A STUDY ON BILATERAL TRADES & INTERLINKAGE BETWEEN ASIAN STOCK MARKET'S

A Dissertation Submitted to Goa University

FSC413 Project Work

Credits:4

Submitted in partial fulfilment of Master's Degree

Master of Business Administration (Financial Services)

By

SHREYAN JOSEPH PINTO

21P030022

Under the Supervision of

DR. NARAYAN PARAB

ASSISTANT PROFESSOR

Goa Business School
Financial Services

Goa University

Date:

Examined by: Seal of the School

DECLARATION BY STUDENT

I hereby declare that the data presented in this Dissertation / report entitled, A Study on Bilateral Trades & Interlinkage Between Asian Stock Market is based on the results of investigations carried out by me in the Financial Service at the Goa Business School, Goa University under the Supervision/Mentorship of Dr/ Narayan Parab Assistant Professor and the same has not been submitted elsewhere for the award of a degree or diploma by me. Further, I understand that Goa University or its authorities will be not being responsible for the correctness of observations / experimental or other findings given the dissertation.

I hereby authorize the University authorities to upload this dissertation on the dissertation repository or anywhere else as the UGC regulations demand and make it available to any one as needed.

Shreyan Joseph Pinto
21P030022
Financial Services
Goa Business School

Date:

Place: Goa University

COMPLETION CERTIFICATE

This is to certify that the dissertation / report "**A Study on Bilateral Trades and Interlinkage Between Asian Stock Market"** is a bonafide work carried out by **Mr** Shreyan Joseph Pinto under my supervision/mentorship in partial fulfilment of the requirements for the award of the degree of **MBA (Financial Services)** in the Discipline Financial Services at the Goa Business School, Goa University.

Dr Narayan Parab
Assistant Professor
MBA (Financial Services)

Date:

Prof Jyoti D. Pawar
Computer Science & Technology
Goa Business School
Date:
Place: Goa University

School Stamp

INDEX

TABLE INDEX

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

1.1 Introduction

Bilateral trades refer to transactions between two countries or entities where goods, services, or financial assets are exchanged. In the context of Asia and India, bilateral trades have been growing in recent years, driven by the region's economic growth and the increasing importance of India in the global economy. The economic and financial ties between India and other Asian countries have brought significant benefits to both regions, such as increased trade, investment, and economic growth.

The Asian region, which includes some of the world's fastest-growing economies such as China, Japan, and South Korea, has become a significant destination for Indian exports. India, in turn, has been importing several goods and services from the Asian region, including electronics, machinery, and petroleum. Additionally, India has been investing in various sectors in Asian countries, such as energy, infrastructure, and manufacturing.(Palamalai et al., 2013)

Moreover, the Asia-India economic relationship has been supported by several bilateral trade agreements. For instance, India has signed several free trade agreements (FTAs) with various Asian countries, such as the Comprehensive Economic Cooperation Agreement (CECA) with Singapore, and the India-Korea Comprehensive Economic Partnership Agreement (CEPA). These agreements have facilitated the movement of goods and services between the two regions and increased trade and investment flows.

However, bilateral trades between Asia and India also present challenges, such as tariff and non-tariff barriers, regulatory differences, and currency fluctuations.

Interlinkages between Asian stock markets have been growing in recent years, driven by various factors such as globalization, technological advancements, and the increasing importance of Asia in the global economy. One form of interlinkage is cross-listing, where a company lists its shares on multiple stock exchanges. This allows investors in different countries to invest in the same company, increasing liquidity and diversification opportunities.(Narayan et al., 2014)Another form of interlinkage is the creation of financial products that allow investors to gain exposure to multiple markets simultaneously. For example, exchange-traded funds (ETFs) that track broad market indices such as the MSCI Asia Pacific Index have become popular among investors seeking exposure to the region.

Joint ventures and partnerships between stock exchanges are also a growing trend, as they enable exchanges to share resources and knowledge, and expand their reach into new markets. For example, the Shanghai-Hong Kong Stock Connect and the Shenzhen-Hong Kong Stock Connect programs have facilitated trading and investment between mainland China and Hong Kong.

The interlinkage between Asian stock markets has become increasingly important in recent years, and this trend has not spared the Indian stock market. India, being the seventh-largest economy in the world, has played a crucial role in driving the growth of the region. The interlinkage between Indian stock markets and other Asian markets has brought new opportunities for investors, companies, and economies in the region.(Shabri Abd Majid et al., 2009)

In recent years, India has taken several initiatives to deepen its integration with other Asian markets. For instance, the National Stock Exchange (NSE) of India has signed agreements with several Asian

stock exchanges, such as the Hong Kong Stock Exchange, the Korea Exchange, and the Singapore Exchange. These agreements have led to the creation of trading links, joint ventures, and the cross-listing of companies.

Furthermore, India's participation in regional forums such as the ASEAN-India Free Trade Area, the Bay of Bengal Initiative for Multi-Sectoral Technical and Economic Cooperation, and the South Asian Association for Regional Cooperation has increased economic and financial linkages with other Asian countries.

The growth of bilateral trades and interlinkages between Indian stock market and other Asian stock markets has opened up new opportunities for investors, companies, and economies in the region, and has helped to deepen regional financial integration. However, it has also increased the potential for contagion and systemic risks, which requires careful management by regulators and market participants.

1.2 Literature Review:

As per (Kroner & Ng, 1998)Although no evidence of a relationship was found among the Asian stock markets, correlation analyses suggest that integration among these markets is likely to occur in the near future. (Nath & Verma, 2003) By studying the transmission of market movements between India, Singapore, and Taiwan, three major stock markets in the Asian region, it was analysed that the level of capital market integration. It was suggested that investing in these stock markets could yield long-term gains for international investors due to the independent nature of these markets. In their paper, (Gupta & Agarwal, 2011) examined the correlation between the Indian stock market and five other major Asian economies, namely Japan, Hong Kong, Indonesia, Malaysia, and Korea. They found a weak correlation, which led to the conclusion that the Indian stock market could provide diversification benefits to institutional and international investors. (Mohsin & Rivers, 2011) In their paper the relationship between Indian stock markets and leading South Asian countries was studied to determine if Indian equity market was more proficient than the other markets in the region. The study utilized daily stock indices from August, 2002 to August, 2011 and conducted bivariate and multivariate co-integration tests and Granger causality tests. The results showed that the markets were either low or negative, indicating that investment in these markets may provide diversification benefits with low portfolio risks to investors. Moreover, none of the South Asian markets had control over each other, meaning that none of them influenced or was influenced by the Indian stock market.(Palamalai et al., 2013) In his study, the integration of major stock markets in emerging Asia-Pacific economies, including India, Malaysia, Hong Kong, Singapore, South Korea, Taiwan, Japan, China, and Indonesia, was analysed using the Johansen and Juselius multivariate co-integration test, Granger causality/Block erogeneity Wald test, and variance decomposition analysis. The findings indicate that while there are possibilities for short-term portfolio diversification benefits from exposure to these markets, the long-term portfolio diversification benefits may be limited. (Asgharian et al., 2013) Has utilized spatial econometrics techniques to explore the impact of economic and geographical relations on stock market co-movements among countries. Their analysis revealed that bilateral trade relationships were particularly effective at capturing returns co-variations. They discovered that a unit shock to dominant countries such as the US, UK, and Japan had a particularly strong effect on other countries through trade linkages. Interestingly, they observed that during times of recession, the relevance of proximity declined while the degree of stock market dependence increased. The researchers also investigated the impact of regional crises such as the Asian crisis and determined that Thailand had a significant impact on its trade neighbours. Bilateral trade was deemed the most important linkage due to its influence on business cycle synchronization across countries. Additionally, the researchers studied the transmission of shocks from dominant countries and found that bilateral trade was crucial for transmitting shocks from the US to other markets, while the effect of the US market on its geographical neighbours was minimal (Shabri Abd Majid et al., 2009)In his research has done an Empirical exploration of market integration in five selected ASEAN emerging markets (Malaysia, Thailand, Indonesia, the Philippines, and Singapore) during the pre- and post-1997 financial crisis periods is the aim of this paper. The study reveals that the stock markets in the ASEAN region are co-integrated during both periods, but they are moving towards greater integration, especially after the 1997 crisis. Moreover, all ASEAN markets except Indonesia are significant short-run adjusters to shocks in the long-run equilibrium relationships in the region during both periods, according to error correction terms.(Abdul Karim & Xin Ning, 2013)The goal of his study is to analyse the factors influencing the integration of stock markets within five chosen emerging stock markets in the ASEAN region, which are Malaysia, Thailand, Indonesia, the Philippines, and Singapore. The results indicate that the level of trade between countries and the volatility of stock markets are significant factors that affect stock market integration. These findings support the belief that stronger trade ties lead to higher correlation between stock markets. Furthermore, if the volatility of one market rises compared to another, the returns for that market should also increase compared to the other market.(Wang, 2018) Investigates the impact of the US dollar's appreciation (or Chinese yuan's depreciation) on the US bilateral trade deficit with China, US exports to China, and US imports from China under China's managed floating exchange rate system, which is a major concern for the public. The findings indicate that both US and Chinese income are important determinants, and while the US dollar's appreciation may reduce US exports to China, it will not greatly promote US imports from China in the long term. Ultimately, the appreciation of the US dollar does not significantly contribute to the US trade deficit with China in the long term. (Caporale et al., 2019) In his paper, the integration of global and regional stock markets in Asia is analysed using Phillips-Sul (2007) tests. The results show that Asian stock markets are integrated both globally (with the US) and regionally (within Asia) at the aggregate level, although convergence slowed after the global financial crisis in 2008. However, not all industries displayed convergence, with Gas & Oil, Healthcare, and Technology being the exceptions. Additionally, clubs in the turn-around phase and divergent economies were found to be contributing factors to the lack of convergence in some industries. Trade linkages and stock market development positively impacted regional integration, while real interest rate differentials and exchange rate risk slowed both regional and global integration. his research also suggests that although regional integration has been slightly stronger than global integration since 1998, the 2008 global financial crisis held back both forms of integration. Therefore, more regional agreements and cooperation are needed to promote integration in Asia. As per (Arya & Singh, 2022) During the COVID-19 pandemic, the paper delves into the dynamic relationship between the stock markets of South Asian Association of Regional Cooperation (SAARC) countries. The research concludes that the SAARC countries' stock returns have suffered due to the COVID-19 contagion. Also, the study reports distinct regularities in the pattern of co-integration and causality in the long and short run during the crisis. In essence, the findings showcase a weakened dynamic connection between SAARC countries' stock markets as a result of the COVID-19 pandemic.(Daly & Daly, 2014) Examines the correlation and co-integration of the stock markets in Southeast Asia and advanced economies such as Australia, Germany, and the United States before and after the 1997 Asian financial crisis. The study finds an increase in interdependence among Southeast Asian markets after the crisis but no significant increase in integration. Similarly, the paper investigates the linkages between major stock markets in Latin America and the US stock market and finds weak contemporaneous correlation and a three-month lead for the US market on those in Brazil, Mexico, and Argentina, providing policymakers and investors with sufficient time to make forecasts. The aim of (Vatsa et al., 2022)study is to analyse the connections between the prominent stock markets in Latin America such as Argentina, Brazil, Chile, and Mexico, and their relations with the global financial market, specifically the US stock market. The findings reveal that there is a slight correlation between the US S&P 500 and the stock market indices in Brazil, Mexico, and Argentina in the present time. However, the US stock market also influences the latter markets by leading them by three months. Hence, decision-makers and financiers have ample time to improve their projections of these markets. (Aggarwal & Raja, 2019) Analysis the co-integration of the stock markets of Brazil, Russia, India, and China to determine if they move together or apart in the long-term. Additionally, the authors examine the transmission of volatility between the Indian implied volatility index and three international indices using daily data and techniques such as generalized impulse response functions and variance decompositions. The paper finds that there is a stable long-term causal relationship between the four stock markets, with the VECM coefficient being negative and highly significant at 1 per cent. The variance decomposition reveals that on average, the indices of Brazil, China, and Russia can explain a small percentage of the forecast error variance of the Indian index, and vice versa. (Diamandis, 2009) In his study examines the interdependent nature of major stock markets in Latin America using data from 1995 to 2000. Co-integration analysis and error correction vector auto regressions (VAR) techniques are employed to model interdependencies, with one co-integrating vector found to explain the dependencies in prices. Results remain strong when indexes are translated to a common currency and when sample periods are split before and after major financial crises. His study suggests that diversifying risk through investments in different Latin American markets may be limited. His research contributes to a relatively scant literature on emerging stock markets, with a focus on Latin America's opening up for foreign investors and its rapid economic growth. The study also examines the behaviour of stock prices in six Latin American stock exchanges based on univariate and multivariate system approaches, with results indicating that the national stock price indexes share one long-term equilibrium relationship up until 1999. The study uses specific linkages to establish fluctuations in market prices in Mexico and movements in other markets except Colombia. Finally, decomposition of the forecast error variances suggests that a significant proportion of the stock market index variance for Argentina, Chile, and Mexico is due to shocks from foreign stock markets within Latin America. As per (Javeria Maryam, Umer Jeelanie Banday, 2018) Recently, the global attention has focused on the emergence of the BRICS economies, specifically Brazil, Russia, India, China, and South Africa. These countries have seen significant growth in their global trade flows in the past 15 years. Their paper aims to explore the trade flows between BRICS countries and between BRICS and the European Union. The study found that there is a large amount of bilateral trade between BRICS members, with Russia being the main trading partner with the EU. The study also found that Brazil and Russia have a comparative advantage in natural resource-based products while India and China have a comparative advantage in manufactured and processed products. Furthermore, their analysis showed evidence of competition between India and China in the EU.

