VILNIUS UNIVERSITY

FACULTY OF ECONOMICS AND BUSINESS ADMINISTRATION

Finance and Banking

Saurabh Mamgain

MASTER THESIS

Techninės analizės taikymas akcijų rinkose: galimybė pasipelnyti ar laiko švaistymas?	Application of technical analysis in equity markets: profit opportunity or waste of time?

Supervisor –

Assoc. Prof. Dr. Greta Keliuotytė-Staniulėnienė

Abstract

118 pages, 2 tables, 13 figures, 70 references

This thesis focuses on empirical analysis on whether technical analysis can in fact accurately forecast the market movements of financial markets of the globe by use of arch, garch, Johansen co integration tests as well as auto regressive integrated moving average. The first purpose is to investigate the applicability of these models for measuring market risks, the extent of market integration, and their forecasting ability in developed and emerging markets.

The results of the GARCH models for the ALL SHARE FTSE, Sensex, and Nifty 50 indices describe the presence of clusters of high volatility. Volatility clustering means that high or low volatility will continue for an extended period, thus, these indices are perfect for technical analysis. This finding is consistent with the basic assumptions of technical analysis that entails the belief that the price movements of securities in the future will mirror those of the past. On the other hand, it may be illustrated that the indices such as UK FTSE 100 exhibits low GARCH coefficients and this imply that the volatility has low sample auto correlation hence it does not have strong persistence. This brings the difficulty in trying to forecast market behaviour on such indices, thereby underlining the weakness of technical analysis in the market with low volatility persistence.

In the long-run aspect, Johansen cointegration test is used for determining the connection of many global financial indices. The findings show highly significant evidence of cointegration in the developed markets like Sensex and ALL SHARE FTSE which imply that the prices of the two markets are interrelated with each other. This finding also suggests that these interdependent relationships may lead to the emergence of cross-market arbitrage. Nevertheless, there is low cointegration in trading volume, implying that whereas technical analysis based information flows is almost universally valid, trading volumes have stronger

components that depend on specific country effects thus limiting the universal usage of trading volume data in technical analysis.

The time series forecasting models that include ARIMA stress autoregressive patterns in developed markets. In indices such as the Sensex and ALL SHARE FTSE, the past behavior of the markets actually gives the future behavior of the prices. However, moderate auto-regressive features are exhibited by emerging market SES and NIFTY fifty making short-term forecasting even more difficult due to more noises in the markets and less pattern forecastability.

The study finds that technical analysis works well exceedingly in more active, interrelated markets with clustered volatility. Nevertheless, it is not as efficient in low volatility or high efficiency areas where trends can be difficult to recognize. As the study is places emphasis on the variations of technical analysis applicable to various markets, it argues that the maturity and persistence of the volatility as fundamental criteria in understanding the effectiveness of technical analysis strategies.

Abstraktus

118 puslapių, 2 lentelės, 13 paveikslai, 70 literatūros šaltinių

Šiame darbe pagrindinis dėmesys skiriamas empirinei analizei, ar techninė analizė iš tiesų gali tiksliai prognozuoti pasaulio finansų rinkų rinkos judėjimus, naudojant arch, garch, Johansen kointegracijos testus, taip pat automatinį regresinį integruotą slenkamąjį vidurkį. Pirmasis tikslas – ištirti šių modelių pritaikomumą rinkos rizikai matuoti, rinkos integracijos mastą ir jų prognozavimo galimybes išsivysčiusiose ir besivystančiose rinkose.

GARCH modelių ALL SHARE FTSE, Sensex ir Nifty 50 indeksų rezultatai apibūdina didelio nepastovumo grupių buvimą. Kintamumo klasterizavimas reiškia, kad didelis arba mažas nepastovumas išliks ilgą laiką, todėl šie indeksai puikiai tinka techninei analizei. Ši išvada atitinka pagrindines techninės analizės prielaidas, kurios reiškia tikėjimą, kad vertybinių popierių kainų pokyčiai ateityje atspindės praeities pokyčius. Kita vertus, galima iliustruoti, kad tokie indeksai kaip UK FTSE 100 turi žemus GARCH koeficientus, o tai reiškia, kad kintamumas turi mažą imties autokoreliaciją, todėl jis nėra stiprus. Dėl to sunku prognozuoti rinkos elgesį pagal tokius indeksus, o tai pabrėžia techninės analizės silpnumą rinkoje, kurioje nepastovumas yra mažas.

Ilgalaikėje perspektyvoje Johanseno kointegracijos testas naudojamas daugelio pasaulinių finansinių indeksų sąsajai nustatyti. Išvados rodo labai reikšmingus kointegracijos išsivysčiusiose rinkose, pvz., Sensex ir ALL SHARE FTSE, įrodymus, o tai reiškia, kad abiejų rinkų kainos yra tarpusavyje susijusios. Ši išvada taip pat rodo, kad dėl šių tarpusavyje susijusių santykių gali atsirasti įvairių rinkų arbitražas. Nepaisant to, prekybos apimties kointegracija yra maža, o tai reiškia, kad technine analize pagrįsti informacijos srautai galioja beveik visuotinai, o prekybos apimtis turi stipresnius komponentus, kurie priklauso nuo konkrečios šalies poveikio, o tai riboja universalų prekybos apimties duomenų naudojimą techninėje analizėje.

Laiko eilučių prognozavimo modeliai, apimantys ARIMA, išsivysčiusiose rinkose pabrėžia autoregresinius modelius. Tokiuose indeksuose kaip Sensex ir ALL SHARE FTSE ankstesnė rinkų elgsena iš tikrųjų parodo būsimą kainų elgesį. Tačiau besivystančių rinkų SES ir NIFTY fifty pasižymi vidutinio sunkumo automatiškai regresyviomis savybėmis, todėl trumpalaikės prognozės dar labiau apsunkinamos dėl didesnio triukšmo rinkose ir mažesnio modelio prognozavimo.

Tyrime nustatyta, kad techninė analizė puikiai veikia aktyvesnėse, tarpusavyje susijusiose rinkose, kuriose kintamumas yra sutelktas. Nepaisant to, jis nėra toks efektyvus mažo nepastovumo ar didelio efektyvumo srityse, kuriose gali būti sunku atpažinti tendencijas. Kadangi tyrime akcentuojami įvairiose rinkose taikomi techninės analizės variantai, teigiama, kad nepastovumo brandumas ir išlikimas yra pagrindiniai kriterijai, padedantys suprasti techninės analizės strategijų efektyvumą.

Contents

1. Historical Viewpoint and Contemporary Comprehensive Literature Review 12

1.1 Empirical Studies on Technical Analysis 15

1.2 Financial Markets and Inter-Market Relationships 26

1.3 Time Series Models: Stationarity, GARCH, and ARIMA 29

1.4 Applications of Quantitative Research in Financial Studies 33

2. Research Framework for Cross-Market Study of UK, China and India Indices 38

2.1 Research design 40

2.2 Quantitative research strategy and justification 43

2.3 Research reliability and Summary 50

3: Empirical Research Outcomes: Analysing Historical Data in the UK, China and India Indices 51

3.1 Evidence of practical work 51

3.2 Digital Comparison and Market Features 55

3.3 Correlation Analysis: Price Correlations 57

3.4 Augmented Dickey-Fuller (ADF) Test 59

3.5 Volatility 61

3.6 Johansen Test 64

3.7 ARIMA model 65

3.8 Technical Analysis (TA) strategy 68

3.9 Interpretation of result 75

Conclusion and Discussions 81

References......86

Appendices......98

Appendix 1: Descriptive statistics......98

Appendix 2: Visualization for PX_LAST indexes......99

Appendix 3: Visualization for CHG_PCT_1D indexes......100

Appendix 4: Visualization for PX_VOLUME indexes......101

Appendix 5: Correlation analysis......102

Appendix 6: Augmented Dickey-Fuller (ADF) Test......104

Appendix 7: Volatility......105

Appendix 8: Johansen Test......111

Appendix 9: Johansen Test......112

Appendix 10: Johansen Test......113

Appendix 11: Forecasting for ASX Index......114

Appendix 12: Forecasting for Sensex Index......115

Appendix 13: Forecasting for FTSE 100 Index......116

Appendix 14: Forecasting for Nifty 50 Index......117

Appendix 15: Forecasting for PX_VOLUME_UKX_FTSE_100......118

Appendix 16: Forecasting for SSE index......119

Introduction

According to the report by Bloomberg, The UK equity market is considered the FTSE all-share index where 98-99% of the market is capitalised by the FTSE all groups (100, 250 and FTSE small-cap indices). It can be said that despite of its complex nature, the technical analysis allows an investor to anticipate the future market trends by closely monitoring the market price and current stock prices .(Rouf et al., 2021) From the existing literature evidence, it can be said that technical analysis using time and bar charts, simplifies the representation of equity market stocks, however, there has been a limited discussion (knowledge gap) on the complexity in stock market trend anticipation because of its dynamic and non-parametric nature (Jamil *et al.*, 2023). As a result, the present study will explore different dimensions of stock market equity analysis by addressing the knowledge gap. The goal of the paper is to critically analyse where the application of technical analysis in UK equity markets is a profit margin or a waste of time (Nti, Adekoya & Weyori, 2020). In stock market predictions, technical and fundamental analysis is used in various soft-computing techniques and algorithms. The ***technical, fundamental and combined analysis*** is done through the nature of data sets, the data timeframe, the machine learning algorithm and various error metrics (Li & Bastos, 2020). The objectives of the technical analysis can predict the stock prices using historical data as the technical indicators. The financial market analysis validates the models through profitability metrics and the model performance (Singh *et al.*, 2022).

The ***Efficient Market Hypothesis Theory*** that the share prices and stocks are always traded at their fair values on exchange (Samuel & Tantia, 2024). Technical analysis in the stock market is described as the set of rules while anticipating future price shifts, purchase and selling prices and volume trading, based on historical market data and current market trends (Vinu, 2020). The ***Dow Theory*** depicts that there are three market movements with ***primary,***

secondary and minor trends. The Market trend has three phases: ***accumulation, public participation and speculation*** (Bhowmik & Wang, 2020).

Rationale of the study

The significance of this research is underpinned by the necessity to assess whether technical analysis works across different market environments. Despite its use, technical analysis's reliability is still an issue of debate, especially in different markets such as the volatile, emerging and the efficient markets (Ni, 2024; Ta, Liu & Tadesse, 2020). This research intends to fill this gap by examining the performance of technical indicators such as ARCH/GARCH models, Johansen cointegration tests, ARIMA models and trading volumes in developed/developing markets (Albertus, 2021). With the help of Sensex, Nifty 50, and UK FTSE 100 indices, the study aims at understanding whether and to what extent maturation, volatility, and globalization affect the efficacy of technical analysis (Weixiang et al., 2022). The results help to refine the trading strategies, focus on the context use – including but not limited to uses of cointegration which would be relevant for low-volatility or efficient markets and thus make better investment decisions (FX Open, 2023).

Research problem

The above-included literature evidence failed to identify the concerns or issues linked to Technical analysis in the stock equity market, as a result the present study will explore the subjective nature of the technical analysis and will develop a strategy to perform technical analysis (which will be more efficient and accurate) (Nti, Adekoya and Weyori, 2020).

Purpose of the research

This study aims at exploring the efficiency of technical analysis in financial markets by presenting a compilation of studies that have addressed different aspects of technical analysis in developed and emerging markets. The proposed study of ARIMA model, hybrid model, and machine learning can ensure the forecasting improvement as the objective of the research focuses on the merit of the type of models in performing the forecast. Moreover, it aims at studying the effect of local markets on trading activities and enhancing investment decisions while in a volatile situation.

Aim of the study

The aim of this research work is to evaluate the effectiveness of technical analysis in equity markets and determine whether it presents a viable profit opportunity or is an inefficient investment strategy with the help of STATA software.

Objectives:

1. To analyse the predictability of equity market movements using technical models such as ARIMA and ARCH/GARCH.
2. To examine long-term relationships among market indices through cointegration analysis.
3. To evaluate the volatility clustering patterns in equity markets to assess trading opportunities.
4. To compare the effectiveness of technical analysis across developed and emerging markets.
5. To identify the limitations and contextual factors impacting the applicability of technical analysis.

Limitations of the Research

There are several limitations involved in this research that might limit the extent to which the findings can be generalized. First, the study is confined to certain indices like Sensex, Nifty 50 and UK FTSE 100 which do not provide the overall picture of global markets especially in other emerging or developed countries (Billah *et al.,* 2024). Second, the forecasting based on past values means that current trends will remain fixed and does not take into consideration new market shocks or shifts in structures (Han, Kim & Enke, 2023). Third, models such as ARCH/GARCH or ARIMA are selective on parameters, and the resultant implications may shift with other configurations or samples. Fourthly, the trading volumes analytical breakdown provides regionalize information but there are other quantitative characteristics such as changes in regulation or market optimism that may be more informative. (Han, Kim & Enke, 2023) Finally, the paper compares the efficiency of existing statistical models without investigating non-linear machine learning approaches, which, in their opinion, may introduce more nuanced characteristics of market data.

1. Historical Viewpoint and Contemporary Comprehensive Literature Review

This chapter provides a literature review of the theories, models, empirical evidence and innovations of the financial market, volatility, and forecasting. The main emphasis is made upon the review of the most essential terms like volatility clustering, market integration, and stationarity, which are vital in the study of financial indices. The review also identifies many econometric techniques including GARCH and ARIMA that are commonly used in time series data and works produced regarding inter-market relationships across developed and emerging economies. This chapter forms the basis for choosing the right research methodologies and gives reason for the choice of statistical methods in this research.

According to Wang and Zheng (2018) Technical analysis is mainly a method to analyse and predict market conditions in the future. **Technical analysis** has an old history from ancient times, according to some historians the first traces of technical Analysis are found in ancient civilizations(Wang and Zheng 2018). In ancient civilizations, the merchant conducted technical analysis according to the **historical price** information data to help and guide them in predicting their decision. The first historical record of technical Analysis was found in **Anatolia** from the **Assyrian merchants.** The **Greek** merchants used environmental data and geographical data to find their trading routes at that time.

Joseph de la Vega details analysis of the **Dutch** market in the **17th century** and after that, he wrote a book **"Confusion of confusions"** that was published in the year of 1688. In this book, he analyses total Dutch markets, and based on his analysis he provides a detailed description of technical analysis and market speculation according to the Dutch Market condition. In history, the first-time technical analysis was documented in Asia by a **Japanese rice trader**, **Homma Munehisa** in **the 18th century**. After that, over the years technical analysis has developed very fast and people have created different types of tools to initiate technical analysis more accurately.

As per Ilham, Sinta and Sinurat (2022) Many key figures and their contributions are found in the history of Technical Analysis. **Charles Dow** Is known as the father of technical analysis he introduced the **Dow theory (**Ilham, Sinta and Sinurat 2022**)**. In this theory, he analyses the understanding and foundation of price movement in any market. Then **Robert D . Edwards** and **John Magee** are very famous for their **Technical analysis of stock trends**. In their book, they introduce technical analysis in very detail and they provide total guidance of market indicators and chart patterns with a significant comprehensive guidance. **Elliott wave theory** was introduced by **Ralph Nelson Elliott**, with the help of this theory traders easily predict the market direction as per specific patterns and analysis of market prices.

As per Braun and Clarke (2021) it is mainly a continuous process and it is developing and changing day by day according to market conditions and **technological improvement**. The first charting method was introduced in **Japan** in the **18th century** and this is called the **candlestick patterns(**Braun and Clarke 2021**)**. The **Japanese rice** traders use this candlestick pattern to detect price fluctuation and market conditions. In the 19th century another chart method appeared that is used for plot pricing movement focusing on price action without time factor consideration is called **point and figure charts**. The chart patterns and the technical indicators are rapidly developed with the help of computers and the internet. With the help of modern technology, people can easily run a **large data set** and **develop complex algorithms** to analyses market conditions more accurately and this is one of the major and significant transformations of technical analysis over time to time. According to Niroomand, Metghalchi and Hajilee (2020) EMH or **Efficient market hypothesis** is a theory or hypothesis based on financial theory and it gives information about stock prices according to fundamental or technical analysis for achieving **higher returns** from the stock. The efficient market hypothesis is mainly analyzed in three forms such as semi-strong form, weak form, and strong form. In **semi-strong form**, it adjusts the stock prices according to the new public information available in the market (Niroomand, Metghalchi and Hajilee 2020). In a **strong form**, it provides information about **public and private data** that reflect the stock prices. **Weak from** suggested market data based on stock prices through technical analysis which mainly depends on **historical data**, it is not so useful and accurate technical analysis. The implementation of the **Effective market hypothesis** is very useful and significant for technical analysis purposes.

As per Sharma and Kumar (2019) These financial theories represent different perspectives on market analysis as per **investor behaviour**, psychological factors, financial condition, and many more. This theory is very much relevant for technical analysis, with using this theory it is very easy to predict future market fluctuation based on volume and price data. The key attribute to determining Behavioural finance theory and its relevance to technical analysis, Behavioural Finance is very relevant for technical analysis according to the **market trend**. This market trend analyses various aspects of market trends based on recent market data and presents technical analysis according to these trends(Sharma and Kumar 2019). Behavioural Finance influences the investors to their **emotions** and **psychological** factors, sometimes investors make investment decisions according to their emotions and some external influence they get from emotion, but technical analysis is a very practical application to understanding **Behavioural Finance** and it also introduces the **chart pattern** as a representation of connected investor sentiment based on market condition.

According to Antony (2020) Different market anomalies face the investor when they invest, sometimes it is not accurate with the **effective market hypothesis**. These market anomalies are the main cause of investor **abnormal returns.** They use technical analysis to determine these anomalies according to historical price and their main motivation is to identify the anomalies to make better **investment decisions(**Antony 2020**)**. The investor uses **the January effect** which affects the stock that underperforms in the fourth quarter of the year this also out performs in January, and according to technical analysis, they easily find out a stock rebounding price and volume at the start of the new financial year. They also use **Low book value** to find out the system that is offering average price to book and it **outperforms** in the market. They also use **the Momentum effect** with the use of technical analysis to find out those stocks that have performed well in the past few years and analyses this trend they set a strategy to capitalize on this stock's growth momentum.

1.1 Empirical Studies on Technical Analysis

As per Edwards, Magee, and Bassetti, (2018) Many studies available demonstrate the effectiveness of specific technical indicators, **MACD** base training strategy indicates the significance of performance matrix and back testing to determine the profitability of technical indicators in the market. As per many studies, different digital assets are very effective for many technical indicators such as **Bollinger Bands and MACD,** and many more(Edwards, Magee, and Bassetti, 2018).

Bollinger Bands (technical analysis indicators) are mostly used to determine the short-term changes in the stock prices and it allows the investors and traders to make decisions based on entry and exit points in Bollinger Bands. For example, from the below diagram, it can be said that the upper band was valued at 25.25 and the lower band was 17.08 (Fidelity, 2024). When the bands tighten, there is a high possibility that there will be a significant change in the stock pricing (in either direction). As a result, the indicator helps in anticipating whether the stock price will increase or decrease by relying on Standard Deviations and Periods (Bollinger Bands parameter).

