distributed ledger technology and sectoral stocks: enhancing the supply chain and investment decisions with digital platforms. *Annals of Operations Research*, *327*(1), 435–464. https://doi.org/10.1007/s10479-022-04882-2

Hii, I. S. H., Li, X., & Zhu, H. (2023). Behavioural Biases and Investment Decisions during COVID-19: An Empirical Study of Chinese Investors. *Institutions and Economies*, *15*(3), 81–103. https://doi.org/10.22452/IJIE.vol15no3.4

Liang, Z., Luo, X., & Yuan, F. (2023). Consumption-investment decisions with endogenous reference point and drawdown constraint. *Mathematics and Financial Economics*, *17*(2), 285–334. https://doi.org/10.1007/s11579-023-00335-x

Liu, S., Wu, S., Xie, F., & Yuan, G. (2021). Computer simulation of investment efficiency function model based on GMM method and artificial intelligence. *Journal of Ambient Intelligence and Humanized Computing*, *0123456789*. https://doi.org/10.1007/s12652-021-03112-0

Lui, A. K. H., Lee, M. C. M., & Ngai, E. W. T. (2022). Impact of artificial intelligence investment on firm value. *Annals of Operations Research*, *308*(1–2), 373–388. https://doi.org/10.1007/s10479-020-03862-8

Manocha, S., Bhullar, P. S., & Gupta, P. K. (2023). Exploring the Determinants of Investment Behavior: Evidence from Agrarian Investor Class of India. *Business Perspectives and Research*. https://doi.org/10.1177/22785337231156659

Manocha, S., Bhullar, P. S., & Sachdeva, T. (2023). Factors determining the investment behaviour of farmers – the moderating role of socioeconomic demographics. *Journal of Indian Business Research*. https://doi.org/10.1108/JIBR-02-2022-0045

Nagpal, R., Singh, P., Angra, P. K., Cheema, G. S., & Rehman, M. (2024). Wearable Computing: Canonical Correlation Analysis (CFA) Statistical Method to Validate the Measurement Models Smart Ergonomic Shoes. *International Journal of Intelligent Systems and Applications in Engineering*, *12*(17s), 404–408.

Padmaja, M., Shitharth, S., Prasuna, K., Chaturvedi, A., Kshirsagar, P. R., & Vani, A. (2022). Grow of Artificial Intelligence to Challenge Security in IoT Application. *Wireless Personal Communications*, *127*(3), 1829–1845. https://doi.org/10.1007/s11277-021-08725-4

Rehman, M., Dhiman, B., Cheema, G. S., & Diwakar, K. (2024). *Market Intelligence Redefined : Big Data Analytics and Machine Learning in Indian Stock Market Analysis*. *1*, 22–29.

Rehman, M., Dhiman, B., Kumar, R., & Cheema, G. S. (2023). *Exploring the Impact of Personality Traits on Investment Decisions of Immigrated Global Investors with Focus on Moderating Risk Appetite : A SEM Approach*. *8984*(August), 95–110.

Rehman, M., Dhiman, B., Nguyen, N., Dogra, R., & Sharma, A. (2024). *Behavioral Biases and Regional Diversity : An In-Depth Analysis of Their Influence on Investment Decisions - A SEM and MICOM Approach*. *4*(2), 70–85.

Rehman, M., Dhiman, D. B., & Cheema, G. S. (2024). Minds and Machines: Impact of Emotional Intelligence on Investment Decisions with Mediating the Role of Artificial Intelligence. *International Journal of Engineering, Business and Management*, *8*(1), 01–10. https://doi.org/10.22161/ijebm.8.1.1

Shao, Y., & Qin, C. (2023). Applied Mathematics and Nonlinear Sciences. *Applied Mathematics and Nonlinear Sciences (Aop) (Aop)*, *3*(2), 571–582.

Shehata, S. M., Abdeljawad, A. M., Mazouz, L. A., Aldossary, L. Y. K., Alsaeed, M. Y., & Sayed, M. N. (2021). The moderating role of perceived risks in the relationship between financial knowledge and the intention to invest in the Saudi Arabian stock market. *International Journal of Financial Studies*, *9*(1), 1–16. https://doi.org/10.3390/IJFS9010009

Sigauke, C., Mukhodobwane, R., Chagwiza, W., & Garira, W. (2022). *Asymptotic Dependence Modelling of the BRICS Stock Markets*.

1. *NSE: National Stock Exchange (India)*
2. *SSE: Shanghai Stock Exchange (China)*
3. *EURONEXT: European New Exchange Technology (Pan-European)*
4. *ASX-200: Australian Securities Exchange (Australia)*
5. *LSX: London Stock Exchange (United Kingdom)*
6. *NASDAQ: National Association of Securities Dealers Automated Quotations (United States)*
7. *NYSE: New York Stock Exchange (United States)*