1.3 Research Gap:

The existing literature on the interlinkage between Asian stock markets mainly consists of studies that focus on the relationship between individual stock markets or between Asian markets and global markets. However, there is a lack of research on the bilateral trades and interlinkage between Asian stock markets. In particular, there is a need to investigate how the bilateral trades between two or more Asian stock markets affect their interconnection and volatility.

1.4 Scope of the Study:

The scope of this study is to investigate the bilateral trades and interlinkage between the stock markets off Asian countries, namely, China, Hong Kong, Singapore, Indonesia and South Korea. The study will focus on the period between January 2002 and March 2022, which is a decade of considerable economic changes in the region.

1.5 Objective of the Study:

- ✓ To study whether Indian stock market has an impact on the Asian stock market.
- ✓ To see whether there is similarity in the movement of the stock market.
- ✓ To study weather Bilateral trades may have any part in the interlinkage of the Asian stock market.

1.6 Data and Methodology:

The study data consists of the daily closing price of the top six Asian stock market with which India has Bilateral trades with more & least import and export we have collected the data from https://commerce.gov.in/trade-statistics/ and from Investment.com in total we have collected two sets of data one is the closing price of major Indices of the respected Asian countries and the second set of data is India's import and export with these Asian countries the data has been collected from the period 2002 to 2022.

The study uses the methodology of vector auto regression (VAR), which was introduced by Sims (1980), to examine the dynamic correlations between selected Cryptocurrencies. The VAR technique has been proven reliable in investigating dynamic interactions between variables. The multivariate framework provided by the VAR model in this case is excellent, as it allows changes in one variable to be related to changes in its delays as well as changes in other variables and their lags. The model can identify the primary routes of interaction and replicate market responses to advances in another coin. The standard form of the VAR model can be expressed as:

$$\mathrm{Rt} = \mathrm{C} + \sum_{K=0}^{P} Ak\, Rt - kt + et$$

where Rt is a column vector of daily returns on the market indices at time t, C is a column vector of constant terms, Ak are matrices of coefficients that measure the effect of change in the jth market on the ith market after k periods, and εt is a column vector of unobserved disturbances assumed to satisfy the usual assumptions of the errors from an OLS regression. In our study, Rt, C, Ak, and εt are 3 × 1, 3 × 1, 3 × 3, and 3 × 1 column vectors/matrices, respectively.

CHAPTER 2: DATA AND ANALYSIS

2.1 DATA TABLE OF INDIA'S BILATERAL TRADES WITH ASIAN COUNTRIES (IMPORT)

IMPORT

COUNTY	CHINA P RP	HONG KONG	KOREA RP	INDONESIA	SINGAPORE
2002-2003	13,51,215.18	4,70,687.04	7,36,582.79	6,68,276.05	6,94,381.35
2003-2004	18,62,513.84	6,85,908.23	13,00,047.91	9,75,121.14	9,58,260.18
2004-2005	31,89,230.68	7,77,373.79	15,76,541.54	11,76,190.06	11,91,311.70
2005-2006	31,89,230.68	7,77,373.79	15,76,541.54	13,31,795.58	14,84,833.35
2006-2007	48,11,665.23	9,77,107.64	20,20,577.01	18,86,485.99	24,83,996.69
2007-2008	1,09,11,607.12	10,86,707.05	24,30,790.74	19,42,053.15	32,68,217.81
2008-2009	1,47,60,559.50	29,73,253.51	39,65,818.96	30,75,129.40	34,56,141.62
2009-2010	1,46,04,861.20	22,31,668.95	40,55,061.49	41,00,880.75	30,62,330.81
2010-2011	2,65,46,561.90	49,57,017.02	61,57,031.43	45,13,629.30	32,54,576.75
2011-2012	2,84,38,458.52	43,03,011.83	71,33,725.25	70,41,989.62	39,70,847.55
2012-2013	2,84,38,458.52	43,03,011.83	71,33,725.25	80,96,569.76	40,76,395.09
2013-2014	3,09,23,495.99	44,10,706.05	75,28,258.41	89,03,542.02	41,06,346.94
2014-2015	3,69,56,536.01	34,08,862.40	82,72,008.53	91,84,535.26	43,55,230.46
2015-2016	4,04,05,084.15	39,63,591.14	85,36,310.91	85,79,957.42	47,73,489.37
2016-2017	4,11,10,329.33	54,90,618.08	84,40,432.93	90,08,193.45	47,54,169.45
2017-2018	4,92,23,616.54	68,77,702.27	1,05,42,283.54	1,05,96,111.95	48,13,281.77
2018-2019	4,92,07,928.34	1,25,97,191.41	1,17,25,531.27	1,11,14,852.90	1,13,91,875.15
2019-2020	4,61,52,476.82	1,19,99,898.32	1,10,88,343.94	1,06,72,726.80	1,04,39,410.04
2020-2021	4,82,49,579.90	1,12,21,827.11	94,47,621.69	92,32,528.22	98,21,958.01
2021-2022	7,05,12,313.21	1,42,40,079.56	1,30,29,934.56	1,32,04,914.08	1,41,57,361.56

The table above displays India's bilateral import data with several Asian countries, including China, Hong Kong, Singapore, Indonesia, and South Korea. The data indicates that China, Hong Kong, and Singapore are India's top import partners, with the highest amounts of imports recorded. On the other hand, Indonesia and South Korea are the countries with the least amount of imports from India.

2.1.2 DATA TABLE OF INDIA'S BILATERAL TRADES WITH ASIAN COUNTRIES (EXPORT)

EXPORT

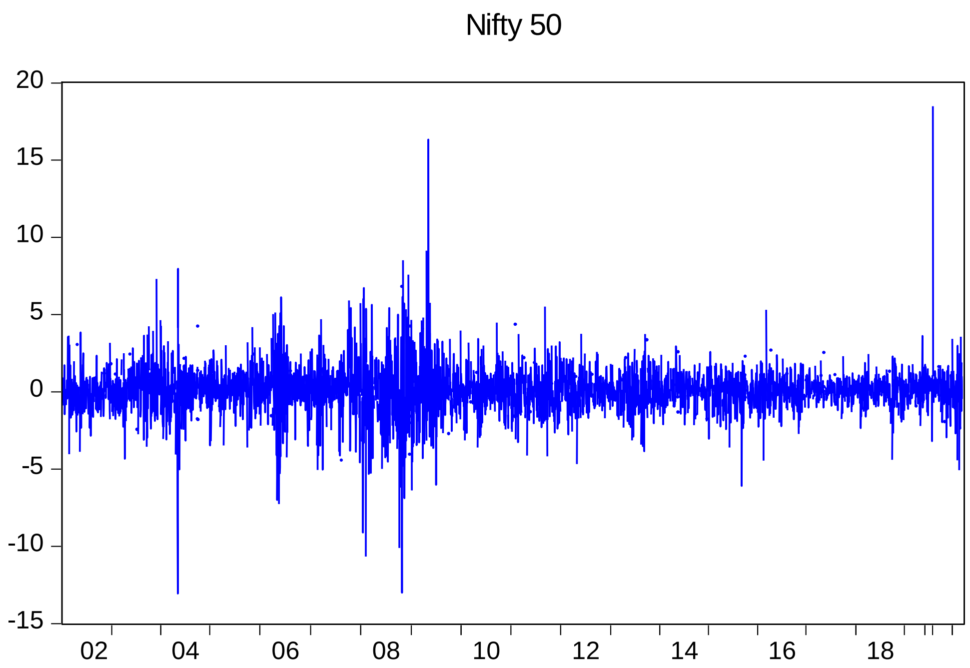
COUNTY	CHINA P RP	HONG KONG	KOREA RP	INDONESIA	SINGAPORE
2002-2003	9,56,039.13	12,64,726.83	3,12,078.10	3,99,773.68	6,87,977.67
2003-2004	13,57,905.85	14,98,851.50	3,51,464.58	5,17,967.68	9,76,392.90
2004-2005	25,23,296.90	16,58,790.01	4,68,043.69	5,98,756.65	17,97,534.89
2005-2006	29,92,491.28	19,79,610.39	8,08,970.14	6,11,063.22	24,01,965.25
2006-2007	37,52,978.03	21,17,937.83	11,37,900.98	9,17,696.77	27,46,160.82
2007-2008	43,59,741.59	25,38,525.32	11,48,153.52	8,69,277.93	29,66,223.24
2008-2009	42,66,133.36	30,39,069.39	18,35,359.19	11,57,782.95	37,75,688.18
2009-2010	54,71,392.87	37,30,053.40	16,12,681.15	14,60,463.91	35,94,829.70
2010-2011	64,31,514.27	47,03,841.63	16,95,280.67	25,92,440.79	44,73,173.31
2011-2012	87,47,082.09	61,87,723.46	20,76,775.91	32,10,069.61	80,36,299.98
2012-2013	73,52,956.23	66,89,817.16	22,87,024.72	28,99,608.70	73,99,496.63
2013-2014	90,56,108.68	77,24,096.13	25,47,092.30	29,33,987.09	74,96,620.27
2014-2015	73,03,043.30	83,11,857.40	28,08,473.91	24,67,435.24	59,85,397.67
2015-2016	58,93,941.16	79,30,702.05	23,04,348.38	18,44,606.51	50,53,132.22
2016-2017	68,25,091.98	94,11,493.32	28,43,671.65	23,40,069.18	64,11,508.51
2017-2018	85,99,429.96	94,67,735.08	28,75,143.99	25,56,175.52	65,78,930.91
2018-2019	1,17,28,910.90	91,11,741.76	32,87,796.88	36,87,106.45	80,94,224.79
2019-2020	1,17,67,331.48	77,75,243.40	34,33,765.43	29,29,938.37	63,02,692.37
2020-2021	1,57,20,159.04	75,20,143.29	34,69,423.42	37,15,668.84	64,38,216.92
2021-2022	1,58,21,547.51	81,83,452.88	60,34,956.81	63,19,650.22	83,01,294.51

As per the data presented in the above table, we can see the bilateral export data of India with several Asian countries, such as China, Hong Kong, Singapore, Indonesia, and South Korea. The data indicates that India's highest exports are with China, Hong Kong, and Singapore, while the countries with the least amount of exports are Indonesia and South Korea.