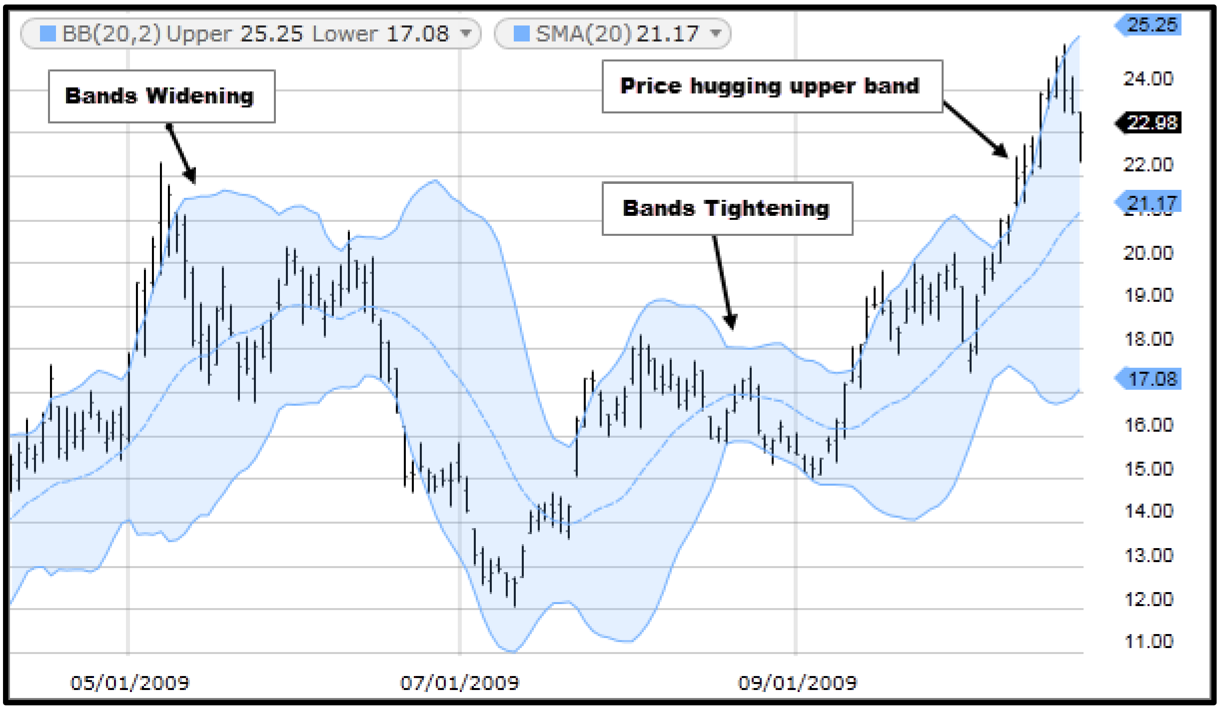


Figure 1.1: Bollinger Bands Source: (Fidelity, 2024)

A published study by the CRM group highlighted that the Moving Average Convergence Divergence indicator helps to determine whether the stock price is moving in the upward or downward direction. For instance, the MACD line (represented as an orange line in the below diagram) can be calculated by subtracting the 26-point exponential from a 12-point exponential moving average in the context of the Zero line (demonstrated in the below diagram) (CME Group, 2024).

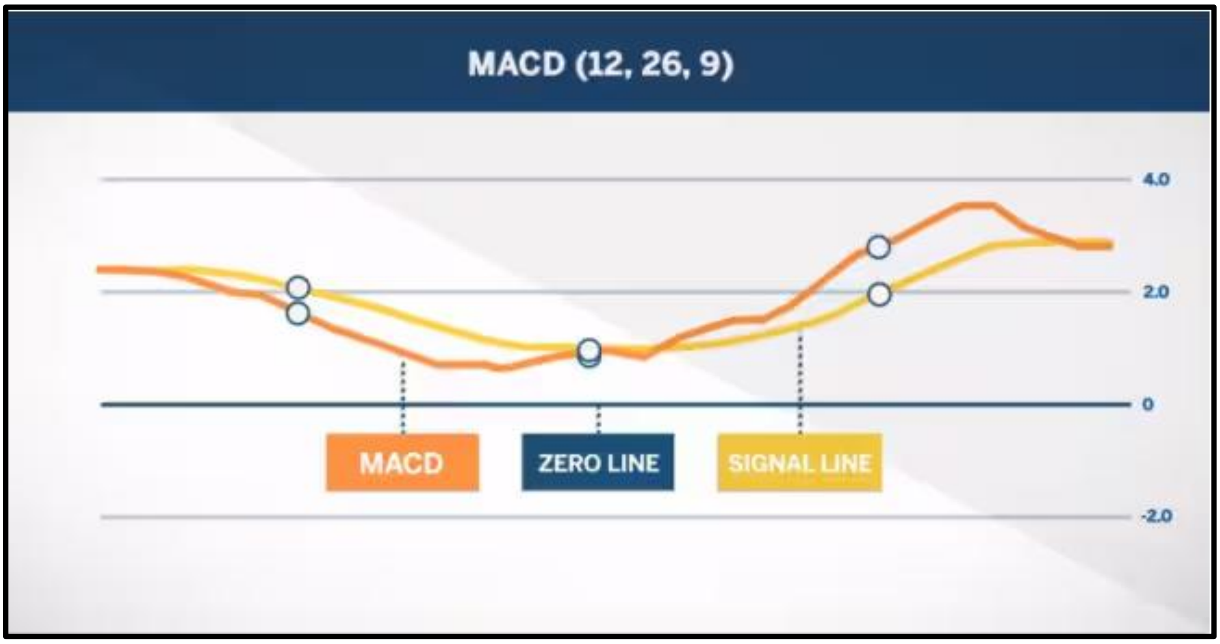


Figure 1.2: Application of MACD indicator

Source: (CME Group, 2024)

N-Period Minimum and Maximum (NPMM)- In the context of the Machine learning trading system in the stock market-based NPMM labelling while using the XGBoost supports in acknowledging the development in the trading system. As it also helps to alter the drawbacks of the conventional labelling methods in stock market analysis (Woo *et al.*, 2020).

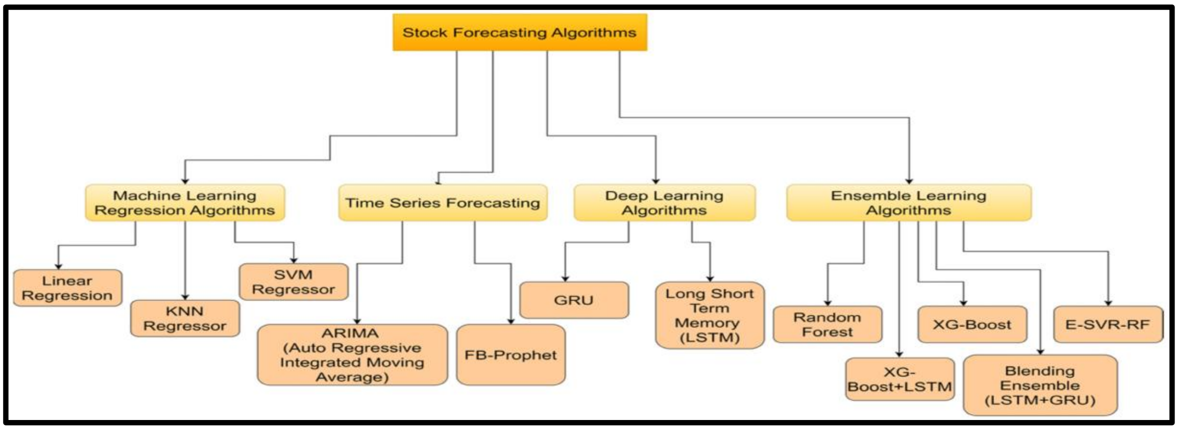


Figure 1.3. Forecasting Stock Market Using Deep Learning

Source: (Olorunnimbe & Viktor, 2023)

The hierarchy of stock forecasting algorithms, categorized into three main types: Machine learning regression algorithms, time series forecasting, and the deep learning algorithm. The

Machine Learning Regression Algorithms include Linear Regression, KNN Regressor and ARIMA (Auto Reg App Moving Avg). The Time Series Forecasting grouping also contains methods like FB-Prophet. Deep Learning Algorithms are related to models such as GRU and Long Short Term Memory (LSTM). Also, the Ensemble Learning Algorithm brings together models like XG-Boost, Random Forest and complex hybrid models like XG-Boost+LSTM & Blending Ensemble (LSTM & GRU). Every algorithm type includes definite techniques for predicting stock prices.

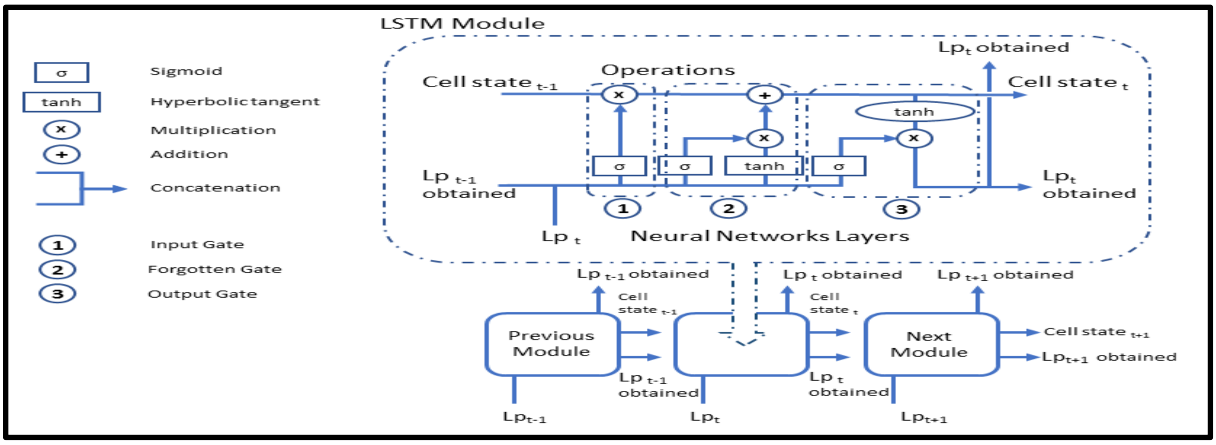


Figure1.4. General Scheme for Long-Short Term Memory Neural Network (LSTM)Source: (Moghar & Hamiche, 2020)

Long-Short Term Memory Neural Network (LSTM)- The Augmented long and short-term memory based on the neural architecture as it also includes various symbolic genetic programming in forecasting different cross-sectional price returns (Moghar & Hamiche, 2020). In financial markets forecasting machine learning algorithms are placed as dominating trends in the form of scientific research (Wu *et al.*, 2020). **Deep Learning Model-** The deep learning techniques added relevant stock features. Amazon, Bidu, Adobe and many other companies started using Machine learning and AI in analysing the stock market (Zou *et al.*, 2022). Deep learning in the stock market predictions related to stock price predictions, stock movements, portfolio management and various trading strategies. The deep learning process worked as, firstly it collects the stock-related information, data processing, stock feature extraction, price movements and the experimental result analysis (Jiang, 2021).

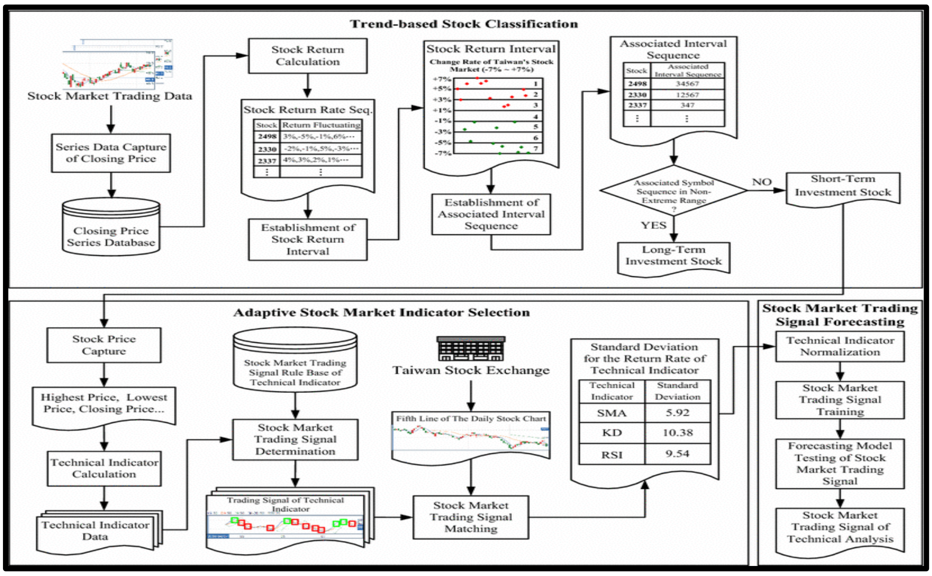


Figure 1.5. Technical Analysis based stock market forecasting process

Source: (Han, Kim & Enke, 2023)

In the Indian equity market, there are different types of technical trading strategies and this is very effective for the Indian equity market. In the equity market, one of the most popular is **Nifty 50** and it is performing the best in the market. According to Nakano, Takahashi and Takahashi (2018) there are several methods of successful trading strategy based on technical analysis. In **Momentum strategies** the invested buying assets that focus on an upward price trend and after that selling those assets with a downtrend. After that **Breakout strategy** is a very popular strategy and it mainly depends on identifying the **perfect price levels** that move into the asset's price(Nakano, Takahashi and Takahashi 2018). The investor and the traders used various **chart patterns to** get future predictions of **price movement** and this will help them to make their **trading decisions** accordingly. In the **Trade following strategies** the investor identifies the total trade and the market and based on these they are making sell and buy decisions.

As per Nti et al (2020) Various critics and methodological approaches in technical analysis research. Sometimes study may be used to collect information that was not present at the time of trade, it is called **Look-Ahead Bias** and it is the reason for optimistic results. The researcher analyses a large number of data sets which improves the **likelihood** of **finding strategies** that work great in a particular data set; this methodology is called **Data-Snooping Bias(**Nti et al 2020**)**. Another critique and methodology is **Risk adjustment**, in this way, the traders adequately adjust the risks that are connected with their trading strategy, and following this adjustment they make their strategy more accurate and profitable.

As per Mertzanis, and Allam, 2018 in some studies, there are many **inefficiencies** over the long term and it provides an opportunity for continuous return to investors. This opportunity requires sophisticated tools and strategy and this is very rare it's known as **Long-term potential(**Mertzanis, and Allam, 2018 **)**. To lead an efficient market the investor sometimes acts on **arbitrage opportunities** and it can be quickly resolved this is called **Short term market inefficiencies**.

Practical Applications and Challenges

As per Gurjar et al (2018) many case studies focus on the successful implementation of technical analysis in the equity market. A technical analysis was conducted on **Tata Consultancy Services** as per **the Indian equity market** and this analysis focuses on trade analysis to create investment decisions in the market (Gurjar et al 2018). This technical analysis became very helpful and used to understand market trends. In another research **BRICS** markets such as Brazil, Russia, India, China, and South Africa these nations use technical analysis to get strategies that become profitable. The technical analysis in the equity market provides an **empirical analysis** of different types of technical strategies and indicators that help them to determine the effectiveness and conditions in different market conditions. This case study set specific evidence that technical analysis is a very powerful tool for three days and investors to invest their money in the equity market. The technical analysis mainly depends on **fluctuating market conditions** and **particular assets**. From a practical point-of-view, Technical Analysis indicators are used to find 'entry' and 'exit' points regardless of the situation that allows for identification of favourable entry and exit points in finding securities over investment in the equity market. To put it simply, Technical Analysis indicators help traders use specific patterns in determining the point of exact time for buying and selling which can be set considering stop-loss orders that can limit potential losses addressing risk management in analysis support and resistance levels, all to analyse past trends and anticipate future direction movement. As the report by Flyvbjerg (2021) confirms the use of Technical Analysis indicators can be applied to derive additional information from the basic trade chart patterns to measure statements based on market sentiment, fund flows and price rate and predict probable changes in the price over a period of time. It is all about rightfully calculating mathematically through the indicators to have a supply and demand underpinning through tools such as Relative Strength Index (RSI) and Moving Average Convergence Divergence (MACD) etc.

According to Attaran, (2022) practitioners of technical analysis face several data availability and quality issues. If the **data update** becomes delayed then the analysis result also becomes **outdated**, so it is very important to conduct technical analysis on the recent and up-to-date information. **Data accuracy** is one of the essential factors for technical analysis because wrong data entry has a significant impact on the technical analysis outcome(Attaran, 2022). To get an accurate analysis result it is so essential to submit **complete data**. **Data consistency** is essential because inconsistent data input from different sources can be the cause of comparing and aggregating information effectively.

According to Weixiang et al (2022) **Behavioural biases** are essential to impact the decision-making process of technical analysis. In **Confirmation Bias** the investors invest their money based on their information based on existing predictions and beliefs. In **Familiarity Bias** the investor likes to invest in **similar territories** like they like to invest in their own country and a similar industry, this limits them in **diversification** investment(Weixiang et al 2022). Sometimes the traders and the investor invest their money based on their own belief and their prediction of the market movement, this is very risky, and trading too frequently is called **Overconfidence Bias**. According to Flyvbjerg, (2021), behavioural bias affects the decision-making process that affects the emotion of an individual. It consists of emotion and cognitive skill that consist of patterns associated with decision making and helps to restrict the phase of inappropriate mistakes. Overconfidence bias arises when an individual overestimates their skills and knowledge that sometimes results in financial losses (Flyvbjerg, 2021). Confirmation bias manipulates the decision-making process within a business organization. Pain of loss is being faced by an individual that sometimes results in high risk. Poor diversified investment is made by investors that results in loss of the investment.

As per Melović et al (2020) the efficiency of technical analysis can depend on various market conditions, **strong market trends** increase the performance of **market indicators** that are very helpful for the investor to make their **investment decision(**Melović et al 2020**).** It is also very essential to understand **market sentiment** based on different factors. Understanding this different type of market condition as per technical analysis helps investors to make an expectation and strategy according to their investment. As per Lu, at al (2020) technical analysis, fundamental analysis and quantitative modelling are the three different types of approaches that are used in the **financial market** to determine the investment plan and predict future **price fluctuation**. In fundamental analysis, the investor uses this for making a long-term **investment decision** and ensures real security, in this section they also consider the company's potential growth and financial health in the market(Lu, at al 2020). In the technical analysis part, the investor uses various tools and charts to identify the signal and pattern to predict the future market. Then the focus is on security price and statistical trends as per market conditions.

According to Picasso et al (2019) many hybrid approaches combine fundamental analysis and technical analysis and their main goal is to help investors be more informed about **trading decisions.** In technical analysis, they examine all security-related statistical trends from all market trading activity, and they make their decision based on volume and price movement using **patterns** and **charts(**Picasso et al 2019**)**. In fundamental analysis, they use a method to access security value by evaluating related **financial factors** and **economic factors**. They use various types of economic indicator earning reports and industry conditions reports to determine these analyses. As per Hegre et al (2020) in **synergies** use risk management to utilize the method that can help to identify and eliminate different types of risks, mainly the risks that are coming from **fundamental factors**. These both also help the c**omprehensive analysis** in this analysis company easily find out their intrinsic value. That helps them in technical analysis and the timing of the market(Hegre et al 2020). In the case of **trade-offs,** the company conducts different types of analysis to find out the risks of overreliance which can cause the missing out on signals. There is a different type of complexity in the analysis process and it requires more **expertise** and **time** to identify **conflicting areas**.

As per Janssen et al (2020) various regulatory frameworks generally depend on country to country for the use of technical analysis in the equity market. For example, in India, the regulatory framework for the equity market is the **Security and Exchange Board of India**. This governing regulatory body regulates different types of illegal action in technical analysis in the equity market(Janssen et al 2020). They are strongly prohibited inside trading and many inside training regulations are maintained in the equity market. They are also a provision of **market manipulation** practice and **misleading information** a criminal offense. It is important to maintain and regulate technical analysis in the equity market to avoid illegal activity in the market. According to Van and Royakkers, (2023) Ethical implications of technical analysis practice including insider trading are based on various factors. Analysts have become

transparent in their method and they do not provide any misleading information to the investor. They also need to maintain **confidentiality** in the case of **sensitive information(**Van and Royakkers, 2023**)**. The analysts do not use any kind of **privileged information** for their gain from the market. Technical analysts should maintain **fairness** in the market, they need to avoid **manipulating** market value. Ethical practice in technical analysis is crucial to properly running the financial market and protecting people and investors from any kind of fraud and scam.

As per Mosteanu, and Faccia (2020) financial professionals utilize technical analysis of compliance requirements to determine various **ethical practices** to meet the regulated standard. The analyst should maintain the ethical guidelines that are coming from various government agencies and this may vary from country to country. Depending on several **jurisdictions** the technical analyst needs **a license and certification** to perform their analysis and provide their investment advice(Mosteanu, and Faccia 2020). To get this certificate license the analyst needs to meet the experience criteria and educational background. The other most essential aspect of this technical analysis is to provide the **security** and **confidentiality** of the client's information. As per Tikhomirov et al (2018) there are various tools and advanced technology methodologies used in the field of technical Analysis. Technical analysis uses **Big data** analysis to analyses huge amounts of information to make better decisions. They also use **High-frequency trading algorithms** to analyses trading information in fractions of a second(Tikhomirov et al 2018). They use **Artificial Intelligence** and **Machine Learning** to get more efficient and accurate analysis of the market. They analyses market sentiment using social media and news articles and get accurate market information using technical analysis tools. There are also developments in **Blockchain** technology that also help to develop new technical indicators and this is very specific to analyses the market condition.

According to Wouters, McKee and Luyten, (2020) in the field of Technical Analysis, several areas need to improve to predict better market research results. In **sentiment analysis**, the analyst used news sources and social media to gather information about the market and they conducted potential analysis according to their information. In technical analysis, the analyst also used various hybrid models for better prediction of the market (Wouters, McKee and Luyten, 2020). It is also very crucial to take care about various market **microstructures** for technical analysis to identify **trading opportunities**. Different kinds of technological advancement need to be implemented, such as artificial intelligence, machine learning, high-frequency trading algorithms, and many more. The author has specifically highlighted analysis of chart patterns to address key stock chart indicators and find out signal transitions between rising and falling trends, only to find out relevant stock details. For instance, identifying patterns to be in distinctive formations developed by movements of security prices in the stock chart is the foundation of Technical Analysis, which is often considered important for pattern identification for a line to connect common price points in a scheduled time period. Connecting dots of closing prices or high and lows of common price points allow Technical Analysis in the equity market seek patterns that can be anticipated to lead future direction to a security's estimated price ratio because these patterns can ultimately be regarded as simple factors of trend lines which can get either complex or double head-and-shoulder formations, depending on understanding of the trade lines to follow along Technical Analysis in spotting support and resistance areas in the price chart. In Figure 4, the chart patterns have been identified to be 'Bullish Continuation', 'Bearish Continuation', 'Bullish Reversal' and 'Bearish Reversal', showcasing Ascending Triangle (bullish pattern) compared to Descending Triangle (bearish pattern), which reveals price action that move into a tighter and tighter range that can indicate toward giving a hint that how market sentiment can shift from buying to selling.

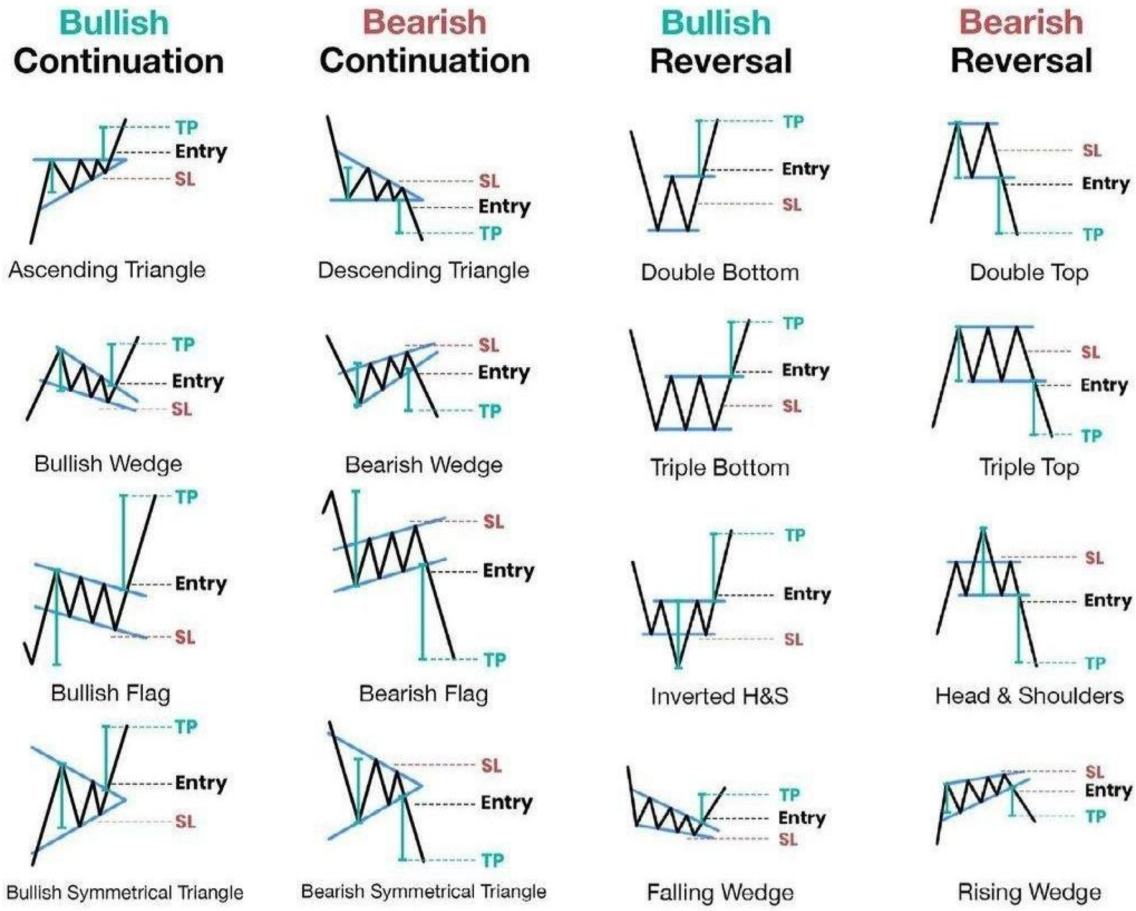


Figure 1.6: Technical pattern chart analysis

Source: (Wouters, McKee and Luyten, 2020)

1.2 Financial Markets and Inter-Market Relationships

Organizations that operate in financial markets are self-organizing networks that may be either connected or separated. It has been observed that global integration has particularly increased and accelerated the growth within financial markets where movements in one particular market financially affect the other. This integration is especially apparent during the ‘contagion’ period which often characterizes the marked instabilities. According to Raddant and Kenett (2021), global stock markets exhibit a degree of integration in the course of a diversified stock market crises. One market move can be extremely dangerous and push another market to enter the field and respond to negative sentiment and panic.

Dey (2022), proposed a remarkable analysis that aimed at emphasizing that market integration is a complex phenomenon. After analysing a number of indicative parameters, they found out that although the stock markets of the world are gradually becoming more connected, this connection is not the same for all markets. Emerging markets as such those of Western Europe, USA and UK normally have higher coefficients as they are more responsive to changes in global economy. On this front, emerging markets imply higher levels of variability and variation as compared to developed markets and for this reason the economic realities and the behavioural pattern of investors in these markets indeed differ from those in developed markets. However, much is changing regarding the international financial structure, especially with emerging players such as China and India integrating their markets quickly. Some of the changes have been due to increased similarity to the global financial markets hence increasing the need for understanding of the interactions between these markets. This integration gives both benefit and risk to the investors and policymakers since the management of these risks become complex and the portfolio diversification become essential in this environment of integration.

The study of the inter-market relationships can be important in several ways. It further allows the investors to make decision with the correlation and possible effects of market movements. For instance, the trader will know that any decline in the US stock market will affect Europe's markets in one or the other and thus should adjust. Second, politicians can use this knowledge to put measures that secure markets, and therefore increase the general level of economic stability.

Volatility and Volatility Clustering

Fluctuations thus help provide an appropriate measure of risk as a concept associated with the price changes of financial assets. Ibragimov *et al*. (2024) provided initial research about the concept of volatility and volatility clustering , who defined it as the way in which large changes in prices are followed by further large changes in the same direction. This clustering effect supports the notion that volatility is never constant and may be characterized by various patterns of exhibitions over time hence the need for effective modelling to capture the true nature of markets.

There are models have been created in econometric to capture this volatility phenomenon with Generalized Autoregressive Conditional Heteroskedasticity (GARCH) among the most popular. Engle initially developed a simple framework for the analysis of ASD which was subsequently enriched by Bollerslev in1986 by introducing the GARCH model that provides for volatilities to change over time. It has particularly considered useful for the forecasting of future volatility (Endri *et al*. 2020). They contend that opening up and variances can easily be detected using GARCH models provided that investors weights their actions according to the volatility level.

The application of the GARCH models is not only confined to the sections of forecasting, but to risk management as well. Gaining the ability to look at extreme occurrences such as market shocks, interest rate unexpected changes, inflation, and all other forms of unwanted and unplanned occurrences, GARCH models place in the hand of investors the tools to handle risks that the market may present to him. Besides, the idea of volatility transmission presents a notion that all markets are related, meaning that what happens in one particular market greatly influences others. This re-emphasises the importance of developing a multi-dimensional approach when modelling volatility so as to consider inter-market correlations.

Market Integration and Cointegration

The market integration refers to the examine of synchronizing of the financial markets in different regions based on the similar economic conditions and application of the integrated risk factors of the world market. Researchers were offered a set of tools for testing whether several time series have long-run co-integrated relationships. For markets to be cointegrated, it means that prices move apart in the short run but will converge back in the long-run due to integration effects of economic forces.

Typically, cointegration test is performed with the Johansen test (Johansen, 1988) and it is frequently used across the financial literature to analyses long-run dynamics between stock markets. More precisely, Derbali and Lamouchi (2020), found that Asian markets were integrated of order 1, implying that the regional financial markets exhibit long-run linkages despite short-run dynamics. The implication of this result is very important to investors because it shows that diversification across cointegrated markets entail little gains since the assets move in similar directions.

However, several researches conducted on developed markets has found evidence of the existence of cointegration between major indices including FTSE 100, and S&P 500. This tends to show market interdependence between the US and the UK; the occurrence of a shock in one market will have a knock-on effect on the other market. They are rather useful in portfolio management as knowing whether the assets are strongly linked or not can help the investors to make the right decision on allocation of assets. Often the use of geographic diversification may be reduced if markets are cointegrated, thus there will be need for a better approach in risk management.

1.3 Time Series Models: Stationarity, GARCH, and ARIMA

Time series characteristics, especially stationarity, are crucial when performing the analysis of financial data. In its definition, a stationary time series has several attributes including mean and variance in any given period of time which do not change. The statistical regression of non-stationary data can distort the relationship in terms of significance while, in fact, there is no substantive relationship between them. In order to overcome these challenges, the academic world uses the Augmented Dickey-Fuller (ADF) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests in order to take a conclusion on the stationarity of the time series data. Haque and Ahmed (2024), showed that using econometric models requires checking for unit roots which most financial time series have.

Augmented Dickey-Fuller (ADF) Test

$$\Delta yt = \alpha + \beta t + \gamma y_{t-1} + \varepsilon t \sum_{i=1}^{p} \Delta y_{t-i}$$

Where,

- yt: Time series value at time t.
- Δyt: First difference of yt.
- α ,β,γ,δi: Coefficients to estimate.
- εt: Error term.

KPSS Test (Kwiatkowski-Phillips-Schmidt-Shin)

$$yt=\mu+\delta t+rt+\varepsilon t, rt=rt-1+ut$$

Where μ is a constant, t is a trend, rt is a random walk, and ut is a white noise error term.

GARCH models for volatility analysis

GARCH models have become the standard models for modelling volatility from the viewpoint of capturing heteroskedasticity existing in the financial data. Wang (2021), singled out their abilities to describe volatility and its temporal changes. In financial work, GARCH (1,1) models are often used due to its higher modelling accuracy and relatively low model complexity. These models concretise that time varying risk can be measured and how portfolios can be managed to achieve a targeted level of volatility.

GARCH Models for Volatility Analysis

$$\sigma t2=\alpha 0+\alpha 1\varepsilon t-12+\beta 1\sigma t-12$$

Where:

- $\sigma t2$: Conditional variance at time t
- $\alpha 0$: Long-term variance component.
- $\alpha 1$: Sensitivity of volatility to recent shocks (ARCH term).
- $\beta 1$: Contribution of past variance (GARCH term).
- ε^2_{t-1}: Lagged squared error term.

ARIMA Models for Forecasting

An Autoregressive Integrated Moving Average (ARIMA) is commonly acknowledged as one of the best for financial time series data. ARIMA models are very effective in analysing those data sets that contain trends and seasonality and thus make very good forecasts based on historical data. ARIMA which combines autoregressive (AR) as well as moving average (MA) to analyse the temporal pattern in a time series data.

The ways of using ARIMA models in forecasting stock prices and returns are explained below. Khan and Aglaia (2020), give a true understanding of how beneficial ARIMA models can be to investors enabling them to invest basing their knowledge on ARIMA predicted movements in the market. By including an element of ARIMA models in investment management perspectives, the investors receive enhanced capacities for correctly predicting future price movements, fine-tuning the respective investment portfolios, and thus, managing potential negative consequences in relation to volatile stock prices.

ARIMA Models for Forecasting

The ARIMA model combines autoregressive (AR) and moving average (MA) components, represented as ARIMA(p,d,q)-

$$\phi(B)(1-B)^d yt=\theta(B)\varepsilon t$$

Where:

- $\phi(B)$: AR polynomial of order p.
- $(1-B)^d$: Differencing operator of order d.
- $\theta(B)$: MA polynomial of order q.
- yt: Time series value at time t.
- εt: Error term.

Cross-Market Comparisons and Emerging Markets

The integration between developed and emergent countries has attracted a lot of discussion in the recent past. According to Siddiqui *et al*. (2022), although emergent markets have greater risk, they provide higher returns to investors, and hence viewed as providing higher reward for risk. Nevertheless, the growing connections between Asian equity markets and global financial structures have changed classical patterns, and new strategies of managing risks and bearing diversification are needed.

Research works conducted on cross-market analysis show that different indices are related differently. Quintus *et al*. (2024) established that the Asian financial crisis in 1997 enhanced the integration between the Asian and the global markets by element of contagion. Likewise, the shock emerging from the financial crisis of 2008 showed that whether locally or globally, shocks originating in the United States affected financial markets in different parts of the world and a synchronized depreciation of major indices.

It also revealed that the emerging markets like India and China are under consideration by the global investors due to high absolute growth rates and developing financial structures. The Sensex and Nifty 50 indices depict the Indian market while SSE Composite Index and CSI 300 indicates the Chinese market and when it comes to research for regional influences on global markets these are widely used.

1.4 Applications of Quantitative Research in Financial Studies

In financial studies, quantitative research provides a rigorous and scientific approach to the study of behaviour in the market. These authors stated that use of statistical models helps investors to understand the trend of the market, the respective volatility and various risks involved used in carrying out the investments. Analysis of correlation, stationarity, GARCH models and cointegration analysis refer to specific methods that help the researchers to notice some patterns and grammar in the financial market (Ross and Wright, 2020).

Quantitative methods are used widely in the other analyses including the forecasting of future trends. They include the Box-Jenkins models of which ARIMA has been used frequently to predict stock prices, returns and market indices in order to prepare investors and or policymakers for future market trends. Using statistical analysis on a large sample, quantitative research guarantees the results to be accurate, easily reproducing and devoid of researchers' prejudices.

Volatility Clustering (ARCH/GARCH Models)

The literature review highlighted some studies including Dey, M. S. A. (2022) & Endri, Imam, & Rahmat's (2020) investigating this concerning the effects of the COVID −19 on the S&P 500 & FTSE 100 markets asserting that volatility persistence is still a remarkably obvious phenomenon. Volatility clustering means that markets which move a lot, tend to have large movements of the same kind in the future, thus giving the free-markets some sort of pattern. The results section also supported volatility clustering in the indices such as Sensex, Nifty 50 and ALL SHARE FTSE; this gave the necessary evidence that these markets are characterized by persistent volatility. The results are consistent with prior literature and imply that an instrument for detecting such patterns, based on technical analysis tools, which has historical price information, could be used solely for generating profits. Nonetheless, the UK FTSE 100 presented itself as an exception: the corresponding GARCH terms proved insignificant indicating regional disparities. This outcome is an extension of Endri et al.'s (2020) finding of volatility spillovers but a variation from them due to the different response indicated by regional factors. The failure to document high volatility clustering in the UK FTSE 100 opposes technical analysis across all developed markets, especially those of lower persistent volatility.

Cointegration and Market Interconnectedness (Johansen Cointegration Test)

In the literature review, Johansen cointegration method was defined as a way of diagnosing the long-term association in financial indices, especially in the financial crisis (Gordon, 2020). This squares with results section in which the Johansen cointegration test estimated up to five cointegrating relationships in the daily percentage changes and the price levels of the major indices. These results therefore vindicate the conception of interconnectedness of the financial markets thus enabling the production of arbitrage portfolios across global indices. Other forms of tests also support identified co integration levels in prices such as DAX and Nikkei which is in concord with Gordon (2020). This means that price changes of one market can affect others making technical analysis a helpful tool for chronology market conditions in related markets. However, the trading volumes, which were investigated in this study, were shown to have only a weak cointegration, particularly within emerging markets. This led to a realization that though price indices are highly interrelated, trading volumes are less influenced by globalization. This is in line with Derbali and Lamouchi (2020) that volatility is relative to regional market features and not the global ones; therefore, arguing for context variables when using the technical analysis.

Autoregressive Behavior (ARIMA Models)

The literature review referred to Billah et al. (2024) where the authors observed that exponential components such as autoregressive in the ARIMA models captured short term movement in developed markets such as Dow Jones and S&P 500. In the results section, similar autoregressive pattern was noticed in developed markets like Sensex and ALL SHARE FTSE;

the behavior of the market over certain period of time had influenced the future market trends. These findings support the literature indicating that ARIMA models can be effectively applied for short-term trend prediction in well-established mature markets, where cyclic trends are identifiable. However, in other Nifty 50 and SSE emerging markets, moderate to a low level of autoregressive parameters of the developed ARIMA models means that previous trends can only play a limited role in determining the market's behavior. This is not surprising given the literature suggesting that in emerging markets technical analysis might have lower accuracy due to the fact that markets in emergent nations are less cyclical more volatile. Here the low maturity of most emerging markets in contrast to developed ones suggests that for technical analysis to be effective, factors such as maturity and region of the market must be taken into account.

Trading Volumes and Their Application in Technical Analysis

Literature review also emphasized that trading volume is generally less cointegrated with price indices further, which supports the concept of local market factors; including, and not limited to, liquidity and regulation; significantly impact trading volumes (Derbali & Lamouchi, 2020). The results section further validated this by presenting evidence of low level of co-movement between trading volumes and price indices of the sampled markets. From this it can be derived that, technical analysis may not be very useful if trading volume data is used as the key signal where the local factors govern the market especially in the developing countries. There has been an argument advanced that trading volume is one of the few elements that are very vital in trading pursuance of this form of technical analysis. The On-Balance Volume (OBV) or the Accumulation/Distribution Line (ADL) are some data that are commonly used for trends indicator, in order to predict future prices. However, the weak coz between volume and price in the study indicate that these may not be as useful, especially in areas where local variables such as sentiments, or Specific events dominating regions may hide the true benefits of flows in the linear fashion as in this study.

Application of Technical Analysis in Context

The review of the literature focused on the premise that the efficiency of technical analysis varies with market conditions and more so with the level of volatility and the market efficiency. The results section reflected this by showing how technical analysis is most efficient in volatile markets like Sensex and also Nifty 50, wherein the past price movements have high forecast ability. However it was established that when market is efficient or have low volatility as it is typical with the UK FTSE 100 market the information used for technical analysis is virtually useless (Thakkar and Chaudhari, 2021). This is in accordance with the earlier researches which indicates that technical analysis is suitable in a market that has conspicuous trends which can be easily exploited. Where the equity is integrated into highly efficient trading palaver markets, in which contents are turned quickly into price swings, technical appraisal may not offer advantage, as prices are awfully probable to retrace themselves nearer to the average, hence reduce the worth of trends-based styles.

Challenges and Limitations in Financial Market Analysis

The use of quantitative methods has its drawbacks that financial market analysis encounters. First, non-stationarities in financial data are an important limitation due to which their transformation is needed to avoid biased results. Furthermore, volatility models like GARCH suffer from the outlier's problem and the major fluctuations, characteristic for the financial crises (Thakkar and Chaudhari, 2021).

The last important issue is data accessibility and credibility, especially with respect to emerging economies for which historical data often prove scarce or questionable. In addition, algorithmic trading and changes in the market microstructure have become crucial new factors which could not be ignored by the researchers as they have brought new dynamics to the system.

The outcomes of this study relate to the findings of prior work, including high-frequency volatility instability, cross-market connections, and self-referenced characteristics of developed places. However, the use of technical analysis should also be looked at in terms of region where for example the analysis of FTSE 100 in the UK, Nifty 50 and other such emerging markets can misleading sometimes. The study also supports the argument that the technical analysis is not one-size-fits-all since the success of a technique depends on the level of market development, the level of fluctuations in stock prices, and Indexes used in evaluating the techniques. Such results demonstrate that the reception of technical analysis should not be exclusively limited to global factors, nor can it be applied mechanistically for local markets.