2.3. Graph Analysis of Trends in Log returns of Stock Market

2.3.1 Nifty 50

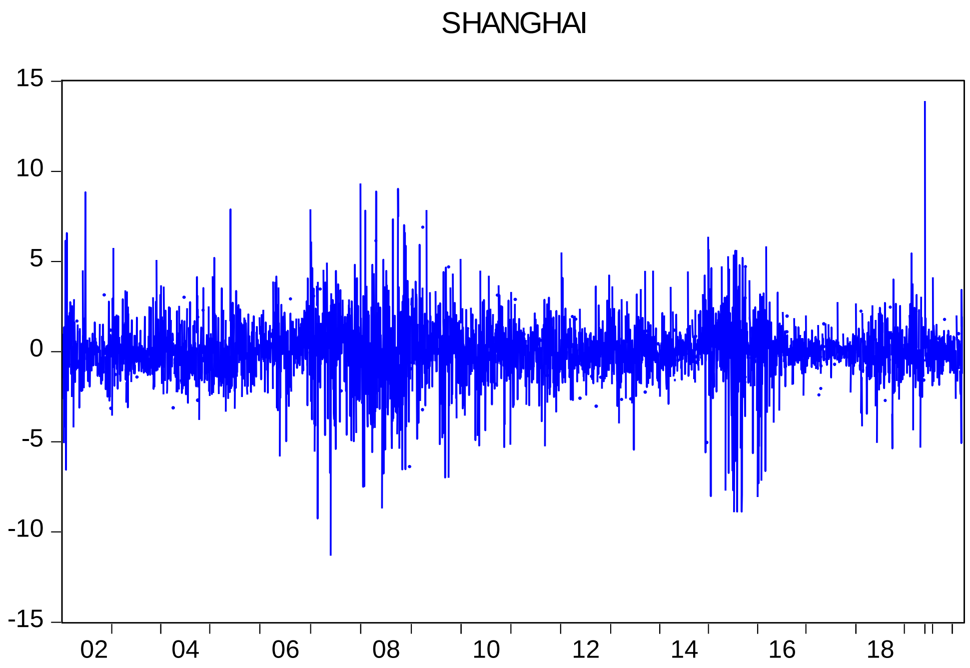
Figure 1: Trends in Nifty 50 Log returns



The graph above illustrates the returns that investors have received from investing in the Nifty 50 index. It is evident from the graph that the Nifty 50 index has generated consistent returns for investors over the entire period. However, during specific periods such as 2004, 2006, and 2008, the Nifty 50 index has generated negative returns for its investors. On the other hand, in 2009 and 2020, the Nifty 50 index has provided its investors with positive returns.

2.3.2 Shanghai

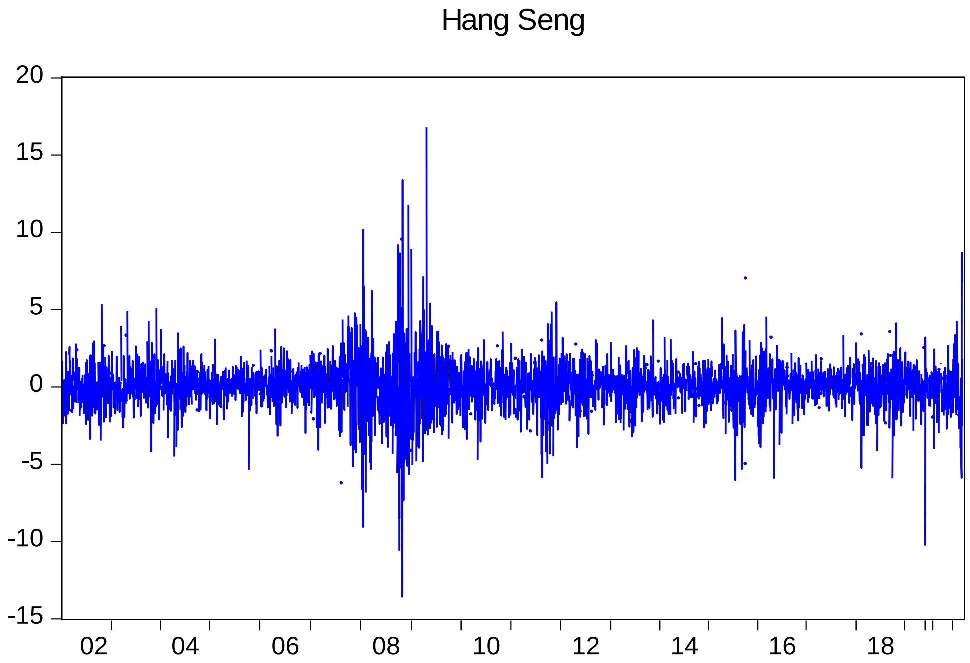
Figure 2: Trends in Shanghai Log returns



The graph presented above provides an insight into the returns generated by the Shanghai index for its investors. From the graph, we can observe that the Shanghai index provided positive returns to its investors from 2002 until 2006. However, from 2006 to 2012, the returns fluctuated significantly, with both positive and negative returns observed. Finally, in 2018, the Shanghai index generated more positive returns for its investors.

2.3.3 Hang Seng

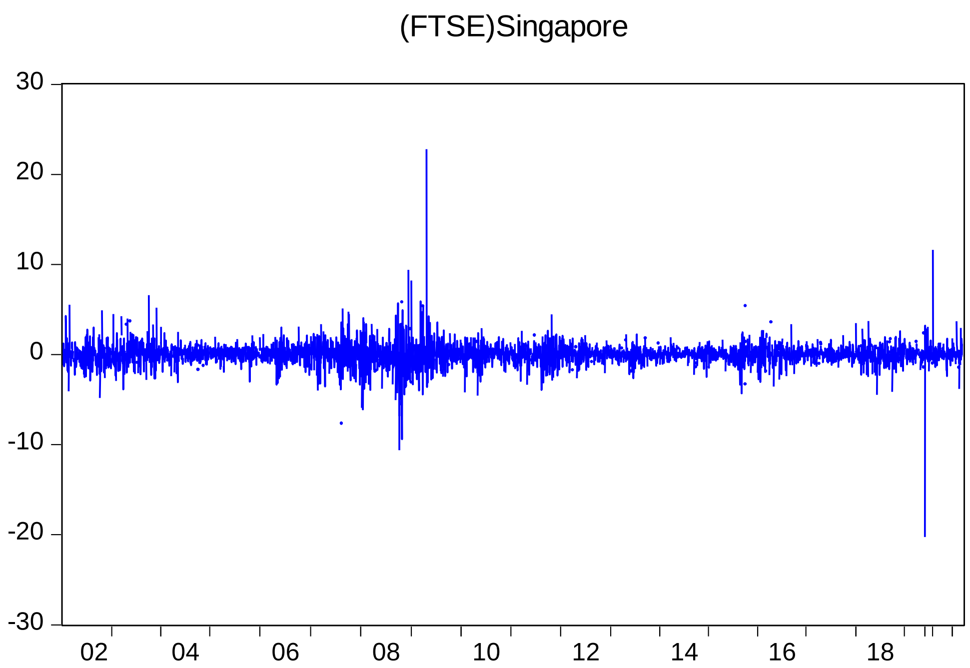
Figure 3: Trends in Hang Seng Log returns



The presented graph offers insight into the returns provided by the Hang Seng index to its investors. From 2002 to 2006, the Hang Seng index generated stable returns for its investors. However, during the period of 2007 to 2008 and 2018 to 2021, the Hang Seng index provided negative returns to its investors.

2.3.4 (FTSE) Singapore

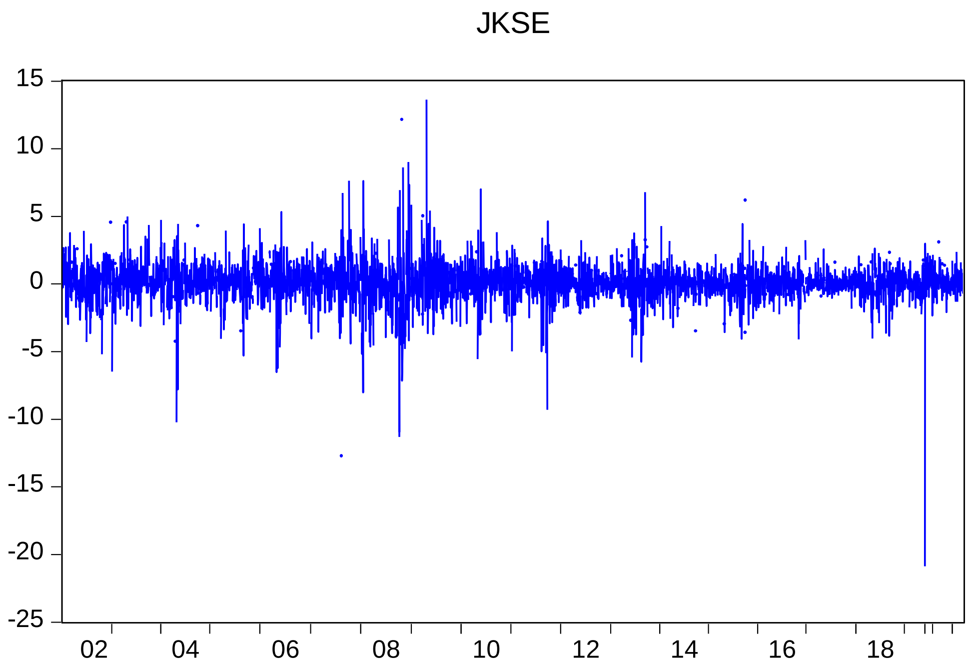
Figure 4: Trends in (FTSE) Singapore Log returns



The graph above displays the returns generated by the FTSE Singapore index for its investors. It is evident from the graph that the FTSE Singapore index provided a stable return to its investors during the period of 2002 to 2007. However, from 2008 to 2009, the index generated both high negative and positive returns. Subsequently, the index provided stable returns to its investors until 2019, where it resulted in negative returns.

2.3.5 JKSE

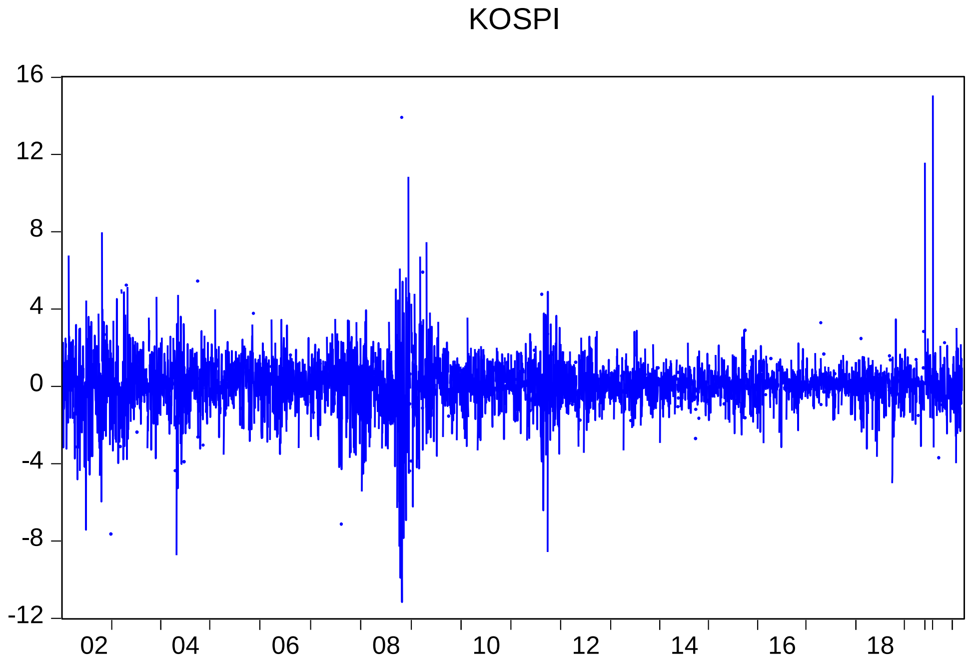
Figure 5: Trends in JKSE Log returns



The graph above presents the returns offered by JKSE to its investors, and it is evident that the returns are mostly negative. However, it should be noted that JKSE provided a significant positive return during the period of 2009 and a massive negative return during the period of 2020.