2. Research Framework for Cross-Market Study of UK, China and India Indices

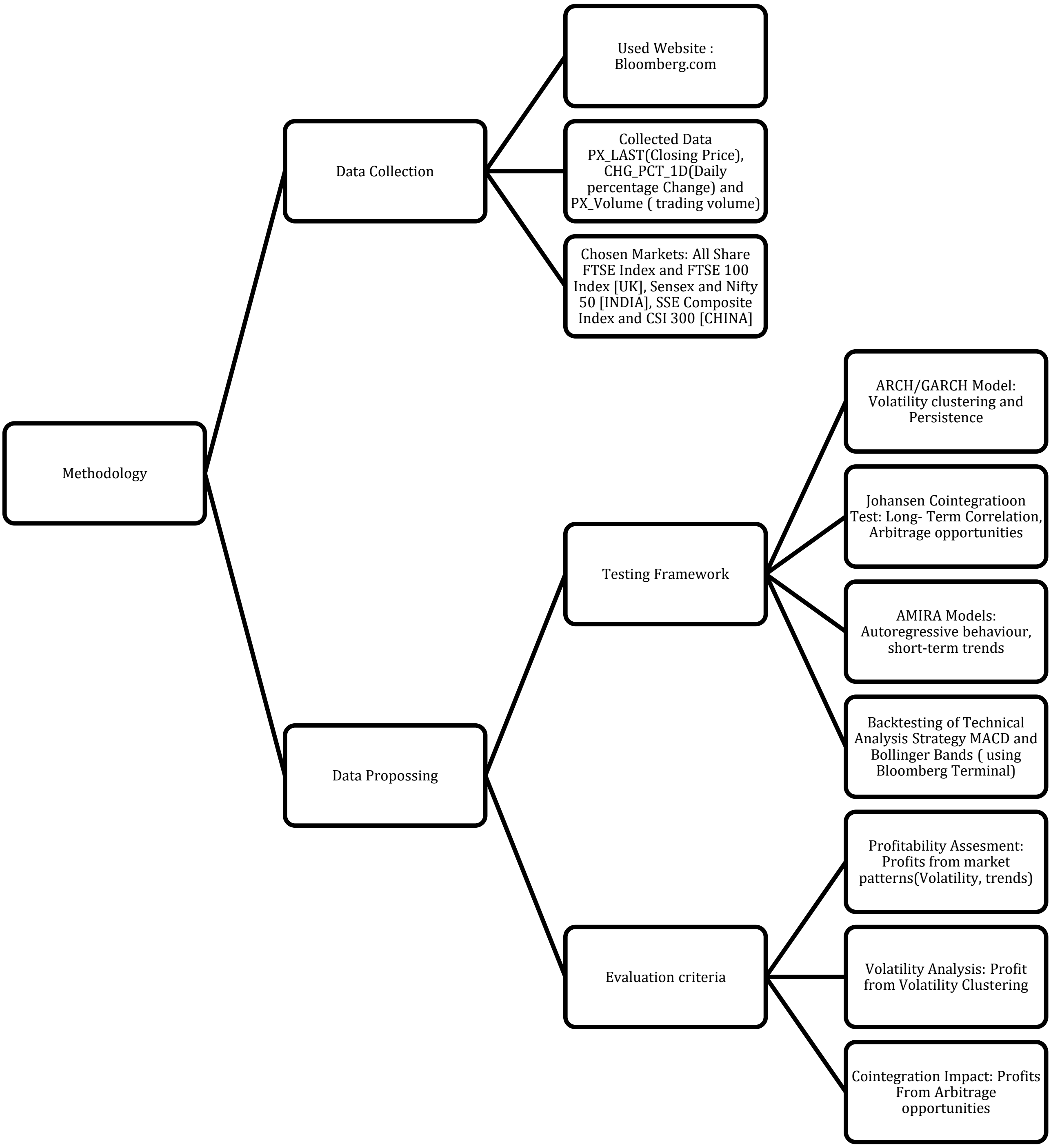


Figure 2.1*: Flow Chart*

This chapter outlines the methodology used in how the analysis of historical financial market indices connect between India, China, UK is done. It provides detailed information on the research methodology, ontology and epistemology, method and justification for choosing a quantitative research method. This chapter also outlines the methods used for data gathering, the methods used in analysing the data and different aspects of ethical consideration in research. Moreover, this report establishes a time scale to indicate the chronological plan of each stage of the study. Last, issues relating to the reliability and validity of research that has been conducted is briefly examined so as to appreciate the quality of the developed findings.

This study intends to utilize both appropriate statistical tools and econometric models to identify the dynamic interactions of the global financial markets as well as to recognize the volatility characteristics, interactions, and development trend. The results are considered useful in the evaluation of market interactions and the decisions made towards risk, forecasts and investment. In order to avoid biases and generalization problems, research procedures were designed consistently with replication in academicians' studies and practical environments.

The rationale for selecting the research methodology is therefore to put in place a sound and comprehensive approach to capturing, analysing and interpreting financial market data. This framework assists the researcher in answering the fundamental research questions touching on market volatility, correlation, cointegration and predictive forecasts. More precisely, the methodology targets discovering how indexes are synchronized and how volatility overflows across regions, with a focus on the All-Share FTSE Index, FTSE 100, Sensex, Nifty 50, SSE Composite Index, and CSI 300.

In addition, the approach minimizes the potential of the analysis being flawed by bias since the criteria are objective, measurable. This paper aims at producing valid findings in the field of international financial markets by employing a thorough data gathering technique, as well as statistical analysis. It also increases the accurateness of the time series forecasting which will enable the researcher to forecast the future market performance.

2.1 Research design

This research uses descriptive and correlational design to examine the historical performance and co-movement of the All-Share FTSE Index, FTSE 100, Sensex, Nifty 50, SSE Composite Index and CSI 300. The descriptive aspect deals with profiling the behaviour of individual indices in terms of trend analysis, patterns and some statistical features. This is done using figures like averages and standard errors, measures of skewness and kurtosis which provide information to do with each index concerning its average value, variability and distribution of returns. In addition to this, descriptive statistics point to the levels of market activity and how far returns depart from the normal distribution in an effort to reveal such indices that present higher risk or changed performance patterns in the long run (Ullah *et al*. 2021).

The correlational design is intended to capture the degree of association between one or more of the chosen indices, that is, how much each index is directly or inversely related to the others. This is done by use of the Pearson's correlation coefficients that put into measurement the intensity and direction of interactions between assorted markets. Positive relationship suggests that indices are either integrated or can experience contagion effects especially during volatile periods or periods of global event. On the other hand, the negative coefficient implies adverse movements, that a few markets could serve as perfect hedge to the other.

At the same time, this research design establishes the framework for additional statistical comparisons. Daily market volatility is calculated using the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model that shows periods of high and low volatility Market time series data is tested for stationarity using ADF (Augmented Dickey Fuller) or KPSS (Kwiatkowski–Phillips–Schmidt–Shin) to determine if it is appropriate for forecasting. Johansen cointegration test provide further check of whether the two indices are cointegrated and may be in long run equilibrium relationship, while they can be short term mean reverting. These effectiveness and optimality levels provide the researcher with the ability to develop ARIMA based time series forecasting models with the general ability to predict the future behaviour of the indices. This broad research method guarantees that the study not only detects trends but also provides insights into relationship and dependency patterns across the international markets.

Research philosophy

The research philosophy employed in this research is positivism research philosophy because it supports scientific methods that utilize quantitative data to develop knowledge. The positivist paradigm matches the analytics of the financial markets where the concentration is put on facts, figures and other real variables inclusive of previous prices, trading volumes and percentage flotation of indices. The primary principle of positivism is that data can only be collected through observable facts and quantitative evidence and will execute research free from individual bias, interpretation or influence without any possibility of attempt reproduction.

In this regard, the positivism philosophy is appropriate because the data collected is real and can easily be obtained from standard sources such as Bloomberg. Markets are not operators in the common use of the word, but rather they have some form of structure or set of rules governing them that make it possible to mathematically analyses their behaviour, which makes it possible to test using econometric or statistical techniques as the case may be. Through the application of positivism, the study does not embrace speculative theories or narratives, as well as counter-stories, but embraces the exploration of patterns, trends, and relationship structures inherent in the data set analytically.

This philosophy is especially so when one is applying complex models such as GARCH (Generalized Autoregressive Conditional Heteroskedasticity) in analysing volatility, or ARIMA (Autoregressive Integrated Moving Average) models in forecasting. These techniques operate based on accurate inputs and need an analytical based approach to produce valid results. In this case, the quantitative, empirical data gives the study precision and avoids distortion, thus enabling the researcher to come up with appropriate conclusions regarding the manner in which markets behave and conduct themselves over time.

In addition, positivism also promotes the empirical aspect of the two streams of research that are fundamental to academic research, in terms of replicability. The results can be replicated by future researchers or analysts who can estimate the same models on different samples or time horizons, and can thus help to establish the knowledge about financial markets. By employing this research philosophy, the study maintains its objective, scientific approach to providing accurate data analysis in the marketing context beneficial for both, market participants, analysts and policymakers.

Research approach

The research therefore employs deductive research approach a paradigm which tests existing proposition about the phenomenon of interest in this case world financial markets, using empirical evidence. Indeed, deduction is most appropriate for this study since this work aims to either confirm or reject existing hypotheses on volatility clustering, market integration and testing for stationarity in time series data. Because the deductive approach involves proposition testing that comes from theory and analysis on the effectiveness of the theory in the selected market indices.

In reality, the deductive approach to the formation of hypotheses is based on certain assumptions of the existence of theories about the functioning of the financial markets. For example, one hypothesis could be that changes in volatility in one market affects the volatility in another market and therefore supporting the view that global markets are integrated. Anoth might be to check if the indices are cointegrated in the long run with the implication that though they may separate in the short-run, are destined to move together in the long-run. These hypotheses are analyzed by employing various methods of statistical and econometric analysis.

The deductive approach makes sure that the study is grounded on analysis since the data collected is from simple observation and this greatly limits room for biased judgment. GARCH models are used in capturing volatility clustering while ARIMA models are used in predicting the future pattern of the data set. In this case, the results, if confirmatory to the hypotheses, support current theories of finance. On the other hand, if the results differ, they are likely to provide fresh information into market directions, which might include irregularities that were not recorded in earlier endeavours. It also helps in developing theories as a way of providing proof that they may well be accurate, or not, in so doing, then enriching on the advancement of theoretical paradigms (Wamalwa and Makori, 2020).

This approach is applicable in achieving the objectives of this study, which aims at finding relations between the financial markets and evaluating their behaviour in a given period. The case selection by using empirical evidence then makes the research procedure more systematic and grounded and makes it possible for other scholars to replicate the research given that they follow a similar approach, technique or procedure hence the validity of the research process is well upheld.

2.2 Quantitative research strategy and justification

This research uses the quantitative research methodology and is most appropriate when dealing with financial markets. Financial indices include numeric values including prices, returns and volumes of trading that can be fitted to statistical models to assess appropriate formulations. Quantitative techniques have the following benefits-

a) Quantitative results are precise

b) The research study is easily replicable

c) The research study is highly objective.

This approach is appropriate to consider in the framework of the research objectives because the strength of the relations between pairs of variables can be quantified, and models for prediction can be constructed.

The following quantitative tools have been chosen- correlation analysis, stationarity tests- ADF and KPSS, GARCH models, cointegration test- Johansen test and finally the ARIMA forecast models. These methods will be applied depending on certain objectives of the research. For example, correlation analysis investigates the extent to which the indices co-vary and stationarity tests are used to identify the presence or otherwise of non-stationary data which requires transformation for correct modelling (Wang and Yildirim, 2021). GARCH models are used to model volatility and cointegration testing is used to test for the existence of long-run relationship between markets. Last but not least, will build forecasts kind of the ARIMA models that take into consideration historical patterns.

In its turn, quantitative research is justified by the necessity of working with vast amount of data encompassing the longer time period. Finally, financial data is generally noisy, containing short-run fluctuations and long-run trends which should be statistically analyzed using accurate apparatus. The use of the quantitative strategy enables the researcher to compare the financial markets, an aspect that enables one to analyses the way in which these markets affect each other.

Besides, it will eliminate biases as well as opinions from the results of the study and increase the level of confidence or reliability of the work. The research also controls for different sources of biases through the use of sophisticated statistical methods that make the findings more generalizable and amenable for tests by other scholars. In summary, the use of quantitative research strategy provides values which entailed objectives structures relationships trends and patterns in financial markets.

Criterion for Technical Analysis

The efficacy of the technical analysis strategy is evaluated based on its ability to achieve statistically significant and economically meaningful results in the following ways-

Volatility Patterns

The GARCH models check if its volatility clusters conducte with technical analysis such as high and low volatility period. Thus, the model's ability to represent volatility patterns, as probed by technical indicators, determines success.

Cointegration for Long-Term Relationships

The Johansen cointegration test decides whether or not markets are cointegrated, or share long-term equilibrium relationships, something that technical analysis may presuppose. The validity of the strategy is argued when cointegration surface and when it is in harmony with technical trading patterns.

Predictive Accuracy of ARIMA Models

These forecasts are obtained from the ARIMA models, it is then used to compare the forecast with actual market results with the aim of establishing the extent of accuracy of these forecasts. Small values of forecast errors suggest that the implemented technical analysis strategy is effective.

Correlation and Contagion Analysis

Analyzing correlation determines the level of conservative coherence providing an understanding of whether technical analysis can forecast cross-market impact during crises. The strategy is effective evidenced by the strong positive statistically significant correlations.

Data collection strategy

The information was obtained from Bloomberg.com, a popular and trustworthy source of the financial market data. Bloomberg provides direct-feed data and evaluation of world's financial indices; it checks data's real-time and archive data's authenticity and comprehensiveness. The dataset includes PX_LAST (closing prices), CHG_PCT_1D (daily percentage change), and PX_VOLUME (trading volume) for the selected indices:

- All Share FTSE Index – captures 98 percent of London Stock Exchange market
- FTSE 100 Index – The index represents that market value of the top one hundred listed companies in the London Stock Exchange market.
- Sensex – This stand for the Bombay Stock Exchange, BSE Index known as Sensitive Stock Exchange Index or Sensex.
- Nifty 50 – Averages the fifty most significant stake in the National Stock Exchange (NSE) in India.
- SSE Composite Index – This one stands for the stock exchange in Shanghai also known as Shanghai Stock Exchange Composite Index.
- CSI 300 Index – provides information on 300 large capitalized shares listed in the stock markets of Shanghai and Shenzhen.

These indices were chosen in an attempt to cover both developed and emerging markets all over the world. Using the dataset enables analysis of the inter-market relation and study of volatility profile across various market settings.

In concerned data collection efforts, an emphasis was made to obtain historical data adequate enough to allow time-series data analysis. This is important as the models such as the ARIMA and GARCH works well with big data to give credible results. Row formats in data were created for different types of statistical testing; stationarity testing, volatility modelling and forecasting to ensure the data was optimally suitable for econometric analysis (Bloomberg.com).

Extra caution was exerted to ensure that the data was accurate and there was no data entry errors. Certain values could contain missing information, and this would somewhat affect the analysis; therefore, the accuracy of the dataset was ensured by validation. Also, in order to avoid a problem of inputting data into the STATA software, the data was formatted cleaned and rearranged as required for analysis.

Data analysis

The information which was gathered was analyzed by using Stata software, which provides a great number tools in the sphere of statistical and econometric calculations. The respective analysis was in fact a series of logical steps in line with the methods that need to be applied to answer every research objective. The key analytical steps included-

Descriptive Statistics

Systematic reporting of the indices was done by use of descriptive statistics. Descriptive statistics like; mean, variance, skewness, and kurtosis gave the researcher a clue to the distribution and nature of the findings. These statistics aided in detecting such things as normality or otherwise of the returns in that they were skewed or had excess kurtosis implying fat tails. In assessing the usefulness of technical analysis in this context, a consideration was made of whether returns could be shown to exhibit features, such as skewness or kurtosis, which would impact on predictive ability. These characteristics are important when deciding whether or not technical approaches can fully explain partly random fluctuations or shocks in the markets, giving a measure of the reliability of these strategies.

Correlation Analysis

Pearsons's coefficients were used to test the relationship between the different indices. To establish the extent to which such indices are correlated, the adopted measure was Pearson's correlation coefficients. This analysis revealed the measures of synchronization and offer knowledge about the contagion effects between the markets during the period of economic crisis.

$$r = \frac{\sum(Xi - X^{-})(Yi - Y^{-})}{\sqrt{\sum(Xi - X^{-})^2 \sum(Yi - Y^{-})^2}}$$

- Xi and Yi represent individual data points in datasets X and Y
- X^{-} and Y^{-} are the means (averages) of X and Y, respectively.

The stability and/or coherency of these correlations were then tested across the time. High persistence of correlations across different indices will support the fact that markets may not be so diverse and therefore affect other strategies based on different and diverse market behaviour. Closely correlated markets are interpreted by technical analysis as a sign that the two markets may rise and fall together; technical analysis then has to take this into consideration for correct trading signals.

Stationarity Tests

The Augmented Dickey-Fuller (ADF) tests were used in this regard for identifying the nature of the time series data that is stationary or non-stationary and requires differencing. It is quite critical to model time series data as the non-stationary data result in spurious relations when regressed. Stationarity tests are conducted to make sure that the data patterns do not change over the time. Price based technical indicators perform better when they deal with stationary data because trends are possible to discern. As applies to disintegration of demand and market non-stationarity, firm concludes that particular problems without reliance on such strategies are unpredictable fluctuations in market conditions.

Volatility Analysis (GARCH)

In order to understand volatility characteristics of the study, a GARCH (1,1) model was adopted. GARCH models are especially helpful when the error process exhibits: Volatility clustering, that implies high volatility tends to be followed by high volatility and low volatility tends to be followed by low volatility. This analysis gave understanding into the risk shifts of the indices. In this case, assessing uses of technical analysis entailed ascertaining whether or not they could shift according to volatility. The problem is that, if the strategy relies on various technical indicators and ignores clustering of volatility, it can produce false signals in aggressive periods. Consequently, whether risk shifts are captured by the model provides a reference point for determining how the technical trading strategies fare when the market becomes more volatile.

Used Stats comment

“arch <dependent_variable>, arch(1) garch(1)”

Johansen Co-integration Test

The Johansen trace test was employed with a view of testing whether the indices exhibit long-run cointegration relationships. This test is essential in determining if markets are integrated in a long run ignoring any short run anomalies. In evaluating technical analysis here, one needs to identify whether it is possible to take advantageous positions out of the deviations before the prices return to normal technical values. If markets are cointegrated, the usability of technical analysis directly correlates to how it is able to find those short-term profitable moves without being deceived by long-term relationships.

ARIMA Forecasting

ARIMA models were used with the historical data to forecast future movements of the indices. ARIMA is also very useful for time series forecasting because it considers the autocorrelative properties in the time series hence provides very accurate forecast as we move ahead in time (Gordon, 2020). A time series model simply shows data that has been gathered over time and can be depicted using a line graph. One of the main components is the historical data points linked by curve, that allows to show trends, seasonal fluctuations and cycles. The model may also contain predicted values beyond the observed data which are usually labelled in a contrasting colour. It gives insights to work out future trends depending on the historical performance accomplished before. Analysing performance of technical analysis incorporated the aspect of benchmarking of ARIMA based forecasts with those got from the technical indicators. If ARIMA models perform well in excess of technical indicators this implies that pursuing historical trends, which form the basis of technical analysis, may not be adequate to generate accurate forecasts.

Used Stats comment

“arima <dependent_variable>, arima(1,0,0)
predict <forecast_variable>, dynamic(Date[_N-11])”

In this way, the process of analysing the research objectives was properly coordinated, so that each of the objectives was investigated as thoroughly as possible. This insight became feasible due to the application of advanced econometric techniques to examine the market interaction and the relationships between the indices where by enhanced reliability and robustness of the findings were exercised. Hence, the research proceduralized each analytical process to enhance the examination of the research questions. It then used a battery of sophisticated econometric tests to determine whether these strategies were indeed capable of painting a picture of the market’s behavior and providing tradable signals that would be robust to changes in that environment.

2.3 Research reliability and Summary

Validity of the study was maintained with credible data collection techniques and credible measures of data analysis. Validity was attained through use of appropriate econometric models that correctly estimated the coefficients and hence the relationship between the variables.

In this chapter, the study’s method is described, and the choice of a positivist and quantitative as well as deductive research approach is explained. Structuring the study to involve collection and analysis of primary data minimizes a number of factors that could reduce the reliability and validity of the results to improve understanding of global financial markets.

3: Empirical Research Outcomes: Analysing Historical Data in the UK, China and India Indices

The results of the research together with the analysis of their findings is presented in chapter 3 of the study. It also considers the findings with regard to the research questions and its comparison with prior studies. The chapter discusses the results and includes analysis of outcomes, the presence of regularities and tendencies, and directions for further development in terms of theory and practice. It also looks at the implications of the study and gives recommendations on the future studies that can overcome the limitations. It adds understanding for the results by placing them into conversation and provides an overview of the general relevance.

3.1 Evidence of practical work

```
. * Describe dataset to review variable properties

.
. describe

Contains data
  obs:          1,187
 vars:             19
 size:        163,806

              storage   display    value
variable name   type    format     label      variable label

Date            int     %td..                 Date
PX_LAST_ASXIn~E double  %10.0g                PX_LAST_ASXIndexAllFTSE
PX_LAST_UKX~100 double  %10.0g                PX_LAST_UKX_FTSE_100
PX_LAST_Sensex  double  %10.0g                PX_LAST_Sensex
PX_LAST_Nifty50 double  %10.0g                PX_LAST_Nifty50
PX_LAST_SSE     double  %10.0g                PX_LAST_SSE
PX_LAST_CSI300  double  %10.0g                PX_LAST_CSI300
CHG_PCT_1D_AS~E double  %10.0g                CHG_PCT_1D_ASXIndexAllFTSE
CHG_PCT_1D_~100 double  %10.0g                CHG_PCT_1D_UKX_FTSE_100
CHG_PCT_1D_Se~x double  %10.0g                CHG_PCT_1D_Sensex
CHG_PCT_1D_N~50 double  %10.0g                CHG_PCT_1D_Nifty50
CHG_PCT_1D_SSE  double  %10.0g                CHG_PCT_1D_SSE
CHG_PCT_1D_~300 double  %10.0g                CHG_PCT_1D_CSI300
PX_VOLUME_ASX~E double  %10.0g                PX _ VOLUME_ASXIndexAllFTSE
PX_VOLUME_U~100 double  %10.0g                PX _ VOLUME_UKX_FTSE_100
PX_VOLUME_Sen~x long    %10.0g                PX _ VOLUME_Sensex
PX_VOLUME_Ni~50 long    %10.0g                PX _ VOLUME_Nifty50
PX_VOLUME_SSE   double  %10.0g                PX _ VOLUME_SSE
PX_VOLUME_C~300 double  %10.0g                PX _ VOLUME_CSI300

Sorted by:
     Note: Dataset has changed since last saved.
```

```
.
.
. * Drop observations with missing values to ensure clean analysis

.
.  drop if missing()
(0 observations deleted)
```

Figure 3.1: Dataset description

(Compiled by the Author based on his own Calculation)

This dataset has 1,187 observations spanning 19 variables include the **PX_LAST** (last traded price), **CHG_PCT_1D** (one-day percentage change), and **PX_VOLUME (trading volume)** for six indices: or ALL SHARE FTSE Index, UK's FTSE 100, India's Sensex, Indian Nifty 50, China's SSE Composite, and China's CSI 300. Almost all parameters and inputs are double precision while some volume parameters are in long format. Any observation that had a missing value was omitted for the analysis but none were removed at this point.

Descriptive Statistics

This analysis looks at basic empirical trends in key benchmark equity markets including the ASX All Share FTSE Index, FTSE 100, BSE Sensex and Nifty 50, Shanghai Composite Index (SSE) and China Enterprise of Stock Index 300 (CSI300). Eliminating the actual exchanges' respective values, it has been identify unique features and patterns in their prices and daily percentage changes as well as traded volumes.

Index Price Trends

The price trends of indices provide a snapshot of their overall performance and resilience to market dynamics-

- ASX All Share FTSE Index: There is no highly volatile index in the ASX All Share FTSE market; all indices have a consistent price level with little fluctuations. Hence, from its region one could deduce that it belongs to a mature market cycle since investors do not feel the impact of external shocks with the intensity that growing markets would and fluctuate with moderate sensitivity. The gradual flow in the figure above suggests that the market is largely in mature market business zone dominated by stable industries including mining, financial and energy sectors, which are in line with the ASX All Share FTSE Index.
- FTSE 100: The UK's FTSE 100 shows variance somewhat higher, which means that the market does undergo occasional changes according to the global economy. It might

be due to different factors such as geopolitical and other changes that have marks like Brexit. Being a developed market index, it depicts cyclical nature of its economy along with sectors of finance, consumer goods & services and healthcare.

- Sensex and Nifty50: The key points of the published indices refer to the in consultations on the high speed of the Indian economy and the growth of international investment. These have experienced fairly big price swings because they are both growing industries and are affected by occurrences locally and globally. The high performance of these indices favours India as an EM with high gains possible that however come with risks inherent in such markets.
- SSE and CSI300: The illustrated daily percentage changes of the two Chinese indices express comparatively restrained P/W which indicates a strong impact of the regulatory systems on the stock market. Despite this, their patterns appear stable although they fluctuate occasionally depending on government policies and other influential events in international business trade.

These indices also point to the transformation in China from an export-oriented economy to a consumption-based economy.

Daily Percentage Changes

Daily percentage changes offer a closer look at market volatility and investor sentiment over short time horizons-

- ASX All Share FTSE Index and FTSE 100: The ASX All Share FTSE Index presents that daily fluctuations are small suggesting that the trading environment is not very volatile and large changes in prices are not frequent. Similarly, the FTSE 100 exhibits equally daily fluctuations, which indicates seeming invulnerability and fairly neutral investor inclinations. Both indices demonstrate that the mature markets dampen diversified economies' structures and policies to avoid extreme volatility.

- Sensex and Nifty50: It is observed that the fluctuations in Indian markets are higher during the day and this indicates that these markets are highly sensitive to triggers outside of the market, for example in corporate earnings announcements, monetary policy changes or global market events. These indices reflect investor participation from both the retail and institutional investors hence easily influenced by herders and speculators.
- SSE and CSI300: Fluctuations in the daily changes we observe in the Chinese indices indicate a rather moderate and controlled market due to most of the regulatory forces being centralized. Nevertheless, sometimes volatility behaves erratically in high ways, caused by essential economic information or changes in the trading policies. This kind of stability and frequent but irregular fluctuation make these indices relatively predictable, yet sensitive to change.

Traded Volumes

Traded volumes provide valuable insights into market liquidity and investor engagement-

- ASX All Share FTSE Index and FTSE 100: The above two indicators show constant trading activities, which confirm persistent investor interest. The lower variability thus indicates that these markets are less susceptible to speculative futures and function within a structure of predictable liquidity behaviour. The volumes on the ASX All Share FTSE Index reflects its value accumulated from its commodity-based economy, the volumetric activity associated with being home to international investors searching for stability is reflected in the FTSE 100.
- Sensex and Nifty50: It has been observed that Indian markets follow significant differences in trading volumes the broader and more liquid Nifty50 as compared to

Sensex. This is because Nifty50 has extended across the various sectors as compared to the earlier days when only finance related stocks were in a majority. However, both our indices do encounter infrequent volumes spikes which usually occur in the context of significant economic or political events.

- SSE and CSI300: The Chinese indices have the highest trading volumes and this puts into perspective the activity on the market. This is a testimony of the presence of the retail investors on stocks as well as Institutional participation. The high liquidity is explained by the fact that the domestic market of economic turnover is extensive in China, and domestic investors actively engage in purchasing securities. However, the trading environment is currently rather formalised and volumes imply the existence of a regulated market.

3.2 Digital Comparison and Market Features

- Stability vs. Growth Potential: The ASX All Share FTSE Index and FTSE 100 perfect depict the swings of well-developed markets where while rates of accrual are moderate they are steady. On the other hand, the two shown are Sensex and Nifty50, presenting the growth prospective of an emergent market and its premiums. This difference clearly highlights the risks of investment decision by choosing between stable returns and volatile upside potential.
- Investor Behaviour and Market Dynamics: Constant values of the ASX All Share FTSE Index and a relatively low level of daily fluctuations in the FTSE 100 point towards risk-averse behaviour of the investors, their mercantilist and, which is more likely, their focus on long-term capital appreciation. However, the Indian and Chinese indices presents relatively high values of the trading activity and short-term volatility indicating both speculative and growth-oriented trading.

- Global Influences: The level of performance of these indices depends on the exposure of their economy to the rest of the world. Another reason why the FTSE 100 that has more international exposure serves the purpose well given its responsiveness to changing international financial and political climate. The SSE and the CSI300 are largely domestic indices, but their performance is linked to trade policies and economic liberalisations – a nod to China's role as the world's factory and consumer.
- Liquidity and Accessibility: The greater contrast exhibited in traded volumes between the indices speaks to the issues of market access and investors target. Whereas the Chinese and Indian markets reveal strong local and international activity, the ASX All Share FTSE Index and the UK markets put more weight on the quality and provide targets to invest in less risky instruments.

Hence, these interpretations show that global market behaviours differ significantly, which have been shaped by such factors as; economic systems, legal frameworks and investors. Broadly stable index such as ASX All Share FTSE Index or FTSE 100 offers relative stability, while high risk high return markets such as Sensex, Nifty50, SSE or CSI300 offer relatively higher volatility. It is crucial to recognize all these subtleties to help investors adjust their intentions and goals with the field characteristics and degrees of risk. ***[Refers to Appendix 1, pp.98]***

Visualizations

The three panels in the included visualizations include: financial indices over the period January 1, 2020 to March 2, 2023; percentage change, on a daily basis, over the same period; and trade volume during the same period. Analysing the PX_LAST, trends are observed to be upward showing continuous increase in market indices of selected indices like Sensex, Nifty50, All Share FTSE Index, SSE and CSI300 during sample period. It will be seen that with more bullish movements, the Sensex and Nifty50 have sharper slopes. The second panel shows the day-to-day fluctuation expressed in percentage for UKX, Nifty50, CSI300 and SSE. It also appears that changes are acute and common, which points to a high market volatility. But the deviations move around zero, and hence, it implies that it is a mean reverting series. The rightmost panel display the trading volume profile for the same indices. Fluctuations of volumes are rather noticeable, while maximum values of them were observed in UKX and SSE. This implies that the trading activity occurs in cycles, this we believe, corresponds with the changes in market sentiment.

Therefore, the graphs of the various indices have exhibited high index performance, moderate to high daily fluctuation and variable trading frequency which is consistent with the ARIMA conduction. ***[Refers to Appendix 2, pp.99, Appendix 3, pp.100, 4, pp. 101]***

3.3 Correlation Analysis: Price Correlations

ASX All Share FTSE Index:

Significant in the direction of a positive, meaning that the changes in the activity of the two stock exchanges are strongly interconnected, ASX All Share FTSE Index and UK ones in particular ($r=0.9153$, $p=0.0000$).

Lower coefficient values foreseen with Sensex ($r= 0.7932$, $p = 0.0000$) and Nifty 50($r=0.7889$, $p = 0.0000$) means moderate level of synchronization between ASX All Share FTSE Index and Indian markets.

Almost no correlation with SSE (correlation coefficient= −0.0053, $p =0.8563$) or CSI300 (correlation coefficient= 0.0000), pointing to weak connections with China ’ s market conditions.

FTSE 100:

Significantly, positively with Sensex 50 ($r=0.8620$, $p= 0.0000$) and Nifty50 ($r=0.8589$, $p= 0.0000$), which signifies a complementary trade between the UK and India.

Indian Indices (Sensex and Nifty50):

A very high level of positive relation between Sensex and Nifty50 (‘r’ = 0.9993), implying that they belong to the same market environment and have many similar factors.

When Indian and CSI300 Index are compared, there is weak or no relationship with the SSE Composite, thereby representing different markets.

Chinese Indices (SSE and CSI300):

Comparing SSE and CSI300, very high internal market consistency has been determined with correlation coefficient of 0.8873 at 0.0000 significance level.

Little or no relationship with other major indices as an indication of their fairly isolated movement.

Daily Percentage Changes Correlations

ASX All Share FTSE Index:

Insignificant positive and weak correlation with Nifty 50 (0.0664, 0.0238) and Sensex (0.0649, 0.0274) indicating slight contemporaneous movement with daily trends in market index.

Unrelated with FTSE 100 (corr.; = −0.0474, p = 0.1073) and Chinese indices; different short-term patterns.

FTSE 100:

A moderate relationship with Sensex (r=0.1750, p=0.0000) and Nifty50(r=0.1745, p= 0.0000), indicating that the two indices have slight parallelism in terms of daily movements with the possibility of overlapping in their interaction with global factors.

SSE and CSI300:

High internal consistency (r =0.9568 t) and statistically significant at $p<0.05$ suggesting the responses are equally influenced by daily market driver within China.

Little relationship with other indexes, which supports evidence that they are not influenced by internal and external markets.

Trading Volume Correlations

ASX All Share FTSE Index:

There is moderate positive correlation crops up with both FTSE 100 ($r=0.4036$, significant at 0.0000) and Nifty 50($r=0.4334$, significant at 0.0000) which shows high liquid stock interconnection both in developing and developed world.

FTSE 100:

Shows moderate relationship with Nifty50 (rsq = 0.4353, $p= 0.0000$) indicating high level of inter-market trading.

Indian Indices:

Comparing, Sensex and Nifty50 demonstrate the weak link with their volumes (corr coef 0.2841, $t=0.0000$), meaning that the two markets involve different patterns of company participation.

Chinese Indices:

The internal correlation in trading between China businesses is very high positive ($r=0.8472$, $p=0.0000$).

The findings show that both developed markets – ASX All Share FTSE Index and FTSE 100 – are strongly interdependent with emerging markets – Sensex and Nifty50 in the price level but weakly correlated in daily moves and volumes. The Chinese indices of SSE and CSI300 are of somewhat immune, as they have different structure and regulate mechanisms. That is how the analyzed insights emphasize the various and multifaceted nature of the global markets.

[Refers to Appendix 5, pp. 102-103]

3.4 Augmented Dickey-Fuller (ADF) Test

PX_LAST

The Augmented Dickey-Fuller (ADF) test, is used to identify the order of integration of a time series. This means whether it is stationary or not, that is whether its mean and variance are constant over time. For the ALL-SHARE FTSE Index, the test statistic was -1.785 with a p-value of 0.3877 >0.05. Likewise, the index of FTSE 100 Index is non-stationarity because the test statistic which is -1.547 has a large p-value of 0.5102. The p-values were even higher for the Sensex and Nifty 50 indices, which were 0.9693 and 0.9806, respectively; the two series thus modelled did not possess an integrated nature. The SSE Index was slightly closer to being stationary with a test statistic of -2.574, however, its corresponding p-value of 0.0984 rejected the null hypothesis of stationarity at a 5 percent level of significance. The CSI 300 Index also did not pass either the test with the test statistic equal to -1.450 and the p-value of 0.5580 (Kalu *et al*. 2020).

Since these results imply that the original series were non-stationary, differencing was used to modify the data. Differencing removes trend and structural shift and produces a new time series that is the first-order difference between the original consecutive observations. This step makes the data even more appropriate for additional econometric analysis, including autoregressive integrated moving average (ARIMA) analysis. If the ADF test is run again on the first differenced series, all indices showed a marked gain in significance. For instance, using the test on the differenced versions of ALL SHARE FTSE Index, the test statistic obtained was -23.573 while the p-value was 0.0000 and hence, the series is stationary. Likewise, when performing the same test on FTSE 100 Index the test statistic was -24.229, and thus, the p- value of 0.0000 also pointed to such conclusion that the series became stationary after differencing. The other indices, namely; Sensex, Nifty 50, SSE, and CSI 300 further produced highly negative test statistics with almost zero p-values implying that the time series are stationary.

Therefore, the preliminary test showed that the initial data series were indeed non-stationary, indicating trends and fluctuations in a specific period. After performing first-order differencing, all the series was stationary.

For other two index

Based on the above results it can be said that all the tested indices- ALL SHARE FTSE Index, FTSE 100, Sensex, Nifty 50, SSE and CSI 300 had high stationarity. Test statistic values for ALL SHARE FTSE Index were -23.270, FTSE 100 was -24.298 and Sensex is -24.664. All of these values are substantially lower than the 5% critical value of -2.860, MacKinnon p-values are 0.0000, which indicates that these series are stationary. This shows that the first differencing was effective in taking the indices from non-stationary series to stationary by removing trends and volatility. Similar to the stock prices, the trading volume series for the indices was also stationary with different test statistics. The ALL-SHARE FTSE Index volume had a test statistic of -11,303 the FTSE 100 volume showed -11,638 and the Sensex volume recorded -19,970. Similarly to the case of Nifty 50, it has been obtained a negative return for the SSE and CSI 300 volumes at -0.116, and -0.161, respectively but all the series to a satisfactory level of stationarity for further analysis. Therefore, the ADF tests' findings support this research that the percentage change in prices and trading volumes for all indices are stationary at the 1% level of significance to avoid spurious data in subsequent autoregressive models. Therefore, it can be concluded that they are suitable for time series modelling, improving forecast accuracy and hence the econometric findings (Pedisic, 2022). ***[Refers to Appendix 6, pp.104]***

3.5 Volatility

The application of the techniques of the regression from the ARCH family to examine different market indices from January 01, 2020, to March 02, 2023, gives an understanding of the volatility and dynamics of the indices. Every regression model applies Gaussian distribution, which is calculated using a pooled sample of 1157 for all indices.

- ALL SHARE FTSE Index: The coefficient of the dummy constant term for the daily percentage change is 0.0436821 and the p-value of 0.099 suggests that the intercept is insignificant at 5% level. The ARCH term (L1) is significant (p = 0.000) which suggests the ARCH effect in the residuals with a coefficient of 0.1430789 for the mean equation.

It has been shown that the GARCH term (L1) is also significant (p = 0.000) with a coefficient of 0.7972059 indicating high volatility persistence. This suggests that deviations in the volatility within the ALL-SHARE FTSE Index are likely to be self-perpetuating in nature.

- UK FTSE 100 Index: As in the case of ALL SHARE FTSE Index the constant term for the UK FTSE 100 daily percentage change is also positive but insignificant, 0.0340446 (p = 0.204). The L1 coefficient in ARCH (0.1393742) and GARCH (L1) coefficient of 0.8071501 *** are positive, suggesting that both, short-run volatility (ARCH) and long-run (GARCH) volatility exist in this index also (Wang *et al*. 2020).
- Sensex: The constant of the daily percentage change in Sensex has emerged as highly significant with a coefficient of 0.0954924 (t=0.000). The L1 ARCH coefficient = 0.1385703 (p = 0.000), and the L1 GARCH coefficient = 0.8341062 (p = 0.000) indicating that volatility is persistent and is statistically significant for this index.
- Nifty 50: The Nifty 50 also presents a highly significant constant term of 0.0949884 (p = 0.000). L1 ARCH coefficient is 0.1405605(p = 0.000) while the L1 GARCH coefficient is 0.8300059 (p = 0.000). This means that the Nifty 50 index is volatile in both the short-run and long run and by the GARCH term, which most probably indicates that volatility in the future depends on volatility in the past.
- CSI 300: This makes the constant term for the daily percentage change in the CSI 300 equal to—0.0097989, but since the calculated p-value equals 0.759, there is no evidence of a positive trend in the data. However, the coefficient of ARCH (L1) is = 0.1155266 and p = 0.000, and the GARCH (L1) is = 0.8375196, p= 0.000. This means that though the daily fluctuation is not very large, volatility is alive and kicking in this index.
- SSE: The SSE index, therefore, has a constant term of 0.0009941 (p = 0.972), which can be deemed statistically insignificant. However, the coefficient of ARCH (L1) is 0.159175 (p = 0.000 and for GARCH (L1) is 0.7497144 (p = 0.000). This shows that there exists great fluctuation even though the average actual return is not very impressive.

The results show that most indices possess high variability, proving both ARCH and GARCH parameters to be statistically significant. This simply means that past volatility determines future volatility which is evidence of volatility clustering in these market indices.