2.3.6 KOSPI

Figure 6: Trends in KOSPI Log returns

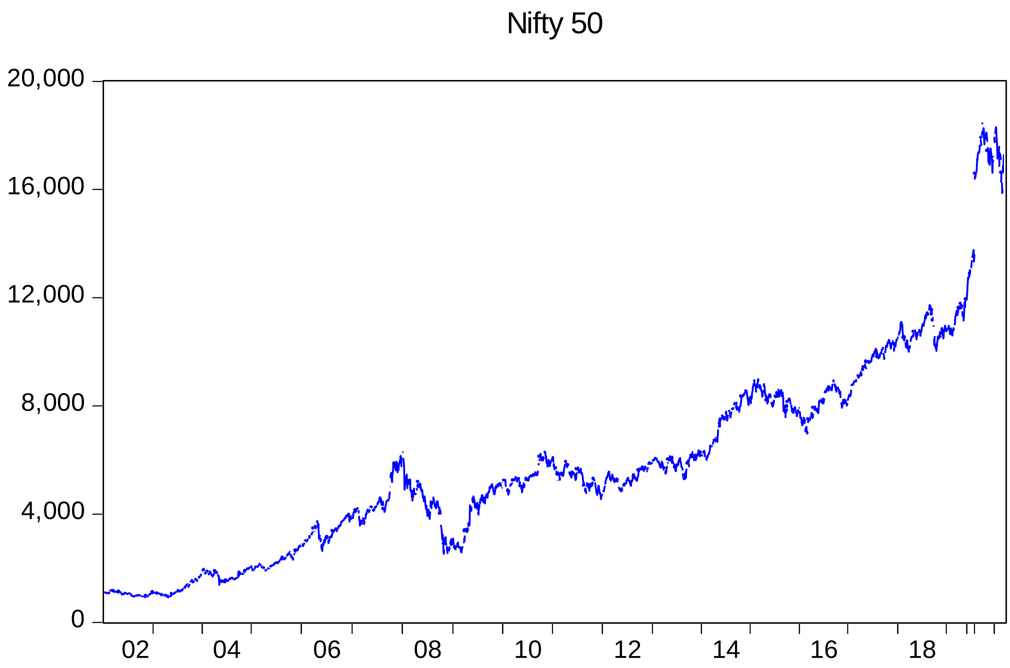


The graph below illustrates the returns generated by KOSPI for its investors. As observed from the graph, KOSPI returns were predominantly negative, and the index experienced high volatility during the period of 2002 to 2013. However, after this period, KOSPI provided a stable return to its investors. Notably, the highest positive return generated by KOSPI was during the period of 2019 to 2020.

2.4 Graphical Analysis of Trends in Closing Price Asian Stock Market

2.4.1 Nifty 50

Figure 1: Trends in Nifty 50 closing price



The graph depicts the trend in Nifty 50 closing prices from 2002 to 2022. It shows a significant rise in the closing price during this period, with a sharp climb observed between 2006 and 2008. However, in 2008, there was a steep decline in the price of Nifty 50, followed by a recovery and a steady growth in its price till date.

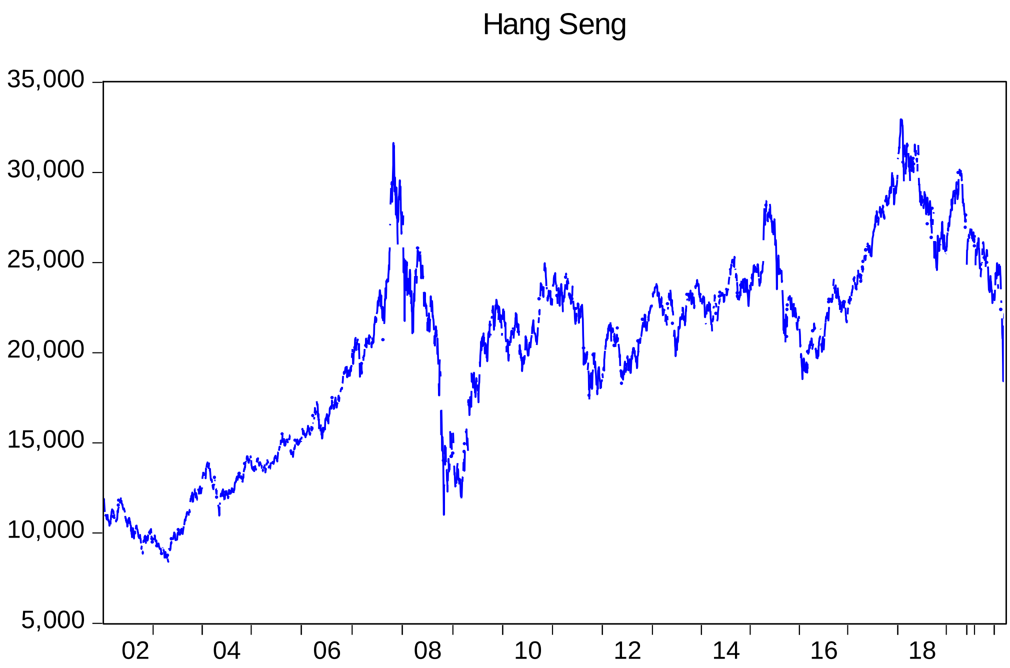
2.4.2 Shanghai

Figure 2: Trends in Shanghai closing price

The graph illustrates the price movements of Shanghai from 2002 to 2022. While there has been an overall increase in the price of Shanghai during this period, a closer look at the graph reveals significant fluctuations in the price. Notably, between 2006 and 2007, the price of Shanghai reached a high of 6000, followed by a significant dip in 2008. The price later stabilized with slight fluctuations, but during 2014-2016, a similar trend to that of 2006-2008 emerged. In summary, Shanghai's price has experienced considerable fluctuation over time.

2.4.3 Hang Seng

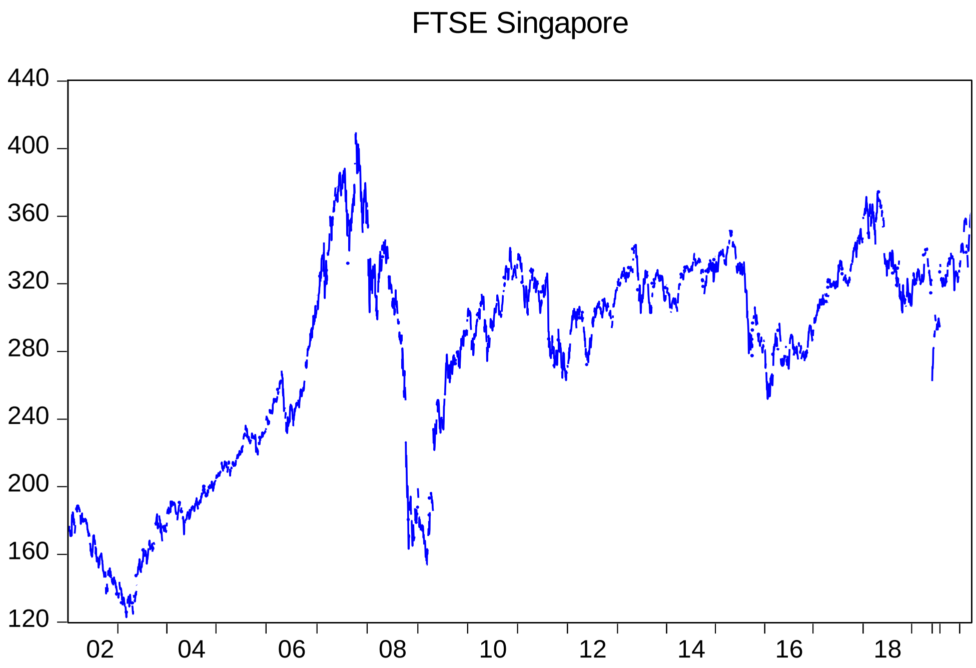
Figure 3: Trends in Hang Seng closing price



The graph displays the movement of Hang Seng prices from 2002 to 2022. The graph indicates a significant progression in the price of Hang Seng over time. However, in 2006, there was a notable fluctuation in the Hang Seng price, which was similar to the trend observed in Shanghai. The movement of Hang Seng prices is volatile overall, indicating that its price has grown over time, but not on a steady basis.

2.4.4 FTSE Singapore

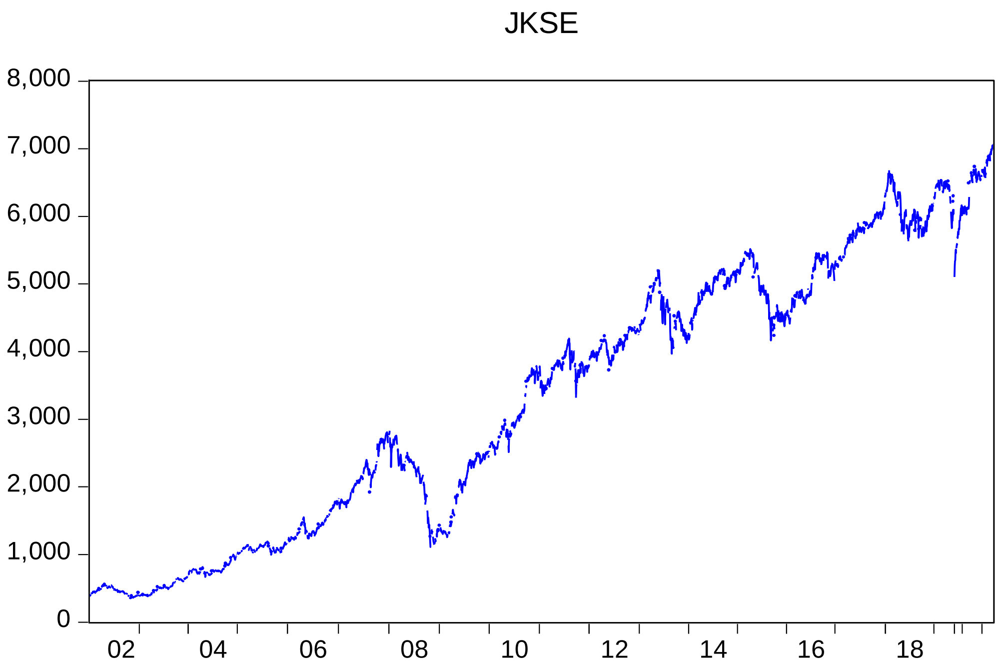
Figure 4: Trends in FTSE Singapore



The graph above showcases the price movements of FTSE Singapore, which have experienced significant growth from 2002 to 2022. During the period of 2002-2008, there was a steep climb in the price of FTSE Singapore, and it reached its highest point to date at 420. However, by the end of 2008, there was a significant fall in the price of FTSE Singapore. Despite this, the overall trend indicates that the price of FTSE Singapore has grown over time.