- ALL SHARE FTSE Index: The coefficient of the dummy constant term for the daily percentage change is 1.02×10^9 with a p-value of 0.000, suggesting that the intercept is significant. The ARCH term test (L1) is also significant ($p = 0.000$), suggesting that the residuals exhibit ARCH with a coefficient of 0.6651 for the mean equation. The GARCH term (L1) is also statistically significant at the 1 percent level with a coefficient of 0.0527 implying high volatility persistence. This implies that shocks in variance within the ALL-SHARE FTSE Index are going to be persistent in shock where they begin.

- UK FTSE 100 Index: The regression model results for the UK FTSE 100 daily percentage change show a constant term of 6.57×10^8 (robust $p = 0.000$), making it significant. The estimated L1 in the ARCH equation is 0.5854 ($p = 0.000$) indicating short-term volatility and the estimated L1 in the GARCH equation is 0.0139 ($p = 0.405$) showing that long-term volatility is not statistically significant in this index.
- Nifty 50: The Nifty 50 also displayed a large and positive constant term of 2.93×10^8, ($p = 0.000$). The coefficients of L1 ARCH are 0.3444 with $p = 0.000$ while the L1 GARCH coefficients are 0.6291 with $p = 0.000$. This means that the Nifty 50 index presents short-term as well as long-term fluctuation and with the help of the GARCH term which depicts that the future variation in the Nifty 50 depends very much on past variation.
- CSI 300: The daily percentage change in the CSI 300 has a constant term of 1.31×10^{10} ($p = 0.000$), therefore it signifies the model. ARCH (L1) estimate is 0.6080 ($p = 0.000$) and GARCH (L1) estimate is 0.2892 ($p = 0.000$). That is, while the changes from day to day may not be significant, it is still possible to speak about rather significant volatility in this index (Wang *et al*. 2020).
- SSE Index: The first coefficient of the daily percentage change in the SSE Index is 2.89×10^{10}, and the p-value is 0.000 highlighting significance. The ARCH (L1) coefficient is 0.6070 ($p = 0.000$), this reveals a very high short-run volatility effect while the GARCH (L1) coefficient is 0.2683 ($p = 0.000$) implying that the volatility is continuing in the long run. This leads to the conclusion that movements in the SSE Index are not small and reveal that volatility clusters.

These findings reveal most of the examined indices to exhibit great variation and confirm both the ARCH and GARCH coefficients. This goes further to mean that past high or low volatility will lead to future high or low volatility respectively in these market indices meaning that there is evidence of volatility clustering. ***[Refers to Appendix 7, pp.105-110]***

3.6 Johansen Test

Percentage Daily Changes

Rank 0: The trace statistic amounts to 4,953.05 while the critical value is 94.15, a clear suggestion that there is at least one cointegrating relationship between indices.

Rank 1 to 5: The trace statistics reduce but are still above the critical levels to support up to five cointegrating relationships.

Rank 6: No other cointegration is apparent because the trace statistic turns out to be insignificant.

Daily percent alteration has a strong connection between the global financial interconnection and market spillover effect for short-term variations.

Absolute Price Levels

Rank 0: The trace statistic (4,867.77) is greater than the critical value and thus we can reject the null hypothesis of no cointegration.

Rank 1 to 5: Cointegration continues to maintain itself as all the trace statistics continue to fall above the thresholds.

Rank 6: As for the latter, the authors find that no other cointegration is discernible.

Real prices are also highly persistent and trend stationary, indicating that markets share a degree of forever love. Fluctuations with one index are more likely to be reflective of the fluctuations of another in the long-term.

Trading Volumes

Rank 0: The trace statistic equalled 1,947.45, which is more than the critical value, so there is cointegration.

Ranks 1 to 3: Granger causality tests reduce but are still statistically significant.

Ranks 4 to 5: Cointegration decreases as the trace statistics are below the critical values.

Liquidity measures show fewer permanent relations with trading volumes than with price levels or percent changes indicating regional or market factors that influence liquidity (David *et al*. 2021).

Overall Implications

The results also reveal long-run co-integrating relationships in levels and first-difference terms between the ASX All Shares Index and other indices. Such findings demonstrate that regional changes in financial markets have an impact on the global trends. But trading volumes are less correlated which can suggest localized liquidity. This analysis is useful for investors who make cross-country investments and for those who would want to compare strategies between different markets. ***[Refers to Appendix 8,pp.111, Appendix 9, pp.112, Appendix 10, pp.113]***

3.7 ARIMA model

The data regressed based on the first ARIMA model includes various financial characteristics: indices, traded quantities, as well as the daily percentage changes and several others from January 01, 2020 to march 02, 2023. All these ARIMA models are restricted to the autoregressive element at lag 1 (L1), constant and the estimated variance: σ In fact, ARIMA models address both trend and volatility.

The returns on the ALL-SHARE FTSE Index and the S&P BSE Sensex are shown by PX LAST ALL SHARE FTSE Index All FTSE and PX LAST Sensex and they have high auto regressive parameters of 0.9932 and 0.9995 respectively depicting that index has high value dependence on its previous value. The standard deviations (σ) depicting the amount of volatility of these indices are 39.97 for ALL SHARE FTSE and 581.80 for Sensex. Time series relationships in both models are statistically significant with high Wald chi-squared statistics and p-value of approximately 0.000 (Assmus *et al*. 2020).

The trends like CHG_PCT_1D_Nifty50 and CHG_PCT_1D_SSE illustrate lower value of autoregressive feature. The regression results indicate that the mean reverts in Nifty50 with

AR(1) coefficient -0.0723 while the SSE has AR(1) = 0.0398 Both of them depict that there is some but however restricted degree of outliers in reference to the past values; however, the variance figures of 1.22 and 1.08 argue suggestive of moderate fluctuation in case of Nifty 50 and SSE respectively. The Wald chi-squared statistic of 5.84 for CHG_PCT_1D_SSE proves the importance of the model but has a relatively weaker probability fit than others.

Analysed in terms of trading volumes, the AR(1) coefficients for the variables PX_VOLUME_UKX_FTSE_100 and PX_VOLUME_SSE moderate to high, which means trading volumes have a clear tendency of persistence over time. This can be attested by their large variance values which mean high volatility in the trading process. The presented strong Wald chi-squared statistics for these models are indicative of the robustness of the ARIMA framework on these forms of volume dynamics.

The analysis based on the models demonstrated the high level of persistence of closing indices, as well as higher volatility of daily percentage change indices which could be explained by short-term factors. Fluctuations in trading volumes are only moderately related to previous trading volumes, indicating that movement is continuous. Most of the models with the Wald chi-squared statistic show good fitness, and all of the models except for the CHG_PCT_1D_SSE show statistical significance on the 0.05 level; still, the last one presents a slightly worse fitness with the Wald chi-squared = 1393,399, p < 0,0001. The insights here provide investors with dangerous weapons in their forecasting arsenal, enabling one to forecast the risks in the market. ***[Refers to Appendix 11, pp.114, Appendix 12, pp.115, Appendix 13, pp.116, Appendix 14, pp.117, Appendix 15, pp.118, Appendix 16, pp.119]***

Time Series analysis

The six panels give time series line plots of the historical and forecasted values of some volumes of financial indices and trading. Each plot encompasses various aspects of market behaviour, for example, price fluctuations, changes in percentage and the volumes, and the forecast is supposed to embody these characteristics.

An analysis of the ALL-SHARE FTSE Index Forecast reveals a kind of oscillation around zero, which can be attributed to the wind power characteristic of the functions after excluding they-intercept terms The forecasted values correlate closely with the actual historical data. This means that there is no discernible long term up or down trend, hence evidence that the index reverts to the long-term average. The forecasted range is still again s rendered narrow showing just how accurate this model is when it comes to further prediction. This is evident from the first-differenced ALL SHARE FTSE, All FTSE index where step shows apparent high frequency oscillations around zero with occasional large values. Differencing essentially strips off any long-term components or trends from the series–an aspect that brand this series as useful for modelling short-term variation rather than trend. The forecast also retains similar fluctuations, which indicates that the model estimates the stochastic nature of the disturbance appropriately (Assous *et al*. 2020).

The plots of first-differenced Sensex index (D_Sensex) exhibit a much higher variability than that of the simplest growth models; their values indicate several moments of maximum variations, mainly observed in the period of 2021 and the beginning of 2023. The same can be said for the forecast that oscillates at the same level, which means that the model gives good short-term variability. Despite all of that, the volatility does not flatten, and supposes large deviations publicity, which indicates the sensitivity to the shocks of the market.

The daily percentage variation of the Nifty50 index (CHG_PCT_1D_Nifty50) is symmetrically distributed with the mean value equaling zero with steep up and down moving's occasionally.

The forecast also follows a similar pattern of random walk like movement, thus capturing the daily volatility well. Here, factors reveal that even percentage fluctuation is small, is consistent over time, which is in accordance with normal movement of market. In the case of FTSE 100 trading volume (PX_VOLUME_UKX_FTSE_100), have several significant spikes, and these spikes are quite visible in the forecasted value. Thus, there is a consistent increase in the correlation, confirming that the volume data has an autoregressive characteristic of high volumes in the future. This persistence characteristic is captured well by the model in the context of using trading volume forecasts.

Again, the PX_VOLUME_SSE for the trading volume at the SSE displays a great variation and these are characteristics of occasional spike. The forecast of such trends also shows high levels of autocorrelation of these patterns. The model of trading activity is accurate in capturing the persistence and indicates that similar levels of activity may occur in future periods as have been observed in prior periods. In general, the forecasts coincide to a large extent with historical trends inside every index as well as trading volumes. From this comparison the models appear particularly suited to short horizon forecasting and they manage the aspects of volatility and persistence well. However, large outliers, and long-term fluctuations are problematic in this regard because of a failure to adjust for structural shifts or sudden market shocks. From these findings, it can be inferred that although the models give fairly accurate estimates, they could be effective for decision making especially for fixed or cyclical situation; they may need fine tuning for the unpredictable or fluctuating market environments.

3.8 Technical Analysis (TA) strategy

The MACD and Bollinger Bands are two of the most crucial indicators when it comes to making informed TA choices. MACD determines momentum change while Bollinger Bands analyse the market’s volatility adding an extra layer of conformation to trade signals. This approach avoids generating false signals because signals need both indexes to be high and low to take good entries and exits (Chio, 2022). If backtested from 2020 to 2023 and one of the most flexible strategies in terms of choosing stop-outs, it did prefer trending and volatile markets. The use of this strategy helps get more accurate entries for breaks out or break down with lower risks. Its total concentration is thus process-oriented and analytical, leading to improved accuracy on trade and better profitability.

All Share FTSE ASX

Backtesting Results Summary

Backtest From	Statistics	Long	Short	Total
01-01-2020	Trades	6	7	13
01-01-2023	Wins	3	2	5
	Losses	3	5	8
	P&L	2.86k	-196.97	2.66K
	%P&L	2.88	-0.2	2.66
Additional Stats				
	Avg P&L	476.89	-28.14	204.95
	Total Wins	10.79K	24.21K	35K
	Total Losses	7.93K	24.41K	32.33K
	Avg Wins	3.6K	12.1K	7K
	Avg Loss	2.64K	4.88K	4.04K
	Max Win	5.85K	19.36K	19.36K
	Max Loss	3.14K	7.11K	7.11K
	Num Bars	315	438	753
	Avg Duration			57.92
	SharpeRatio			0.1
	Sortino Ratio			0.12
	Total Return			2.66
	%Max Return			34.16
	%Min Return			-7
	%Winning Ratio			38.46
	%Losing Ratio			61.54
	%Max DD			30.68
	Max DD Length			477
	Recover From Max DD			N/A
	Max DD Recover Period			N/A
	%Max Increase			34.16
	Max Increase Length			57

Total Return Analysis From 01/02/2020 - 01/03/2023

Holding Strategy		Total Retı	AnnualEq	Gain/Loss
Price Change		-2.3690%	-7.9460%	-100.25
Divs Reinvested In the Index		7.5803%	2.4609%	+320.772
Dividends Reinveste	4.7078%	6.6675%	2.1708%	+282.1446

Figure 3.2: ASX Back test Results

(Compiled by the Author based on Bloomberg Terminal Back-testing Feature)

Hence, the performance of ASX backtest was reasonable with total P&L \$2.66 k, that was mainly contributed by long trades with average profit of \$ 476. 89. It is also evident from a winning ratio of 38.46% that the portfolio is highly susceptible to low volatility with a draw down of 30.68%. The risk adjusted returns are still suboptimal proven by the Sharpe ratio of 0.1. The state of affairs indicate the need for stronger risk management measures like stop loss as well as evaluation of trends in trend following models so that risk measures are enhanced to prevent increased losing streaks.

UKX FTSE - 100

Backtesting Results Summary

Backtest From	Statistics	Long	Short	Total
01-01-2020	Trades	6	7	13
01-01-2023	Wins	3	2	5
	Losses	3	5	8
	P&L	797.63	-1.82K	-1.02K
	%P&L	0.8	-1.82	-1.02
Additional Stats				
	Avg P&L	132.94	-259.61	-78.43
	Total Wins	7.9K	21.34K	29.25K
	Total Losses	7.11K	23.16K	30.27K
	Avg Wins	2.631K	10.67K	5.85K
	Avg Loss	2.37K	4.63K	3.78K
	Max Win	4.76K	19.12K	19.12K
	Max Loss	4.13K	6.07K	6.07K
	Num Bars	282	471	753
	Avg Duration			57.92
	SharpeRatio			0.02
	Sortino Ratio			0.02
	Total Return			-1.02
	%Max Return			33.7
	%Min Return			-7.96
	%Winning Ratio			38.46
	%Losing Ratio			61.54
	%Max DD			31.15
	Max DD Length			477
	Recover From Max DD			N/A
	Max DD Recover Period			N/A
	%Max Increase			33.7
	Max Increase Length			57

Total Return Analysis from 01/02/2020 - 01/03/2023

Holding Strategy		Total Retu	AnnualEq	Gain/Loss
Price Change		-.6603%	-.2202%	-50.2100
Divs Reinvested In the Index		10.2381%	3.2963%	+778.5342
Dividends Reinvested At	4.7229%	9.4416%	3.0474%	+717.9651

Figure 3.3: UKX Back test Results

(Compiled by the Author based on Bloomberg Terminal Back-testing Feature)

The backtest using the UKX resulted in the total losing $1.02k mainly from the short trade - $1.82k P&L. The Sharpe ratio of 0.02 and the losing ratio of 61.54% imply that the system had a problem to perform in conditions conducive to the market. The annualized return of the return with reinvestment was slightly positive when dividends were assumed to be reinvested indicating possible worth in value-screening dividend strategies. Strategies proposed aim at retrofitting the short trade approach and increasing the likelihood of using methods with better profit margins during declining markets such as mean reversion.

Nifty 50

Backtesting Results Summary

	Statistics	Long	Short	Total
Backtest From	Trades	6	7	13
01-01-2020	Wins	5	3	5
01-01-2023	Losses	1	4	8
	P&L	41.29K	-17.33K	23.96K
	%P&L	41.29	-17.33	23.96
Additional Stats				
	Avg P&L	6.88K	-2.48K	-78.43
	Total Wins	49.32K	18.25	29.25K
	Total Losses	8.03K	35.58K	30.27K
	Avg Wins	9.86K	6.08K	5.85K
	Avg Loss	8.03K	8.9K	3.78K
	Max Win	14.36K	15.05K	19.12K
	Max Loss	8.03K	17.53K	6.07K
	Num Bars	398	338	736
			Avg Duration	56.62
			SharpeRatio	0.55
			Sortino Ratio	0.66
			Total Return	23.96
			%Max Return	41.26
			%Min Return	-3.95
			%Winning Ratio	61.54
			%Losing Ratio	38.46
			%Max DD	23.42
			Max DD Length	297
			Recover From Max DD	N/A
			Max DD Recover Period	N/A
			%Max Increase	47.07
			Max Increase Length	234

Total Return Analysi: From 01/02/2020 - 01/03/2023

Holding Strategy	Total Ret	AnnualEq	Gain/Loss
Price Change	48.4469%	14.0476%	+5.9504K
Divs Reinvested In the Index	54.7183%	15.6286%	+6.7206K
Dividends Reinveste 6.3900%	53.7252%	15.3812%	+6.5986K

Figure 3.4: Nifty 50 Back test Results

(Compiled by the Author based on Bloomberg Terminal Back-testing Feature)

The Nifty 50 backtest showed a robust total return of $23.96k, supported by a 61.54% winning ratio and strong long trade performance (P&L: $41.29k). Their Sharpe ratio is 0.55, which shows that portfolio has reasonable amount of risk relative to its returns and the maximum draw down of the portfolio is 23.42% which reveals that the portfolio is exposed to moderate risk. From these outcomes, it would be possible to conclude that the current strategic orientation has its basis in the overall market. Improvements might concern the application of momentum approaches and increasing effectiveness of trading periods for greater profitability.

Sensex

Backtesting Results Summary

	Statistics	Long	Short	Total
Backtest From	Statistics	Long	Short	Total
01-01-2020	Trades	6	7	13
01-01-2023	Wins	5	2	7
	Losses	1	5	6
	P&L	37.54K	-12.43K	25.11K
	%P&L	37.54	-12.43	25.11
Additional Stats				
	Avg P&L	6.26K	-1.78K	1.93K
	Total Wins	45.54K	15.89K	61.43K
	Total Losses	7.99K	28.32K	36.32K
	Avg Wins	9.11K	7.95K	8.78K
	Avg Loss	7.99K	5.66K	6.05K
	Max Win	16.94K	13.14K	16.94K
	Max Loss	7.99K	10.82K	10.82K
	Num Bars	402	334	736
			Avg Duration	56.62
			SharpeRatio	0.61
			Sortino Ratio	0.72
			Total Return	25.11
			%Max Return	40.83
			%Min Return	-3.39
			%Winning Ratio	53.85
			%Losing Ratio	46.15
			%Max DD	18.52
			Max DD Length	115
			Recover From Max DD	N/A
			Max DD Recover Period	N/A
			%Max Increase	45.77
			Max Increase Length	416

Total Return Analysis from 01/02/2020 - 01/03/2023

Holding Strategy		Total Reti	AnnualEq	Gain/Loss
Price Change		47.2475%	13.7402%	+19.6676k
Divs Reinvested In the Index		52.4563%	15.0634%	+21.8358k
Dividends Reinvested At	6.3900%	51.6549%	14.8618%	+21.5022k

Figure 3.5: Sensex Back test Results

(Compiled by the Author based on Bloomberg Terminal Back-testing Feature)

The Sensex backtest resulted in a total return of 2511 USD with long trades adding to the P&L' of 3754 USD. The maximum drawdown amounted to 18.52%, and it is nearly impossible to build a system with high returns that has a lower maximum drawdown, and the Sharpe ratio was 0.61. Short trades on the other hand posted negative results regularly this implying that there were inefficiencies in being able to capture bearish prices. Some of the solutions involve getting a varied short ideas list and getting the right point of entry to leverage on any available market swing without compromising the portfolio's position.

SSE Composite (SHCOMP)

Backtest From 01-01-2020 01-01-2023

Backtesting Results Summary

Statistics	Long	Short	Total
Trades	9	8	17
Wins	3	2	5
Losses	6	6	12
P&L	-7.13K	-10.34K	-17.47K
%P&L	2.88	-10.34	-17.47
Additional Stats			
Avg P&L	-792.66	-1.29K	-1.03K
Total Wins	19.02K	9.81K	28.83K
Total Losses	26.16K	20.15K	46.3K
Avg Wins	6.34K	4.9K	5.77K
Avg Loss	4.36K	3.36K	3.86K
Max Win	12.71K	7.1K	12.71K
Max Loss	10.83K	4.96K	10.83K
Num Bars	381	363	744
		Avg Duration	43.76
		SharpeRatio	-.42
		Sortino Ratio	-.48
		Total Return	-17.47
		%Max Return	3.89
		%Min Return	-28.06
		%Winning Ratio	29.41
		%Losing Ratio	70.59
		%Max DD	30.76
		Max DD Length	238
		Recover From Max DD	N/A
		Max DD Recover Period	N/A
		%Max Increase	31.9
		Max Increase Length	219

Total Return Analysis from 01/02/2020 - 01/03/2023

Holding Strategy		Total Return	AnnualEq	Gain/Loss
Price Change		1.0150%	.3366%	+31.3140
Divs Reinvested In the Index		8.4965%	2.7505%	+262.1343
Dividends Reinveste	6.3900%	9.3798%	3.0280%	+289.3857

Figure 3.6: SHCOMP Back test Results

(Compiled by the Author based on Bloomberg Terminal Back-testing Feature)

In the SHCOMP backtest, the net profit was negative of $17, 470 and is at the bottom in the list of various indices. Every single longer trade and short trade had a negative average P&L of -$1.03k. Although the outcome indicated that dividends have improved returns by a small margin, risk-reward ratios depicted by Sharpe ratio as well as Sortino ratio were negative. This performance indicates a call for a complete change of the strategy where the firm deploys machine learning based predictive models and invests in less volatile securities.