2.4.5 JKSE

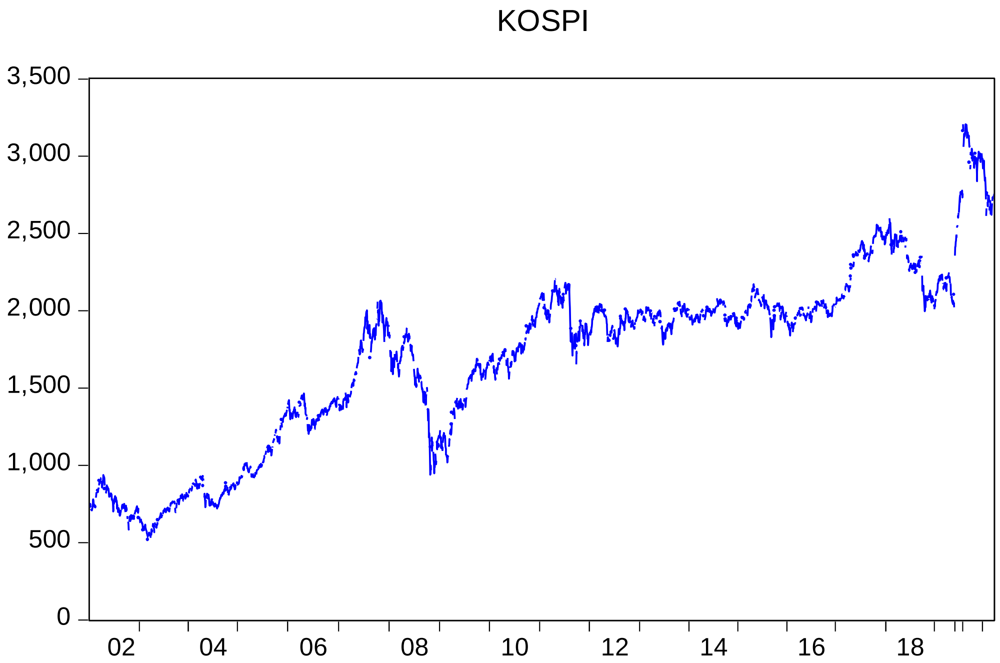
Figure 5: Trends in JKSE closing price.



The graph below portrays the price movement of JKSE from 2002 to 2022. During this period, JKSE has experienced steady growth in its price with little volatility, as shown in the graph. Starting at a price of 500, JKSE has shown remarkable progress and reached a price of 7,000 over time. This growth in the price of JKSE indicates positive market sentiment and a stable economic environment.

2.4.6 KOSPI

Figure 6: Trends in KOSPI closing price.



The graph above displays the price movement of KOSPI from 2002 to 2022. Notably, the price of KOSPI has shown steady growth during this period, with a significant jump in 2018 and a deep dip in 2008, as observed in the graph. Overall, KOSPI has performed well, indicating a positive market sentiment and a stable economic environment from 2002 to 2022.

2.5 DESCRIPTIVE STATISTICS

Table 5: Descriptive Statistics.

	NIFTY_50	SHANGHAI	HANG_SENG	KOSPI	JKSE	_FTSE_SINGAPORE
Mean	0.075803	0.019229	0.017282	0.035737	0.079684	0.019931
Median	0.100609	0.042767	0.061687	0.070460	0.121151	0.040037
Maximum	18.49576	13.89965	16.80068	15.06007	13.62432	22.78926
Minimum	-13.05386	-11.30372	-13.58202	-11.17200	-20.86394	-20.26500
Std. Dev.	1.578434	1.779531	1.576272	1.490762	1.508181	1.321084
Skewness	0.241580	-0.120715	0.252012	0.140980	-0.978618	0.441923
Kurtosis	17.35981	8.294559	15.01868	14.04495	22.62910	48.47044

Source: Authors Compliance

The data analysis above displays descriptive statistics for six different stock market indices: Nifty 50, Shanghai, Hang Seng, KOSPI, JKSE, and FTSE Singapore. The table reveals that among these indices, Nifty 50 exhibits the highest mean return of 0.075803, while Hang Seng and Shanghai have the lowest mean return of 0.017282 and 0.019229, respectively. Additionally, the median for Nifty 50, KOSPI, and JKSE is greater than the mean, indicating potential high-return outliers. Conversely, Shanghai and Hang Seng exhibit a median lower than the mean, suggesting the presence of negative-return outliers. Nifty 50, Hang Seng, KOSPAI, and FTSE Singapore possess positive skewness, while JKSE and Shanghai have negative skewness. All six indices are Lepto Kurtic.

2.6 AUGMENTED DICKEY-FULLER TEST.

Table 6: Augmented Dickey–Fuller Test.

Index	Test Statistic	Probability
Nifty 50	-57.69472	0.0001
Shanghai	-60.28139	0.0001
Hang Seng	-61.15374	0.0001
FTSE Singapore	-61.31133	0.0001
JKSE	-56.83814	0.0001
KOSPI	-59.114	0.0001

Source: Authors Compliance

The table above displays the results of the Augmented Dickey-Full Test (ADF) conducted on multiple Asian stock markets, including Nifty 50, Shanghai, Hang Seng, KOSPI, JKSE, and FTSE Singapore. The purpose of the test was to assess the stationarity of the data, and it was found that all variables were stationary at a level with a p-value of less than 0.05. Specifically, the p-value of Nifty 50, Shanghai, Hang Seng, KOSPI, JKSE, and FTSE Singapore were 0.0001.

Table 7: Correlation Matrix.

2.7 CORRELATION MATRIX.

Correlation						
Probability	SHANGHAI	HANG_SENG	_FTSE_ SINGAPORE	JKSE	KOSPI	NIFTY_50
SHANGHAI	1.000000					

HANG_SENG	0.4249	1.000000				
	0.0000	-----				
_FTSE_SINGAPORE	0.2588	0.7277	1.000000			
	0.0000	0.0000	-----			
JKSE	0.1994	0.5822	0.6114	1.000000		
	0.0000	0.0000	0.0000	-----		
KOSPI	0.2704	0.6128	0.5691	0.4819	1.000000	
	0.0000	0.0000	0.0000	0.0000	-----	
NIFTY_50	0.2294	0.5441	0.5494	0.4769	0.4697	1.000000
	0.0000	0.0000	0.0000	0.0000	0.0000	-----

Source: Authors Compliance

The above table consisting of data analysis that shows correlation coefficients between six different stock market indices, including the Indian Nifty 50, Chinese Shanghai, Hong Kong Hang Seng, South Korean KOSPI, Indonesian JKSE, and the FTSE Singapore. If we take a look at the above analysis we see that in India's case there is a moderate positive correlation between Nifty 50 and KOSPI (0.47), Nifty 50 and JKSE (0.48), Nifty 50 and Hang Seng (0.54), and Nifty 50 and FTSE Singapore (0.55). There is also a weak positive correlation between Nifty 50 and Shanghai (0.23). Whereas if we see the analysis as a whole we find out that there is high correlation between Hang Seng and FTSE Singapore at (0.72), followed by KOSPI and Hang Seng at (0.61). Generally, the correlations between the indices are moderate, ranging from (0.19) between JKSE and Shanghai to (0.54) between Nifty 50 and FTSE Singapore. In the end we find out that strongest positive correlation is observed between Hang Seng and FTSE Singapore (0.73), while the weakest positive correlation is observed between Nifty 50 and Shanghai (0.23).

2.8 PAIRWISE GRANGER CAUSALITY TEST

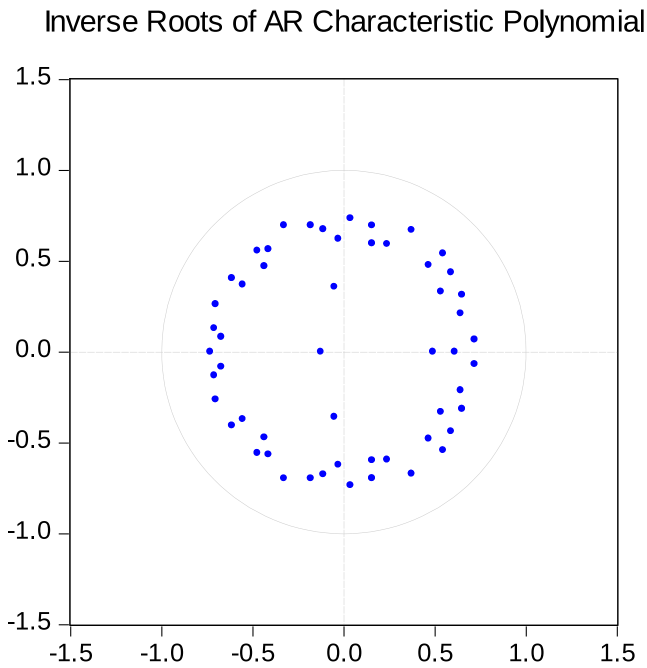
Null Hypothesis:	Obs	F-Statistic	Prob.
SHANGHAI does not Granger Cause NIFTY_50	3650	1.75435	0.1732
NIFTY_50 does not Granger Cause SHANGHAI		8.78610	0.0002
HANG_SENG does not Granger Cause NIFTY_50	3650	1.83662	0.1595
NIFTY_50 does not Granger Cause HANG_SENG		26.4137	4.E-12
_FTSE_SINGAPORE does not Granger Cause NIFTY_50	3650	0.01629	0.9838
NIFTY_50 does not Granger Cause _FTSE_SINGAPORE		8.84571	0.0001
JKSE does not Granger Cause NIFTY_50	3650	1.68557	0.1855
NIFTY_50 does not Granger Cause JKSE		19.3367	4.E-09
KOSPI does not Granger Cause NIFTY_50	3650	4.28983	0.0138
NIFTY_50 does not Granger Cause KOSPI		26.5252	4.E-12
HANG_SENG does not Granger Cause SHANGHAI	3650	3.86922	0.0210
SHANGHAI does not Granger Cause HANG_SENG		5.40688	0.0045
_FTSE_SINGAPORE does not Granger Cause SHANGHAI	3650	6.45657	0.0016
SHANGHAI does not Granger Cause _FTSE_SINGAPORE		1.40084	0.2465
JKSE does not Granger Cause SHANGHAI	3650	3.31945	0.0363
SHANGHAI does not Granger Cause JKSE		0.02529	0.9750
KOSPI does not Granger Cause SHANGHAI	3650	0.71383	0.4898
SHANGHAI does not Granger Cause KOSPI		2.32003	0.0984
_FTSE_SINGAPORE does not Granger Cause HANG_SENG	3650	18.5893	9.E-09
HANG_SENG does not Granger Cause _FTSE_SINGAPORE		4.44519	0.0118
JKSE does not Granger Cause HANG_SENG	3650	0.52052	0.5943
HANG_SENG does not Granger Cause JKSE		8.23306	0.0003
KOSPI does not Granger Cause HANG_SENG	3650	6.07153	0.0023
HANG_SENG does not Granger Cause KOSPI		7.31088	0.0007
JKSE does not Granger Cause _FTSE_SINGAPORE	3650	0.13633	0.8726
_FTSE_SINGAPORE does not Granger Cause JKSE		6.00019	0.0025
KOSPI does not Granger Cause _FTSE_SINGAPORE	3650	0.11578	0.8907
_FTSE_SINGAPORE does not Granger Cause KOSPI		8.14030	0.0003
KOSPI does not Granger Cause JKSE	3650	3.26515	0.0383
JKSE does not Granger Cause KOSPI		4.64168	0.0097

Source: Authors Compliance

Based on the data analysis above, we can conclude that the Grangers causality test reveals several causal relationships between the variables. Firstly, Nifty 50 has a causal effect on Shanghai, FTSE Singapore, and KOSPAI, as indicated by P-values less than 0.05 and rejection of the null hypothesis in all cases. Secondly, there is a reciprocal causal relationship between

Hang Seng and Shanghai, with a P-value less than 0.05 supporting this result. Thirdly, FTSE Singapore and JKSE also have a causal effect on Shanghai. However, there is evidence to support the hypothesis that Hang Seng causes FTSE Singapore, with a P-value of less than 0.05. Finally, the analysis reveals various other causal relationships between the variables: FTSE Singapore causes JKSE, KOSPAI causes Hang Seng, FTSE Singapore causes KOSPAI, KOSPAI causes JKSE, and JKSE causes KOSPAI.