CSI 300

Backtest From 01-01-2020 01-01-2023

Backtesting Results Summary

Statistics	Long	Short	Total
Trades	7	6	13
Wins	2	3	5
Losses	5	3	8
P&L	-4.28K	-1.27K	-5.56K
%P&L	-4.28	-1.27	-5.56
Additional Stats			
Avg P&L	-612.01	-212.17	-427.47
Total Wins	16.87K	15.78K	32.64K
Total Losses	21.15K	17.05K	38.2K
Avg Wins	8.43K	5.26K	6.53K
Avg Loss	4.23K	5.68K	4.77K
Max Win	14.06K	9.53K	14.06K
Max Loss	11.13K	6.6K	11.13K
Num Bars	319	421	740
		Avg Duration	56.92
		SharpeRatio	-0.06
		Sortino Ratio	-0.06
		Total Return	-5.56
		%Max Return	11.18
		%Min Return	-23.57
		%Winning Ratio	38.46
		%Losing Ratio	61.54
		%Max DD	27.42
		Max DD Length	228
		Recover From Max DD	N/A
		Max DD Recover Period	N/A
		%Max Increase	45.48
		Max Increase Length	231

Total Return Analysis from 01/02/2020 - 01/03/2023

Holding Strategy		Total Retu	AnnualEq	Gain/Loss
Price Change		-6.3662%	-2.1649%	-264.3400
Divs Reinvested In the Index		-.4536%	-.1512%	-18.8362
Dividends Reinveste	6.3900%	0.4167%	0.1384%	+17.3011

Figure 3.7: CSI300 Back test Results

(Compiled by the Author based on Bloomberg Terminal Back-testing Feature)

The CSI300 backtest conducted between 1st January, 2020, and 1st January 2023, showed the overall loss of $5.56k, loss through long trades being -$4.28k and through short trades, -$1.27k. The proportion of winning was 38.46:100 while the proportion of the losing cases was 100: 61.54. The average profit or loss per trade was -$427.47 or an annualized -$2,692k; maximum drawdown was to 27.42% over 228 bars of profit. Other two ratios; the Sharpe and Sortino ratios were both -0.06 implying that the firm's risk adjusted returns were subpar. As painful as it is, dividends reinvestment slightly reduce the loss but the overall strategy underperformed due to inefficiencies in gaining from the market up moves in this highly volatile market. Future performances need positive changes made in strategic development and preparing meaningful risk prevents.

Engaging in TA within the context of equity markets offers a demonstration of how the approach typically has Index direction indicate period consistency in profitability, that is versatility of the strategy, Look at its weakness also. The back testing results are evident, in a way that TA can make whopping amounts of money in the up-trending or the down-trending markets such as Nifty 50 & Sensex in case of India making a strong stand to the momentum style of investment. However, poor trading in SHCOMP, UKX, and CSI300 has been attributed to inefficiency while in volatile or oscillating market periods. However, if combined with the sound risk management, TA offers profit opportunities and, due to the flashing performance, means to further adjust are a reason to persistently question that technical analysis can be a reliable method to make regular profits in the markets.

3.9 Interpretation of result

Based on the values of financial indices and coefficients from ARCH, GARCH, Johansen cointegration tests, and ARIMA models, it is possible to understand the level of volatility, the interconnectedness and persistence across the worldwide markets. In its turn, such results give useful information about the markets' behaviour in the short and long terms, which is significant for different groups of consumers, including investors and politicians.

In this research we have identified and explained several ARCH-and-GARCH-based models used in volatility analysis.

The use of ARCH and GARCH models confirms that the majority of the indices considered in this study present high levels of volatility clustering. The ALL-SHARE FTSE Index, Sensex and Nifty 50 have relatively high coefficients in GARCH terms that suggests a volatility of time. This means that states both of high and low volatility are maintained, which relates well to the theory of volatility clustering. On the other hand, such indices as UK FTSE 100 exhibit a statistically insignificant GARCH term in the long-term mean, which would indicate lower persistence of volatility. Short term oscillation in the SSE and CSI 300 indices are moderately fluctuating and the findings highlight that previous change has a meaningful impact on future changes.

These results reaffirm the need for both ARCH and GARCH models with respect to observing short term innovations and the enduring impact of volatility. Such models help in improved risk management and prevalence of forecasts that can be used by investors to forecast market movement patterns based on past volatility data.

Market Integration and Co-integration

Regarding the Indices, the Johansen's cointegration test shows highly significant correlation levels where the indices include up to five different cointegrating relationships in the percentage daily changes and absolute price levels. This implies that integral interconnection of global financial markets exists and that alterations in one market will be transmittable to others. For instance, the ASX All Shares Index demonstrates that this index has been embodied and integrated with other indices in the long-term picture as the regional as well as global financial indexes. Nonetheless, trends in the volume of trades demonstrate comparatively diminished cointegration to price levels and percentage shift. This means that liquidity flow and pattern are rather dictated by local market forces than global trends. It also opens up an understanding of how global connectivity interacts with local liquidity to affect investors' decision making.

Integrating the Technicals for the Purpose of Analyzing Profitability

This research majorly assess financial indices with statistical models, namely, ARCH, GARCH, Johansen cointegration tests, and ARIMA. Despite the effectiveness of these model in capturing the characteristics of volatility clustering, market integration and self-similarity structure of returns series, it is robust to note that they complemented with some technical indicators to test their efficiency in real world profitability. Such a focus on volatility clustering, cointegration, and autoregressive trends provides for the comprehending of market behavior, yet incorporating technical analysis to describe the outcomes of these strategies can show profit-making potential more convincingly.

Volatility and Profitability: Implication from ARCH/GARCH Models

The results using the ARCH and GARCH models support the existence of high volatility clustering in indices such as the ALL-SHARE FTSE, Sensex and Fifty although volatility is characterized as “clustered” it repeats the same volatility levels. This characteristic is useful in technical analysis because it prescribes the possibility of earning money from foreseeable volatile ranges. In contrast, the UK FTSE 100 has relatively low and insignificant coefficients for GARCH terms, which points to low volatility clustering and therefore during trading, technical traders may find it difficult to predict the movement of the market. These patterns of volatility clustering which has been observed in the developed markets fit into the technical analysis medium term mean reversion principle. For example, if markets with volatile price movements have frequent sharp price fluctuations, then the use of Bollinger Bands or the Moving Average Convergence Divergence (MACD) Charting technique can be used to take advantage of such fluctuations. However, where the volatility characteristic is less persistent, as evidenced in the UK FTSE 100 for instance, the technical indicators will come with less than optimal results given the decrease in market anomalies.

Market Integration: Arbitrage opportunities: prospect and pitfalls

Finally, the Johansen cointegration test points to up to five cointegrated links between at least more of these indices, which points to long-run interaction between the global markets. Given this connectivity, specialists can take advantage of the fact that price movements in one market can be used to influence another market offering the traders an arbitrage opportunity. However, by applying the trading volume, the evidence for cointegration is relatively week to support the idea of price synchronization in trading activity, which technical analysis needs to consider in conformity with volume driven price movement.

This presents an important implication for technical analysis. In detail, price-based strategies may produce successful outcomes because of cointegration despite the fact that volume-based strategies may perform worse in markets that exhibit local effects. The strong cointegration relationships point to appreciable arbitrage opportunity that defines the potentials of strategies such as pairs trading but simultaneously, the results raise an alert on the volume indicators which if depended on can lead to an aviators loss.

ARIMA Models And Short Term Forecasting

In indices like Sensex and ALL-SHARE FTSE the self-starting value of ARIMA models are also high which also implies that the market has become stabilized and the prices are being largely determined by previously set benchmarks. These findings compliment the technical analysis approach that involves the estimation of future stock price by reverse contouring from prior data in the belief that systematic behaviors can be capitalized on in the short run. Nevertheless, because of the moderate autoregressive parameters of frequently used technical indicators in emerging markets such as SSE and Nifty 50, it is difficult completely to avoid or oppose technical analysis in general applying for the various maturity of the markets.

Preliminary conclusions from the described observations are concerned with adapting technical analysis strategies to the emerging markets' autoregression coefficient, which is lower than that apparent in developed markets. This raises particular questions about the relevance of some standard technical indicators, particularly in the markets that are in a less developed state in their economic or in terms of regulation.

Implication for Investment and Policy Making

The findings of the study indicate that integrated technical analysis is good in high volatile and cointegrated markets. These market characteristics inform the manner in which an institutional investor chooses his strategies when volatility clustering and autoregressive conditional features are particularly evident in the markets in which the investor operates. Nonetheless, technical analysis can be inaccurate in more efficient or less volatile markets where other methods are required to be used concurrently with technical analysis or as an independent method. In order to regulators, the studies on market integration and cointegration suggest that even as M&As escalate cross border market spillovers, consistent policy across borders is needed to avoid a domino effect. With trading volume being indicative of global integration having a weaker rebound, researchers propose local policies that may be necessary for conditions in those specific markets.

Technical analysis profitability under certain conditions

The findings of the paper support the conclusion that, although technical analysis may execute a profitable performance under specific market conditions, its applicability and effectiveness depend heavily on such conditions. Thus, technical analysis can be rather useful in the markets that reveal high volatility and integration. This, however, disqualifies technical strategies in efficient, low-volatile markets or emerging markets with moderate auto-regressive patterns. Thus, technical analysis has to be considered as an addition to other investment techniques; its efficiency depends on market conditions and the level of its development.

Model	*Previous Research*	*Outcomes of this research*	*Comparison & Interpretation*
ARCH/GARCH	Found significant volatility clustering in financial indices, with persistence in markets such as the S&P 500 and FTSE 100 (Dey, 2022).	Indices such as ALL SHARE FTSE, Sensex, and Nifty 50 exhibit strong volatility clustering and persistence.	Consistent with previous research for most indices, confirming the presence of volatility clustering.
	High GARCH terms indicated long-term volatility spillovers (Endri *et al*. 2020).	UK FTSE 100 showed insignificant GARCH terms.	UK FTSE 100 deviates, suggesting regional variations.
Johansen Cointegration	Established significant cointegration among major indices, especially during financial crises (Gordon, 2020).	Found up to five cointegrating relationships in daily percentage changes and price levels.	Aligns with prior findings of strong cointegration in price levels but highlights weaker volume integration, possibly due to local factors.
	Long-term price convergence noted in global indices like DAX and Nikkei.	Weak cointegration in trading volumes compared to price indices.	
ARIMA	Demonstrated strong autoregressive patterns in developed markets like the Dow Jones and S&P 500.	High autoregressive parameters observed for indices like Sensex and ALL SHARE FTSE.	Results are comparable for indices with strong autoregressive features.
	ARIMA models effectively captured short-term trends and cyclical behaviours (Billah *et al*. 2024).	Moderate parameters for indices such as SSE and Nifty 50.	Moderate ARIMA coefficients reflect unique dynamics in emerging markets.
Trading Volumes	Previous studies suggest lower cointegration in trading volumes compared to price indices.	Confirmed weak cointegration in trading volumes.	Matches earlier research, reinforcing the observation that trading volumes are influenced more by local factors than global market conditions.
	Volumes tend to reflect local market conditions rather than global trends (Derbali, and Lamouchi, 2020).	Moderate variance in ARIMA models for volumes, indicating limited fluctuation.	

Analysed models like ARCH/GARCH do depict a strong evidence of volatility clustering which in a way allows for the sentiment of technical analysis to precisely capture predictable patterns in equity markets that could result in profits. Similarly, the result obtained from the Johansen method of cointegration test means that long-run relationship exist between price indices that facilitate the opportunity of arbitrage among the global indices. However, trading volume which has a weaker Cointegration raises concerns about the validity of the technical analysis across diverse contexts; moderate ARIMA parameters in emerging markets also pose questions on the validity of the technical analysis. A comparison of results in developed and emerging markets underlines the sensitivity of the results represented by technical analysis to the market's maturation level and regional attributes.

Lastly, therefore, though technical analysis gives indications of when particular market anomalies exist that can be profited from, its applicability is based on conditions and not absolute. This becomes less accurate in highly efficient markets, therefore, making technical models a less reliable strategy. , it can be concluded that there is evidence that technical analysis offers good possibilities as a Profit generation tool in certain situations although it may be a suboptimal strategy in others especially in low volatile or efficient markets.

Conclusion and Discussions

1. Profit Potential in Volatile Markets

These findings validate the efficiency of technical analysis in volatile markets because patterns of volatility tend to recur. The application of such charts and indicators increases predictive ability and provides good investment returns in such circumstances.

2. Market Interconnectedness and Trend Predictability

Hence, by employing the Johansen cointegration test, the paper also established that financial markets are integrated and that, therefore, technical analysis is useful in predicting market trends across borders.

3. Limited Effectiveness in Low-Volatility Markets

This paper shows that technical analysis is less accurate in low volatility or efficient markets since it is difficult to capture trends, indicating that factors of the market plays a crucial role in making it function.

4. Questionable Role of Trading Volume

It was discovered that trading volume tries to explain less than prices in especially the emergent markets where local forces reign leaving its appropriateness in technical analysis a huge question mark.

5. Market Maturity and ARIMA Models

Based on building ARIMA models, it was found that technical analysis works best with maturing markets (for example – Sensex, FTSE) as it successfully identifies the phenomenon of given market history controlling its future behavior. Technical analysis was less useful with emerging markets that were infamous for depicting little or no autoregressive features.

Overall Conclusion

Technical analysis is relative, with great implications for high, low, mature and inter-connected markets. However, they work less well in low volatility, efficient, or emerging markets because, external factors, dominate the price changes.

Recommendations

1.Technical analysis should be targeted at volatile markets

Thus, the proposal is as follows: The investors should use the technical tools predominantly to work with the highly volatile and clustered APT as observed in the ALL-SHARE FTSE, Sensex, and, the Nifty 50. These markets exhibit large reliance on the past prices, thus making the markets more easily manipulable and more technical analysis inclined. Special attention should be paid to the short-term trading, and those technical indicators that are used to determine the moving average, oscillators, and other velocity indicators.

2.Introduce Global Interconnectedness in Trading Policies

The Johansen cointegration test showed that the global financial markets are integrated. This means that the investors have to take time and consider correlations between the Global indices in their decisions. The technical analysis should not be done only for one market but for their interactions as well. Whereas information is available that one or another market rises or declines, and applying modern technologies, investors can track many markets and plan operations with their help, taking advantage of the interdependences in the markets. For example, the systematic analysis of price fluctuations in one market with the purpose to apply this information in another market could increase the effective profit rate.

3.Adapt Technical Analysis for Efficient and Low-Volatility Markets

In highly efficient or low risky markets, including UK FTSE 100, the studies suggest that the technical analysis may not be particularly useful. More emphasis should therefore be placed in analysing such market using fundamental analysis data since past behaviour is not a good predictor of the market’s behaviour in the future. Macroeconomics analysis or Sentiment analysis are but some of the other forms of analysis that the investors should incorporate in their analysis to raise their odds of making the correct decisions on their investments.

4.Amend the Use of Trading Volumes in Technical Analysis

The evidence of weak cointegration found in trading volumes implies that using volume data for analysis in technical trading could be misleading. Most future trading strategies should pay less attention of volume while paying much heed to more of price indicators. Some interesting things that traders can look at might be different measures of volatility or trend-following where they are easier to apply in some markets than others because the local buying and selling action is so dominant.

5.Market-oriented ARIMA Models Improvements

As earlier established by the ARIMA models the autoregressive behaviour is relatively strong in the developed markets but not as effective in the emergent ones; therefore, future work should also engage in developing country-specific or stock market-specific ARIMA models into the analysis. These models would benefit from other macroeconomic factors and the structure of the market that may affect autoregressive operations, for example, interest rates or political events. These elements could be incorporated into adjusting the ARIMA models for enhancing prediction and better presentations of forecasts.

Future Work

1.Develop Hybrid Models for Volatility and Trend Prediction

The research done in the future could involve the development of combined basic and technical analysis models as applied to volatile markets. These models could use parameters like international, political and economic factors and sentiment analysis, along with technical indicators to provide precision. This could be important for the traders who want to get the most of their profits especially in volatile market.

2.Analysing the Various Machine Learning Approaches for Enhancing Forecasting

The implication of the present work to future research is that while other studies have used exogenous variables to examine the effects of market factors, future studies could use neural networks and random forests to analyses the market data. These models can model and estimate market variables when their relationships are non-linear and they are less sensitive to noise than statistical models such as ARIMA.

3.Study on the Effects of Local Market Environment

From the analysis of local factor affecting trading volumes, subsequent study should explore how such factors as economic conditions, regulations and sentiments affect technical analysis results. By including such local factors, researchers would be able to design better trading strategies which are more appropriate to any region or new markets.

Overall, this research reveals the weak signal nature of technical analysis and its level of success in the foreign exchange markets. Thus, it can be concluded that technical analysis is a powerful tool that can provide a lot of useful information, especially in situations where highly unpredictable stock prices are expected to behave in the same manner in the future. However, usefulness lowers with high quality, low volatility or emergent stocks for which price changes are less dependent on prior periods stock price data , more on macroeconomic factors. The information derived from the Johansen cointegration test vegetation of the world's financial markets deepens the rationale for investment consideration of the interconnectivity of the markets. It is now insight that the combining of global phenomena in technical analysis eventually give the investors the most value for their money. However, as revealed in the article, technical analysis still plays a noteworthy role in the financial markets as long as it pertains to the traders working in short-term framework that presides over instable markets. It is important however to adapt the strategy depending on how mature or how stable or the contrary is the market of concerned. Similarly, the combination of using technical, sentiment, or macroeconomic analysis in the given cases also increases the reliability of forecasts, for example, in the developing or less active markets.

Lastly, there is the fact that technical analysis is not an infallible tactic, importance of which to a great extent depends on the situations into which it is integrated. There are so many areas which require further investigation and the future research should aim at employing mix models which utilize technical, fundamental as well as machine learning for the purpose of increasing the accuracies for every condition of the market.

References

Albertus, R. H. (2021). The Effect of Current Ratio, Total Asset Turnover, and Earnings Per Share on Stock Prices in Banking Sub-Sectors Listed on The Indonesia Stock Exchange 2018-2019. *Strategic Management Business Journal*, *1*(02), 30-39.https://journal.smbjupmi.com/index.php/smbj/article/download/19/24

Antony, A., 2020. Behavioral finance and portfolio management: Review of theory and literature. *Journal of Public Affairs*, *20*(2), p.e1996.https://www.researchgate.net/profile/Anu-Antony-7/publication/334765342_Behavioral_finance_and_portfolio_management_Review_of_theory_and_literature/links/5d53bcd192851c93b62e684c/Behavioral-finance-and-portfolio-management-Review-of-theory-and-literature.pdf

Aslam, F., Mohmand, Y.T., Ferreira, P., Memon, B.A., Khan, M. and Khan, M., 2020. Network analysis of global stock markets at the beginning of the coronavirus disease (Covid-19) outbreak. *Borsa Istanbul Review*, *20*, pp.S49-S61. https://www.sciencedirect.com/science/article/pii/S2214845020300521

Assous, H.F., Al-Rousan, N., Al-Najjar, D. and Al-Najjar, H., 2020. Can international market indices estimate TASI's movements? The ARIMA model. *Journal of Open Innovation: Technology, Market, and Complexity*, *6*(2), p.27. https://scholar.google.com/scholar?output=instlink&q=info:9xlSJVdL8rQJ:scholar.google.com/&hl=en&as_sdt=0,5&as_ylo=2020&scillfp=12448663488800965631&oi=lle

Attaran, M., 2022. Blockchain technology in healthcare: Challenges and opportunities. *International Journal of Healthcare Management*, *15*(1), pp.70-83.https://e-tarjome.com/storage/panel/fileuploads/2022-08-15/1660561895_e17081.pdf

Bhowmik, R., and Wang, S. (2020). Stock market volatility and return analysis: A systematic literature review. *Entropy*, *22*(5), 522.https://www.mdpi.com/1099-4300/22/5/522/pdf

Billah, M. M., Sultana, A., Bhuiyan, F., and Kaosar, M. G. (2024). Stock price prediction: comparison of different moving average techniques using deep learning model. *Neural Computing and Applications*, 1-11.https://link.springer.com/article/10.1007/s00521-023-09369-0

Bloomberg - Are you a robot? (no date). https://www.bloomberg.com/.