2.9 AR ROOT GRAPH



Source: Authors Compliance

The above graph shows the Inverse root of AR characteristic Polynomial therefore. By examining whether the dots lie within the circle on the graph depicting the inverse root of the AR characteristic polynomial, we can determine the stability of our model. In this case, the dots are indeed within the circle, indicating that our model is stable and open to interpretation.

2.10 VARIANCE DECOMPOSITION

2.10.1 Forecast Error Variance Decomposition of Nifty 50.

Variance Decomposition of NIFTY_50:							
Period	S.E.	NIFTY_50	SHANGHAI	HANG_SENG	_FTSE_SINGAPORE	JKSE	KOSPI
1	1.555452	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
		(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
2	1.560530	99.55455	0.065290	0.037841	0.007009	0.073123	0.262185
		(0.23803)	(0.09391)	(0.07494)	(0.03502)	(0.09465)	(0.18224)
3	1.562271	99.33305	0.072386	0.116300	0.042641	0.080921	0.354697
		(0.29176)	(0.10107)	(0.14246)	(0.08428)	(0.11351)	(0.20683)
4	1.564717	99.02537	0.073819	0.141956	0.090785	0.290301	0.377769
		(0.36083)	(0.11136)	(0.14213)	(0.11505)	(0.18939)	(0.22080)
5	1.567192	98.71838	0.141821	0.208859	0.093884	0.328541	0.508520
		(0.41056)	(0.13759)	(0.18303)	(0.11870)	(0.19901)	(0.24103)
6	1.571271	98.27241	0.247231	0.230926	0.321069	0.419899	0.508467
		(0.46557)	(0.18478)	(0.19095)	(0.20533)	(0.22265)	(0.23839)
7	1.572592	98.12568	0.255925	0.259158	0.371134	0.454896	0.533203
		(0.51603)	(0.19315)	(0.21248)	(0.22448)	(0.24065)	(0.25285)
8	1.586442	96.82139	0.504154	0.294157	1.197645	0.637255	0.545396
		(0.65231)	(0.24258)	(0.21517)	(0.40213)	(0.29924)	(0.26184)
9	1.589538	96.45051	0.523918	0.489812	1.315701	0.635304	0.584758
		(0.65990)	(0.25077)	(0.22721)	(0.43360)	(0.29636)	(0.27104)
10	1.591198	96.25891	0.551537	0.607323	1.360063	0.637424	0.584740
		(0.68034)	(0.25785)	(0.26002)	(0.45056)	(0.30648)	(0.27356)

Source: Authors Compliance

The table above demonstrates the FEVD derived from VAR analysis of the selected variable. The first table indicates that on day 1, the forecast error variance in the Nifty 50 is solely explained by innovation within the Nifty 50 itself, as other variables such as Shanghai, Hang Seng, FTSE Singapore, JKSE, and KOSPAI do not significantly contribute to the explanation of the error variance. Similarly, on other days, these variables exhibit significantly lower contributions to the explanation of the forecast error variance in the Nifty 50, ranging from 0.55% to 1.36%.

2.10.2 Forecast Error Variance Decomposition of Shanghai.

Variance Decomposition of SHANGHAI:							
Period	S.E.	NIFTY_50	SHANGHAI	HANG_SENG	_FTSE_SINGAPORE	JKSE	KOSPI
1	1.762724	5.100236	94.89976	0.000000	0.000000	0.000000	0.000000
		(0.72463)	(0.72463)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
2	1.767464	5.439326	94.41378	0.020639	0.040885	0.001262	0.084108
		(0.74241)	(0.74768)	(0.05892)	(0.08047)	(0.03383)	(0.10163)
3	1.768084	5.439431	94.37250	0.022017	0.046468	0.033877	0.085704
		(0.74065)	(0.75740)	(0.06670)	(0.10611)	(0.09344)	(0.10821)
4	1.770835	5.439502	94.20930	0.092444	0.107943	0.036960	0.113847
		(0.75173)	(0.77440)	(0.10612)	(0.12613)	(0.10307)	(0.12534)
5	1.773689	5.499659	93.90740	0.139340	0.223170	0.058111	0.172321
		(0.75903)	(0.77284)	(0.13205)	(0.17968)	(0.11735)	(0.15235)
6	1.775681	5.487331	93.80035	0.152184	0.246277	0.108700	0.205156
		(0.75798)	(0.76825)	(0.14842)	(0.18638)	(0.15054)	(0.16866)
7	1.778658	5.598924	93.65053	0.177953	0.245968	0.111277	0.215345
		(0.75766)	(0.77365)	(0.16349)	(0.18184)	(0.14962)	(0.17256)
8	1.780969	5.648235	93.45208	0.185606	0.258159	0.129258	0.326665
		(0.75391)	(0.78703)	(0.16406)	(0.18659)	(0.16439)	(0.19426)
9	1.788411	5.696568	92.79305	0.380826	0.497594	0.307741	0.324217
		(0.76580)	(0.83466)	(0.22515)	(0.25724)	(0.20722)	(0.20220)
10	1.790058	5.736978	92.65801	0.381086	0.497788	0.331189	0.394943
		(0.76696)	(0.84953)	(0.22592)	(0.26434)	(0.21705)	(0.23265)

Source: Authors Compliance

In the second table, the Forecast Error Variance Decomposition results for Shanghai are presented. Log accounts for 94.89% of error variance on day 1, while the innovation in Nifty 50 explains 5.73% of error variance, indicating that Nifty 50's development is impacting Shanghai. The contribution of Hang Seng, FTSE Singapore, JKSE, and KOSPAI in explaining the forecast error variance in Shanghai is considerably lower at (0.38, 0.49, 0.33, 0.39) % respectively.

2.10.3 Forecast Error Variance Decomposition of Hang Seng.

Variance Decomposition of HANG_SENG:							
Period	S.E.	NIFTY_50	SHANGHAI	HANG_SENG	_FTSE_SINGAPORE	JKSE	KOSPI
1	1.551723	29.20414	9.592159	61.20370	0.000000	0.000000	0.000000
		(1.11910)	(0.75191)	(1.06497)	(0.00000)	(0.00000)	(0.00000)
2	1.569422	29.31829	9.868735	60.16002	0.429750	0.216812	0.006392
		(1.15473)	(0.78332)	(1.05037)	(0.20060)	(0.15853)	(0.05848)
3	1.571929	29.25608	9.873145	59.96918	0.532555	0.218369	0.150678
		(1.14864)	(0.78378)	(1.05108)	(0.23338)	(0.16266)	(0.14521)
4	1.574396	29.16445	9.875499	59.85483	0.578362	0.288694	0.238160
		(1.14784)	(0.78975)	(1.04733)	(0.23077)	(0.18183)	(0.16798)
5	1.575738	29.14131	9.952176	59.76144	0.578135	0.324994	0.241946
		(1.15051)	(0.77722)	(1.05316)	(0.23590)	(0.19097)	(0.16625)
6	1.579127	29.06259	10.19154	59.60255	0.576478	0.325412	0.241426
		(1.14858)	(0.75619)	(1.03177)	(0.23732)	(0.19565)	(0.16566)
7	1.580998	29.05452	10.16766	59.55061	0.587845	0.365129	0.274237
		(1.14371)	(0.75687)	(1.04968)	(0.24811)	(0.20126)	(0.16896)
8	1.585460	28.92234	10.26654	59.24074	0.819434	0.472083	0.278857
		(1.14534)	(0.72915)	(1.04731)	(0.31856)	(0.23030)	(0.17184)
9	1.587520	28.86915	10.26532	59.09872	0.958094	0.491820	0.316896
		(1.13226)	(0.71574)	(1.04309)	(0.35550)	(0.23423)	(0.19112)
10	1.588156	28.88690	10.26583	59.07132	0.964444	0.494321	0.317181
		(1.13903)	(0.72318)	(1.04002)	(0.36275)	(0.24061)	(0.19452)

Source: Authors Compliance

In the third table, the Forecast Error Variance Decomposition results for Hang Seng are presented. On day 1, Log accounts for 61.20% of the error variance, while Nifty 50 and Shanghai's innovations explain 28.88% and 10.26% respectively, indicating their impact on Hang Seng. However, the contribution of FTSE Singapore, JKSE, and KOSPAI in explaining the forecast error variance for Hang Seng is significantly lower, above (0.96%, 0.49%, and 0.31% respectively).

2.10.4 Forecast Error Variance Decomposition of FTSE Singapore.

Variance Decomposition of _FTSE_SINGAPORE:							
Period	S.E.	NIFTY_50	SHANGHAI	HANG_SENG	_FTSE_SINGAPORE	JKSE	KOSPI
1	1.311127	30.22222	1.887366	24.90292	42.98749	0.000000	0.000000
		(1.08834)	(0.38489)	(1.08980)	(1.13539)	(0.00000)	(0.00000)
2	1.316499	30.15441	2.016611	25.12894	42.64635	0.033225	0.020465
		(1.08835)	(0.40501)	(1.12306)	(1.12358)	(0.07450)	(0.06523)
3	1.318595	30.14444	2.045282	25.09453	42.62238	0.045026	0.048348
		(1.10722)	(0.41056)	(1.12037)	(1.09925)	(0.08880)	(0.09392)
4	1.319678	30.09633	2.042273	25.07618	42.56876	0.168177	0.048277
		(1.11190)	(0.41424)	(1.11843)	(1.10019)	(0.14328)	(0.09931)
5	1.320904	30.04500	2.141098	25.03229	42.54480	0.185974	0.050834
		(1.10313)	(0.42858)	(1.12083)	(1.10190)	(0.15417)	(0.10804)
6	1.323801	29.93264	2.482744	24.97779	42.35976	0.195989	0.051071
		(1.09245)	(0.45435)	(1.12432)	(1.10305)	(0.16116)	(0.11174)
7	1.324395	29.92570	2.488982	24.95971	42.33323	0.224256	0.068118
		(1.08859)	(0.45648)	(1.11855)	(1.09596)	(0.16231)	(0.12741)
8	1.327373	29.91299	2.533942	24.88114	42.28298	0.261759	0.127181
		(1.09037)	(0.44790)	(1.13376)	(1.08073)	(0.19936)	(0.15977)
9	1.328041	29.89225	2.544645	24.86575	42.27699	0.265875	0.154490
		(1.08630)	(0.44197)	(1.12570)	(1.08137)	(0.19386)	(0.17680)
10	1.331593	29.74344	2.532830	25.09232	42.05177	0.397060	0.182576
		(1.07693)	(0.45396)	(1.13901)	(1.10012)	(0.23009)	(0.17991)

Source: Authors Compliance

The results of the Forecast Error Variance Decomposition in FTSE Singapore are presented in the 4th table. Log itself explains 42.98% of the error variance on day 1, while the innovation in Nifty 50 and Hang Seng explains 29.74% and 25.09% of the error variance, respectively. This suggests that the developments in Nifty 50 and Hang Seng are impacting FTSE Singapore. However, the contribution of Shanghai, JKSE, and KOSPI explaining the forecast error variance in FTSE Singapore is significantly lower at above (2.53, 0.39, 0.18) percent.

2.10.5 Forecast Error Variance Decomposition of JKSE.

Variance Decomposition of JKSE:							
Period	S.E.	NIFTY_50	SHANGHAI	HANG_SENG	_FTSE_SINGAPORE	JKSE	KOSPI
1	1.483799	22.56300	0.858468	14.66695	4.905989	57.00559	0.000000
		(1.19904)	(0.27537)	(0.96934)	(0.48597)	(1.39070)	(0.00000)
2	1.493756	23.09896	0.858038	14.86592	4.843170	56.33339	0.000508
		(1.24893)	(0.27976)	(0.97187)	(0.47476)	(1.39619)	(0.03589)
3	1.499309	23.14641	0.895026	14.76528	4.807368	56.38491	0.001004
		(1.25755)	(0.29054)	(0.96713)	(0.46895)	(1.38765)	(0.06595)
4	1.505545	23.19858	0.901070	14.64322	4.789454	56.45300	0.014671
		(1.28716)	(0.29191)	(0.95593)	(0.46498)	(1.40285)	(0.08028)
5	1.507805	23.15096	0.949507	14.60098	4.799140	56.31034	0.189078
		(1.29392)	(0.31005)	(0.95645)	(0.46979)	(1.40538)	(0.15709)
6	1.511618	23.12778	1.254489	14.54889	4.840775	56.03342	0.194652
		(1.29622)	(0.36697)	(0.95887)	(0.47421)	(1.42832)	(0.16485)
7	1.512133	23.11320	1.274355	14.53955	4.837477	56.03095	0.204462
		(1.29393)	(0.37835)	(0.95471)	(0.46848)	(1.42970)	(0.17975)
8	1.516130	23.11607	1.287719	14.46315	5.059120	55.86969	0.204249
		(1.28210)	(0.38210)	(0.95950)	(0.48224)	(1.42204)	(0.18344)
9	1.517979	23.10704	1.322880	14.47768	5.090361	55.76547	0.236573
		(1.26977)	(0.39786)	(0.96509)	(0.47795)	(1.43751)	(0.20625)
10	1.519236	23.07556	1.332267	14.51634	5.099553	55.67901	0.297268
		(1.27140)	(0.41264)	(0.98010)	(0.48063)	(1.44645)	(0.21446)

Source: Authors Compliance

The results of the Forecast Error Variance Decomposition in JKSE are presented in the 5th table. Log explains 57% of error variance on day 1, while the remaining error variance is explained by the innovation in Nifty 50 and Hang Seng at 23.07% and 14.51%, respectively. This indicates that the development in Nifty 50 and Hang Seng is having an impact on JKSE. Meanwhile, the contribution of Shanghai, FTSE Singapore, and KOSPAI in explaining forecast error variance in JKSE is significantly lower at above 1.33%, 5.09%, and 0.29%, respectively.

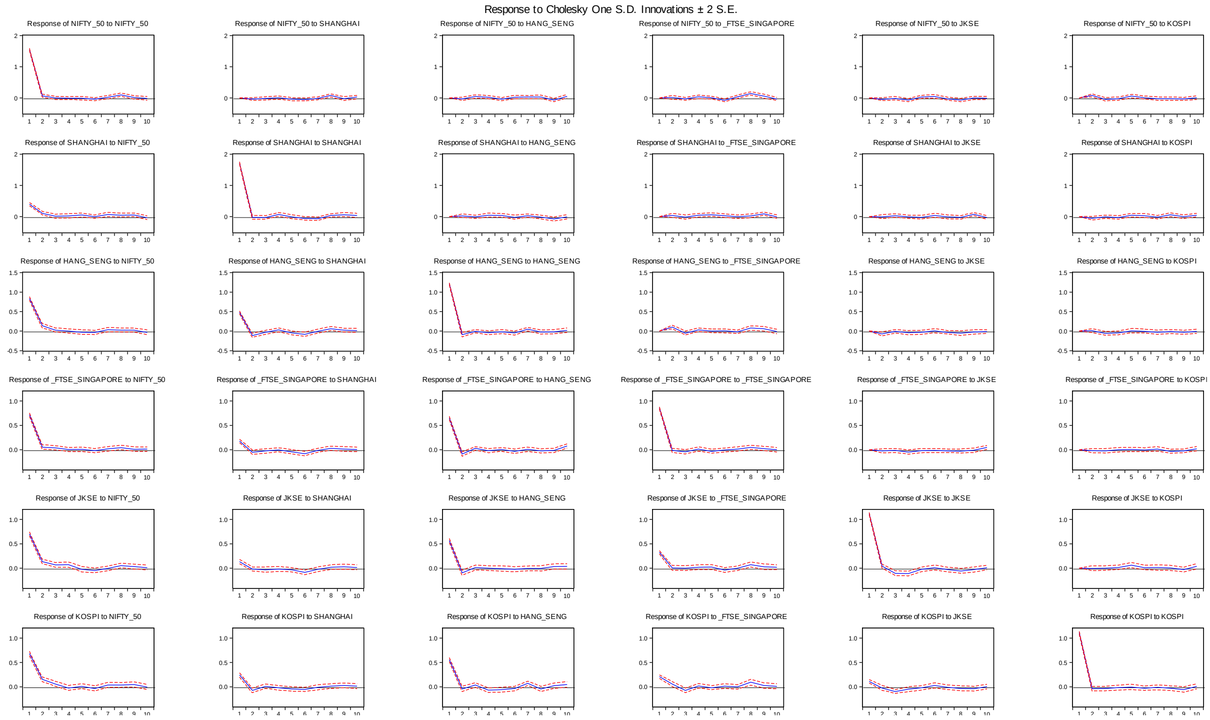
2.10.6 Forecast Error Variance Decomposition of KOSPI.

Variance Decomposition of KOSPI:							
Period	S.E.	NIFTY_50	SHANGHAI	HANG_SENG	_FTSE_SINGAPORE	JKSE	KOSPI
1	1.463709	21.94240	2.857940	14.65865	2.063576	0.601789	57.87565
		(1.21797)	(0.51339)	(0.92091)	(0.38116)	(0.19151)	(1.23238)
2	1.475913	22.68326	3.046142	14.49027	2.179825	0.612540	56.98796
		(1.28843)	(0.53502)	(0.90391)	(0.40434)	(0.19486)	(1.27783)
3	1.482788	22.64173	3.025327	14.42181	2.387844	1.009574	56.51371
		(1.26666)	(0.52520)	(0.88615)	(0.44176)	(0.29305)	(1.28472)
4	1.485608	22.57474	3.031526	14.56976	2.399436	1.114966	56.30958
		(1.26618)	(0.53359)	(0.90461)	(0.44339)	(0.32932)	(1.28950)
5	1.487713	22.51869	3.112182	14.68461	2.403754	1.130158	56.15061
		(1.25920)	(0.53383)	(0.92146)	(0.44590)	(0.33288)	(1.28474)
6	1.489990	22.49979	3.220096	14.69163	2.406286	1.170234	56.01196
		(1.24841)	(0.54641)	(0.92589)	(0.44559)	(0.35412)	(1.28041)
7	1.492432	22.50176	3.212655	14.88350	2.398427	1.170377	55.83328
		(1.24685)	(0.54421)	(0.95026)	(0.43983)	(0.35455)	(1.27938)
8	1.497243	22.43031	3.202234	14.87055	2.786082	1.203311	55.50751
		(1.24508)	(0.54185)	(0.93908)	(0.50114)	(0.35235)	(1.29868)
9	1.500260	22.44948	3.229070	14.83711	2.809143	1.259196	55.41601
		(1.24435)	(0.54602)	(0.93756)	(0.50007)	(0.37435)	(1.32065)
10	1.501285	22.41949	3.233250	14.92993	2.810875	1.259069	55.34739
		(1.24655)	(0.55231)	(0.93615)	(0.50306)	(0.37468)	(1.32264)

Source: Authors Compliance

In Table 6, the Forecast Error Variance Decomposition results for KOSPAI are presented. Log explains 57.87% of the error variance on day 1, whereas Nifty 50 and Hang Seng each explain 22.41% and 14.92%, respectively. This suggests that the developments in Nifty 50 and Hang Seng are impacting KOSPAI. In contrast, the contribution of Shanghai, FTSE Singapore, and JKSE in explaining forecast error variance in KOSPAI is considerably lower, at 3.23%, 2.81%, and 1.25%, respectively.

2.11 IMPULSE RESPONSE



Source: Authors Compliance

2.11.1 Impulse Response of Nifty 50.

As can see from the above graphs, the response of Nifty 50 to its shock on day one is 1.7 which goes down to zero on day 2 and it remains the same till day 10. Response to Shanghai on day one shock is reported 0 and it remains the same till day 10. The same thing goes for Hang Seng on day one is reported 0 and it remains the same till day 10. On the other hand, we see that in the case of FTSE Singapore on day one shock is reported 0 and remains the same till day 7on day 8 the shock is 0.4 and remains the same till day 10. We see a similar thing with JKSE and KOSPI on day one both of their shock is 0 and the same thing continues till day 10.

2.11.2 Impulse Response of Shanghai.

The graph above displays that Shanghai's initial response to its shock on day one was 2.9, which gradually decreased to zero by day two and persisted until day 10. In contrast, the response of Hang Seng, FTSE Singapore, JKSE, and KOSPI to their respective shocks on day one was zero, and it remained constant until day 10.

2.11.3 Impulse Response of Hang Seng.

The above graph indicates that Hang Seng had an initial response of 1.4 to its shock on day one, which decreased to zero on day two and remained constant until day 10. Similarly, Nifty 50 had an initial response of 0.9 on day one, which decreased to zero on day three and remained constant until day 10. On day one, Shanghai had a response of 0.5, which showed a negative shock of -0.2 on day two. There were minor fluctuations until day 6, after which the response was zero from day 9 onwards. As for FTSE Singapore, JKSE, and KOSPI, there were minor fluctuations until day 7, after which the response was zero from day 9 onwards.

2.11.4 Impulse Response of FTSE Singapore.

The graph above illustrates that FTSE Singapore initially had a response of 0.9 to its shock on day one, which decreased to zero on day two and showed minor fluctuations until day 10. Nifty 50 had an initial response of 0.7 on day one, which decreased to zero on day two and remained constant until day 10. Shanghai had an initial response of 0.3 on day one, which fell below zero on day two and showed some ups and downs until day 10. Hang Seng had an initial response of 0.6 on day one, which decreased on day two and showed minor fluctuations until day 10. The response of both JKSE and KOSPI was zero on day one and remained constant until day 10.

2.11.5 Impulse Response of JKSE.

Based on the above graph, JKSE showed a response above 1.0 on day one, which then became negative (-0.3) and had minor ups and downs until day 10. Nifty had an initial response of 0.6 on day one, which decreased on day two and then had minor ups and downs until day 10. Hang Seng had an initial response of 0.5 on day one, which became zero on day two and remained constant until day 10. FTSE Singapore had an initial response of 0.3 on day one, which decreased to zero on day two and remained constant until day 10. In contrast, Shanghai and KOSPI had an initial response of zero on day one and remained constant until day 10.

2.11.6 Impulse Response of KOSPI.

Based on the above graph, KOSPI had a response of 1.2 to the shock on day one, which decreased to zero on day two and remained constant until day 10. Nifty 50 had an initial response of 0.6 on day one, which decreased to zero on day two and remained constant until day 10. Shanghai had an initial response of 0.3 on day one, which decreased to zero on day two and remained constant until day 10. Hang Seng had an initial response of 0.5 on day one, which decreased on day two and then had minor ups and downs until day 10. FTSE Singapore had an initial response of 0.2 on day one, which had minor ups and downs until day 10. In contrast, JKSE had an initial response of zero on day one and remained constant until day 10.

CHAPTER III
FINDINGS AND CONCLUSIONS

3.1 Finding

From the graph of trend in Log returns of Asian stock market

- ✓ Nifty 50 index provided consistent returns over the entire period, with negative returns observed in specific periods such as 2004, 2006, and 2008, and positive returns in 2009 and 2020.
- ✓ Shanghai index provided positive returns from 2002 to 2006, fluctuating returns from 2006 to 2012, and more positive returns in 2018.
- ✓ Hang Seng index generated stable returns from 2002 to 2006, negative returns in 2007-2008 and 2018-2021.
- ✓ FTSE Singapore index provided stable returns from 2002 to 2007, high negative and positive returns in 2008-2009, and stable returns until negative returns in 2019.
- ✓ JKSE returns were mostly negative, with significant positive returns in 2009 and massive negative returns in 2020.
- ✓ KOSPI returns were predominantly negative, with high volatility from 2002 to 2013, but provided stable returns afterward. The highest positive return was observed during 2019-2020.

From the graph of trend in closing price of Asian stock market

- ✓ Nifty 50 has experienced a significant rise in closing prices from 2002 to 2022, with a sharp climb between 2006 and 2008, followed by a steep decline and steady growth till date.
- ✓ Shanghai has shown an overall increase in price from 2002 to 2022, but with significant fluctuations, notably between 2006 and 2008 and during 2014-2016.
- ✓ Hang Seng prices have grown over time but are volatile, with a notable fluctuation in 2006 similar to that observed in Shanghai.

- ✓ FTSE Singapore experienced significant growth from 2002 to 2008, reaching its highest point at 420, followed by a significant fall in 2008, but still showing overall growth over time.
- ✓ JKSE has shown steady growth with little volatility, starting at a price of 500 and reaching a price of 7,000 over time.
- ✓ KOSPI has shown steady growth with a significant jump in 2018 and a deep dip in 2008, indicating a positive market sentiment and a stable economic environment from 2002 to 2022.

From Descriptive Statistics.

- ✓ Nifty 50 exhibits the highest mean return of 0.075803, while Hang Seng and Shanghai have the lowest mean return of 0.017282 and 0.019229, respectively.
- ✓ Nifty 50, KOSPI, and JKSE have a median greater than the mean, suggesting potential high-return outliers, while Shanghai and Hang Seng have a median lower than the mean, indicating negative-return outliers.
- ✓ Nifty 50, Hang Seng, KOSPAI, and FTSE Singapore exhibit positive skewness, while JKSE and Shanghai have negative skewness.
- ✓ All six indices are Lepto Kurtic.

From Correlation Matrix.

- ✓ There is a moderate positive correlation between Nifty 50 and KOSPI (0.47), JKSE (0.48), Hang Seng (0.54), and FTSE Singapore (0.55).
- ✓ There is a weak positive correlation between Nifty 50 and Shanghai (0.23).
- ✓ The strongest positive correlation is observed between Hang Seng and FTSE Singapore (0.73).
- ✓ The correlations between the indices are moderate, ranging from (0.19) between JKSE and Shanghai to (0.54) between Nifty 50 and FTSE Singapore.
- ✓ The highest correlation after Hang Seng and FTSE Singapore is between KOSPI and Hang Seng (0.61).
- ✓ Generally, there is a high correlation between the Hang Seng and the FTSE Singapore, followed by moderate correlations between the other indices.

From Gangers Causality Test.

- ✓ Nifty 50 has a causal effect on Shanghai, FTSE Singapore, and KOSPAI.
- ✓ Hang Seng and Shanghai have a reciprocal causal relationship.
- ✓ FTSE Singapore and JKSE have a causal effect on Shanghai.

From Forecast Error Variance Decomposition.

- ✓ The FEVD analysis shows that Nifty 50 has a significant impact on its own forecast error variance, while the contribution of other variables such as Shanghai, Hang Seng, FTSE Singapore, JKSE, and KOSPAI is considerably low.
- ✓ Shanghai's forecast error variance is significantly explained by its own log, with a minor impact from Nifty 50. The contribution of other variables is low.
- ✓ Hang Seng's forecast error variance is mainly explained by its own log, with significant impacts from Nifty 50 and Shanghai. The contribution of other variables is low.
- ✓ The developments in Nifty 50 and Hang Seng are having a significant impact on FTSE Singapore's forecast error variance, while the contribution of other variables is low.
- ✓ JKSE's forecast error variance is significantly explained by its own log, with major impacts from Nifty 50 and Hang Seng. The contribution of other variables is low.
- ✓ KOSPAI's forecast error variance is mainly explained by its own log, with significant impacts from Nifty 50 and Hang Seng. The contribution of other variables is low.

From Impulse Response.

- ✓ Nifty 50: initial response of 1.7 on day one, decreased to zero on day 2, remained zero until day 10.
- ✓ Shanghai: initial response of 2.9 on day one, gradually decreased to zero by day two and persisted until day 10.
- ✓ Hang Seng: Initial response of 1.4 on day one, decreased to zero on day 2, remained zero until day 10.
- ✓ FTSE Singapore: Initial response of 0.9 on day one, decreased to zero on day 2, showed minor fluctuations until day 10.

- ✓ JKSE showed a response above 1.0 on day one, which then became negative (-0.3) and had minor ups and downs until day 10.
- ✓ KOSPI had a response of 1.2 to the shock on day one, which decreased to zero on day two and remained constant until day 10.

3.2 CONCLUSION

Based on the findings, it can be concluded that the Nifty 50 index has consistently provided positive returns over the entire period with occasional negative returns. The Hang Seng and Shanghai indices also provided positive returns with some periods of negative returns and volatility. FTSE Singapore and KOSPI indices provided stable returns with occasional fluctuations. JKSE provided mostly negative returns, except for significant positive returns in 2009 and a massive negative return in 2020.

The trend in closing prices of the indices shows that Nifty 50 and Shanghai indices have experienced an overall increase in prices with significant fluctuations, while Hang Seng, KOSPI, and FTSE Singapore have shown steady growth with occasional fluctuations. Nifty 50 has the highest mean return, while Hang Seng and Shanghai have the lowest mean returns.

The correlation analysis indicates a moderate positive correlation between most of the indices, with the strongest positive correlation observed between Hang Seng and FTSE Singapore. Nifty 50 has a causal effect on Shanghai, FTSE Singapore, and KOSPI, while Hang Seng and Shanghai have a reciprocal causal relationship. The forecast error variance decomposition analysis shows that Nifty 50 has a significant impact on its own forecast error variance, while the contribution of other variables is considerably low. Forecast Error Variance Decomposition has revealed that the Nifty 50 and Hang Seng have a dominant role in transmitting the impacts of innovations from previous years. The effects are particularly noticeable in Shanghai, FTSE Singapore, JKSE, and KOSPI, and there is also evidence of an impact on Hang Seng by Nifty 50.

In conclusion, investors should consider the consistent positive returns of the Nifty 50 index and the stable growth of Hang Seng, KOSPI, and FTSE Singapore indices, while being aware of occasional negative returns and volatility. As seen we could say that Nifty 50 has an impact on the rest of the Asian market this could be because of India's export with the Asian countries because as per the data we see that India export more than it Imports likewise we could say that Asian markets are somewhat related as we could see the same trend in the Log returns

References

Abdul Karim, B., & Xin Ning, H. (2013). Driving forces of the ASEAN-5 stock markets integration. *Asia-Pacific Journal of Business Administration*, *5*(3), 186–191. https://doi.org/10.1108/APJBA-07-2012-0053

Aggarwal, S., & Raja, A. (2019). Stock market interlinkages among the BRIC economies. *International Journal of Ethics and Systems*, *35*(1), 59–74. https://doi.org/10.1108/IJOES-04-2018-0064

Arya, V., & Singh, S. (2022). Dynamics of relationship between stock markets of SAARC countries during COVID-19 pandemic. *Journal of Economic and Administrative Sciences*. https://doi.org/10.1108/jeas-10-2021-0213

Asgharian, H., Hess, W., & Liu, L. (2013). A spatial analysis of international stock market linkages. *Journal of Banking and Finance*, *37*(12), 4738–4754. https://doi.org/10.1016/j.jbankfin.2013.08.015

Caporale, G. M., You, K., & Chen, L. (2019). Global and regional stock market integration in Asia: A panel convergence approach. *International Review of Financial Analysis*, *65*(September), 101381. https://doi.org/10.1016/j.irfa.2019.101381

Daly, K. J., & Daly, K. J. (2014). *Southeast Asian Stock*. *20*(1), 73–85.

Diamandis, P. F. (2009). International stock market linkages: Evidence from Latin America. *Global Finance Journal*, *20*(1), 13–30. https://doi.org/10.1016/j.gfj.2009.03.005

Gupta, N., & Agarwal, V. (2011). Comparative Study of Distribution of Indian Stock Market with other Asian Markets. *International Journal of Enterprise Computing and Business Systems*, *1*(2), 1–20.

Javeria Maryam, Umer Jeelanie Banday, A. M. (2018). Trade intensity and revealed comparative advantage: an analysis of Intra-BRICS trade. *International Journal of Emerging Markets*, *13*(5), 1182–1195. https://doi.org/10.1108/IJoEM-09-2017-0365

Kroner, K. F., & Ng, V. K. (1998). Modeling asymmetric comovements of asset returns. *Review of Financial Studies*, *11*(4), 817–844. https://doi.org/10.1093/rfs/11.4.817

Mohsin, H. M., & Rivers, P. A. (2011). Financial Market Integration of South Asian Countries: Panel Data Analysis. *International Journal of Economics and Finance*, *3*(2), 45–53. https://doi.org/10.5539/ijef.v3n2p65

Narayan, S., Sriananthakumar, S., & Islam, S. Z. (2014). Stock market integration of emerging Asian economies : Patterns and causes. *Economic Modelling*, *39*, 19–31.

https://doi.org/10.1016/j.econmod.2014.02.012

Nath, G. C., & Verma, S. (2003). Study of Common Stochastic Trend and Co-Integration in the Emerging Markets A Case Study of India, Singapore and Taiwan. *NSE Research Paper*, *June*, 1–24.

Palamalai, S., Kalaivani, M., & Devakumar, C. (2013). Stock market linkages in emerging Asia-Pacific markets. *SAGE Open*, *3*(4). https://doi.org/10.1177/2158244013514060

Shabri Abd Majid, M., Kameel Mydin Meera, A., Azmi Omar, M., & Abdul Aziz, H. (2009). Dynamic linkages among ASEAN-5 emerging stock markets. *International Journal of Emerging Markets*, *4*(2), 160–184. https://doi.org/10.1108/17468800910945783

Vatsa, P., Basnet, H., & Mixon, F. (2022). Stock market co-movement in Latin America and the US: evidence from a new approach. *Journal of Financial Economic Policy*, *14*(2), 162–171. https://doi.org/10.1108/JFEP-02-2021-0047

Wang, Y. (2018). Effects of exchange rate and income on the US bilateral trade with China under Chinese managed floating exchange rate system. *Journal of Chinese Economic and Foreign Trade Studies*, *11*(3), 236–246. https://doi.org/10.1108/jcefts-04-2018-0009

https://www.investing.com/

https://www.yahoo.com/

https://stats.wto.org/

https://commerce.gov.in/trade-statistics/

https://www.trade.gov/country-commercial-guides/india-trade-agreements