Braun, V. and Clarke, V., 2021. Can I use TA? Should I use TA? Should I not use TA? Comparing reflexive thematic analysis and other pattern-based qualitative analytic approaches. *Counseling and psychotherapy research*, *21*(1), pp.37-47.https://edisciplinas.usp.br/pluginfile.php/7410289/mod_resource/content/1/Braun%20%20Clarke%20%282020%29%20-%20Can%20I%20use%20TA.pdf

Chio, P.T., 2022. A comparative study of the MACD-base trading strategies: evidence from the US stock market. *arXiv preprint arXiv:2206.12282*. https://doi.org/10.48550/arXiv.2206.12282

CME Group (2024). Oscillators: MACD, RSI, Stochastics. Retrieved from: https://www.cmegroup.com/education/courses/technical-analysis/oscillators-macd-rsi-stochastics.html

David, S.A., Inácio Jr, C.M. and Machado, J.A.T., 2021. The recovery of global stock markets indices after impacts due to pandemics. *Research in International Business and Finance*, *55*, p.101335. https://www.sciencedirect.com/science/article/pii/S0275531920309429?casa_token=co4Vn11pfTEAAAAA:nphcTgVwGMNos5p7nIYnrivP0VnBtn_6npkV-ggzxUhfjH9BDRLfw8BK24VlQSRQcrM3CQm3os8

Derbali, A. and Lamouchi, A., 2020. Global financial crisis, foreign portfolio investment and volatility: Impact analysis on select Southeast Asian markets. Pacific Accounting Review, 32(2), pp.177-195. https://www.emerald.com/insight/content/doi/10.1108/PAR-07-2019-0090/full/pdf?casa_token=3WbUaX7sAGgAAAAA:VN5ZyYsTx6R7aMCxJu5I1nP6puHjVWdkpGD2_I9CeQPj5KAVEiKvT4NSvm-soW5LJuCmPGhp8RN864fcRXOm3xWiaFRZihqNKbVFEP0sAL8R_9n8pb_P

Dey, D., 2022. Domestic financial market integration: a study on inter-linkage amongst Indian money, capital and foreign exchange market (Doctoral dissertation, University of North Bengal). https://ir.nbu.ac.in/bitstream/123456789/4808/4/04_abstract.pdf

Edwards, R.D., Magee, J. and Bassetti, W.C., 2018. *Technical analysis of stock trends*. CRC press.http://www.ftaa.org.hk/Files/2016.pdf#page=77

Endri, E., Abidin, Z., Simanjuntak, T.P. and Nurhayati, I., 2020. Indonesian stock market volatility: GARCH model. Montenegrin Journal of Economics, 16(2), pp.7-17. http://repec.mnje.com/mje/2020/v16-n02/mje_2020_v16-n02-a11.pdf

Fidelity (2024). Bollinger Bands. Retrieved from: https://www.fidelity.com/learning-center/trading-investing/technical-analysis/technical-indicator-guide/bollinger-bands#:~:text=Bollinger%20Bands%20are%20envelopes%20plotted,Period%20and%20Standard%20Deviations%2C%20StdDev.

Flyvbjerg, B., 2021. Top ten behavioral biases in project management: An overview. *Project Management Journal*, *52*(6), pp.531-546.https://journals.sagepub.com/doi/pdf/10.1177/87569728211049046

FX Open, (2023). Problems of Technical Analysis. Available at: https://fxopen.com/blog/en/problems-of-technical-analysis/#:~:text=One%20of%20the%20main%20technical,retracements%2C%20to%20interpret%20price%20charts.(Accessed on: 24th June 2024)

Gordon, D.V., 2020. A short-run ARDL-bounds model for forecasting and simulating the price of lobster. Marine Resource Economics, 35(1), pp.43-63. https://www.journals.uchicago.edu/doi/pdf/10.1086/707063?casa_token=4PCOXIeGK0QAAAAA:oC5ie-enCUn0ILuydMXLvv8bQVZ1r8f1xQpuUjWWpwa1do8U0woAiIMe3Yl7KdNKmLvHUvY7O7eO

Gurjar, M., Naik, P., Mujumdar, G. and Vaidya, T., 2018. Stock market prediction using ANN. *International Research Journal of Engineering and Technology*, *5*(3), pp.2758-2761.https://www.academia.edu/download/56786680/IRJET-V5I3634.pdf

Han, Y., Kim, J., and Enke, D. (2023). A machine learning trading system for the stock market based on N-period Min-Max labeling using XGBoost. *Expert Systems with Applications*, *211*, 118581.https://www.sciencedirect.com/science/article/abs/pii/S0957417422016414

Haque, M.A. and Ahmed, A., 2024. Time Series Modeling and Forecasting on GDP Data of Bangladesh: An Application of Arima Model. International Journal of Latest Technology in Engineering, Management & Applied Science, 13(4), pp.199-207. https://www.researchgate.net/profile/Md-Haque-234/publication/380839871_Time_Series_Modeling_and_Forecasting_on_GDP_Data_of_Bangladesh_An_Application_of_Arima_Model/links/6651aa520b0d2845745841a9/Time-Series-Modeling-and-Forecasting-on-GDP-Data-of-Bangladesh-An-Application-of-Arima-Model.pdf

Hegre, H., Petrova, K. and Von Uexkull, N., 2020. Synergies and trade-offs in reaching the sustainable development goals. *Sustainability*, *12*(20), p.8729.https://www.mdpi.com/2071-1050/12/20/8729

Ibragimov, R., Pedersen, R.S. and Skrobotov, A., 2024. New approaches to robust inference on market (non-) efficiency, volatility clustering and nonlinear dependence. Journal of Financial Econometrics, 22(4), pp.1075-1097. https://academic.oup.com/jfec/article-pdf/22/4/1075/58927485/nbad020.pdf?casa_token=fcTDxHKXYegAAAAA:QpTalkpgqDcNIloxhtaNBs78zp4e_QPwxjJ8XCY_dKIgI3dU50UWmYINWfy6bTieK6NyDegoudZxtgw

Ilham, R.N., Sinta, I. and Sinurat, M., 2022. The Effect Of Technical Analysis On Cryptocurrency Investment Returns With The 5 (Five) Highest Market Capitalizations In Indonesia. *Jurnal Ekonomi*, *11*(02), pp.1022-1035.https://ejournal.seaninstitute.or.id/index.php/Ekonomi/article/download/481/391

Jamil, M. N., Rasheed, A., Maqbool, A., and Mukhtar, Z. (2023). Cross-cultural study the macro variables and its impact on exchange rate regimes. *Future Business Journal*, *9*(1), 9.https://link.springer.com/content/pdf/10.1186/s43093-023-00189-1.pdf

Janssen, M., Weerakkody, V., Ismagilova, E., Sivarajah, U. and Irani, Z., 2020. A framework for analysing blockchain technology adoption: Integrating institutional, market and technical factors. *International journal of information management*, *50*, pp.302-309.https://bradscholars.brad.ac.uk/bitstream/handle/10454/17358/Ismagilova_et_al_IJIM.pdf

Jiang, W. (2021). Applications of deep learning in stock market prediction: recent progress. *Expert Systems with Applications*, *184*, 115537.https://arxiv.org/pdf/3.01859

Kalu, E.U., Arize, A.C., Okoro, O.E., Onaga, F.I. and Alio, F.C., 2020. A cross-country and country-specific modelling of stock market performance, bank development and global equity index in emerging market economies: A case of BRICS countries. *PloS one*, *15*(11), p.e0240482.
https://journals.plos.org/plosone/article/file?id=10.1371%2Fjournal.pone.0240482&type=printable

Khan, S. and Alghulaiakh, H., 2020. ARIMA model for accurate time series stocks forecasting. International Journal of Advanced Computer Science and Applications, 11(7).
https://pdfs.semanticscholar.org/0f86/bc34afa9f222873cc42c4516746a3911342d.pdf

Li, A. W., and Bastos, G. S. (2020). Stock market forecasting using deep learning and technical analysis: a systematic review. *IEEE access*, *8*, 185232-185242.https://ieeexplore.ieee.org/iel7/6287639/8948470/09220868.pdf

Lu, W., Li, J., Li, Y., Sun, A. and Wang, J., 2020. A CNN-LSTM-based model to forecast stock prices. *Complexity*, *2020*, pp.1-10.https://www.hindawi.com/journals/complexity/2020/6622927/

Melović, B., Jocović, M., Dabić, M., Vulić, T.B. and Dudic, B., 2020. The impact of digital transformation and digital marketing on the brand promotion, positioning and electronic business in Montenegro. *Technology in Society*, *63,* p.101425.https://www.sciencedirect.com/science/article/pii/S0160791X20310162

Mertzanis, C. and Allam, N., 2018. Political instability and herding behaviour: Evidence from Egypt's stock market. *Journal of Emerging Market Finance*, *17*(1), pp.29-59.https://www.researchgate.net/profile/Charilaos-Mertzanis/publication/323368416_Political_Instability_and_Herding_Behaviour_Evidence_from_Egypt%27s_Stock_Market/links/5eaaf7b8299bf18b958a55e4/Political-Instability-and-Herding-Behaviour-Evidence-from-Egypts-Stock-Market.pdf

Moghar, A., and Hamiche, M. (2020). Stock market prediction using LSTM recurrent neural network. *Procedia computer science*, *170*, 1168-1173.https://www.sciencedirect.com/science/article/pii/S1877050920304865

Moghar, A., and Hamiche, M. (2020). Stock market prediction using LSTM recurrent neural network. *Procedia computer science*, *170*, 1168-1173.https://www.sciencedirect.com/science/article/pii/S1877050920304865/pdf?md5=f0f2446923ca23a6818f69ae22186b4c&pid=1-s2.0-S1877050920304865-main.pdf

Mosteanu, N.R. and Faccia, A., 2020. Digital systems and new challenges of financial management–FinTech, XBRL, blockchain and cryptocurrencies. *Quality–Access to Success*, *21*(174), pp.159-166.https://pureportal.coventry.ac.uk/files/30597575/Binder3_1_.pdf

Nakano, M., Takahashi, A. and Takahashi, S., 2018. Bitcoin technical trading with artificial neural network. *Physica A: Statistical Mechanics and its Applications*, *510*, pp.587-609.https://www.sciencedirect.com/science/article/pii/S0378437118308811

Ni, Y., 2024. Navigating Energy and Financial Markets: A Review of Technical Analysis Used and Further Investigation from Various Perspectives. *Energies*, 17(12), p.2942.https://www.mdpi.com/1996-1073/17/12/2942/pdf

Niroomand, F., Metghalchi, M. and Hajilee, M., 2020. Efficient market hypothesis: a ruinous implication for Portuguese stock market. *Journal of economics and finance*, *44*, pp.749-763.https://link.springer.com/article/10.1007/s12197-020-09514-8

Park, H. and Kim, J.D., 2020. Transition towards green banking: role of financial regulators and financial institutions. *Asian Journal of Sustainability and Social Responsibility*, *5*(1), pp.1-25.https://link.springer.com/article/10.1186/s41180-020-00034-3

Pedisic, R., 2022. Cointegration Analysis of Financial Market Indices During Financial Shocks: Focus on Global Financial Crisis and COVID-19 Pandemic Crisis. *Bulletin of*

Applied Economics, *9*(2), pp.59-78. https://search.proquest.com/openview/e73ba713f69b0c33e8ff858ed5e260e0/1?pq-origsite=gscholar&cbl=5074387&casa_token=u_2OZKCEqMUAAAAA:udzEjy8DdYHHdfT06SVbXj5fqpDIbMACHhJwo_PQ5PJg_gJWOjn3TmATpNUgwAWWd3aBBuLAzq0

Picasso, A., Merello, S., Ma, Y., Oneto, L. and Cambria, E., 2019. Technical analysis and sentiment embeddings for market trend prediction. *Expert Systems with Applications*, *135*, pp.60-70.https://sentic.net/market-trend-prediction.pdf

Quintus, M., Mayr, K., Hofer, K.M. and Chiu, Y.T., 2024. Managing consumer trust in e-commerce: evidence from advanced versus emerging markets. International Journal of Retail & Distribution Management. https://www.emerald.com/insight/content/doi/10.1108/IJRDM-10-2023-0609/full/pdf

Raddant, M. and Kenett, D.Y., 2021. Interconnectedness in the global financial market. Journal of International Money and Finance, 110, p.102280. https://www.sciencedirect.com/science/article/pii/S0261560620302369?casa_token=JWRdzBIDS28AAAAA:NZ-jvkKq38fx45WRuL6M9puIXWRPLabRip64NWsJZGMXbKAapThBUtGUkLZX9Gv4-or9fys87vA

Ross, M.M. and Wright, A.M., 2020. Quantitative skill and introductory finance. Journal of Financial Education, 46(2), pp.193-220. https://www.jstor.org/stable/pdf/48646931.pdf?casa_token=9bwNQmy0jjsAAAAA:1s7GLiV5x_VhQ5uulIDM1tiBjwa4JEAeHBDtZJ1nfEaqkjTQ9PQVpzKP84GI3fLcPllnXFpP17NQ9qKv_rbJFiM4nx0sZpSoOCKARn7Umvodq4OQIwte

Rouf, N., Malik, M.B., Arif, T., Sharma, S., Singh, S., Aich, S. & Kim, H.C. (2021). Stock market prediction using machine learning techniques: a decade survey on methodologies, recent developments, and future directions. Electronics, 10(21), p.2717.https://www.mdpi.com/2079-9292/10/21/2717

Samuel, M. S. S., & Tantia, V. (2024). A Study On The Contrasting Theories Of Investment Behaviour. *Migration Letters*, *21*(S5), 329-338.https://migrationletters.com/index.php/ml/article/view/7715

Sharma, A. and Kumar, A., 2019. A review paper on behavioral finance: study of emerging trends. *Qualitative research in financial markets*, *12*(2), pp.137-157.https://www.emerald.com/insight/content/doi/10.1108/QRFM-06-2017-0050

Siddiqui, T.A., Khan, M.F., Naushad, M. and Syed, A.M., 2022. Cross-Market Correlations and Financial Contagion from Developed to Emerging Economies: A Case of COVID-19 Pandemic. Economies, 10(6), p.147. https://www.mdpi.com/2227-7099/10/6/147/pdf

Singh, A., Bhardwaj, G., Srivastava, A. P., Bindra, A., and Chaudhary, P. (2022, April). Application of neural network to technical analysis of stock market prediction. In *2022 3rd International Conference on Intelligent Engineering and Management (ICIEM)* (pp. 302-306). IEEE.https://sceweb.uhcl.edu/boetticher/ML_DataMining/Kimoto.pdf

Ta, V.D., Liu, C.M. and Tadesse, D.A., 2020. Portfolio optimization-based stock prediction using long-short term memory network in quantitative trading. *Applied Sciences*, 10(2), p.437.https://www.mdpi.com/2076-3417/10/2/437/pdf

Thakkar, A. and Chaudhari, K., 2021. A comprehensive survey on deep neural networks for stock market: The need, challenges, and future directions. Expert Systems with Applications, 177, p.114800. https://www.sciencedirect.com/science/article/pii/S0957417421002414?casa_token=0lxfiNupIbIAAAAA:Npw0Ql9UCTfwwM6IU9TAtvAAKyZvyBrNGQk9TfUdpvZ6-zKNM8YDH0NCfnFaSh4PE0UbIWSlpKw

Tikhomirov, S., Voskresenskaya, E., Ivanitskiy, I., Takhaviev, R., Marchenko, E. and Alexandrov, Y., 2018, May. Smartcheck: Static analysis of ethereum smart contracts. In *Proceedings of the 1st international workshop on emerging trends in software engineering for blockchain* (pp. 9-16).https://orbilu.uni.lu/bitstream/10993/35862/1/smartcheck-paper.pdf

Ullah, S., Zaefarian, G., Ahmed, R. and Kimani, D., 2021. How to apply the event study methodology in STATA: An overview and a step-by-step guide for authors. Industrial marketing management, 99, pp.A1-A12. https://www.sciencedirect.com/science/article/pii/S0019850121000328?casa_token=KLyo0McVi58AAAAA:9uKisvWhYCXVQ8tzwEUx0U3ryTCHeRDqYq649e4xR341K-C2-qjK5MFmEiV9dvprtDmPFVcUVB4

Van de Poel, I. and Royakkers, L., 2023. *Ethics, technology, and engineering: An introduction*. John Wiley & Sons.https://books.google.com/books?hl=en&lr=&id=SYq4EAAAQBAJ&oi=fnd&pg=PR10&dq=Van+de+Poel,+I.+and+Royakkers,+L.,+2023.+Ethics,+technology,+and+engineering:+An+introduction.+John+Wiley+%26+Sons.&ots=O44fKcf2Dx&sig=V9A23DxNFH9AQLcDZupm72jBvuY

Vinu, R.C. (2020). A Study of Investment Behaviour of Mumbai Residents with Reference to Behavioural Finance. *International Journal Peer Reviewed Journal Refereed Journal Indexed Journal Impact Factor MJIF*, 4, pp.22-32.https://wwjmrd.com/upload/a-study-of-investment-behaviour-of-mumbai-residents-with-reference-to-behavioural-finance_1588256512.pdf

Wamalwa, N. and Makori, J.M.P.D., 2020. Moderating Effect of Exchange Rate on the Relationship Between Firm Characteristics and Financial Stability of Commercial Banks in Kenya. https://irlibrary.ku.ac.ke/bitstream/handle/123456789/20829/Moderating%20Effect%20of%20Exchange%20Rate%20on%20the%20Relationship%20Between.pdf?sequence=1

Wang, C., 2021. Different GARCH models analysis of returns and volatility in Bitcoin. Data Science in Finance and Economics, 1(1), pp.37-59. https://www.aimspress.com/aimspress-data/dsfe/2022/1/PDF/DSFE-01-01-003.pdf

Wang, J., Ma, F., Bouri, E. and Zhong, J., 2022. Volatility of clean energy and natural gas, uncertainty indices, and global economic conditions. *Energy Economics*, *108*, p.105904. https://www.sciencedirect.com/science/article/pii/S0140988320846?casa_token=Kb31t_CxUnIAAAAA:mukjHDD9vHcIgKV7QucRJHarNHnbaWYUyqtHGEU2G5c_0fliF0Wu3tM8-q6L6lhRDgr_tAY7Flo

Wang, Q., Xu, W. and Zheng, H., 2018. Combining the wisdom of crowds and technical analysis for financial market prediction using deep random subspace ensembles. *Neurocomputing*, *299*, pp.51-61.https://www.sciencedirect.com/science/article/pii/S0925231218303540

Wang, W. and Yildirim, G., 2021. Applied time-series analysis in marketing. In Handbook of market research (pp. 469-513). Cham: Springer International Publishing. https://link.springer.com/content/pdf/10.1007/978-3-319-57413-4_37.pdf

Weixiang, S., Qamruzzaman, M., Rui, W. and Kler, R., 2022. An empirical assessment of financial literacy and behavioral biases on investment decision: Fresh evidence from small investor perception. *Frontiers in psychology*, *13*, p.977444.https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2022.977444/full

Woo, K. Y., Mai, C., McAleer, M., and Wong, W. K. (2020). Review on efficiency and anomalies in stock markets. *Economies*, *8*(1), 20.https://www.mdpi.com/2227-7099/8/1/20/pdf

Woo, K.Y., Mai, C., McAleer, M. and Wong, W.K., 2020. Review on efficiency and anomalies in stock markets. *Economies*, *8*(1), p.20 https://www.mdpi.com/2227-7099/8/1/20

Wouters, O.J., McKee, M. and Luyten, J., 2020. Estimated research and development investment needed to bring a new medicine to market, 9-2018. *Jama*, *323*(9), pp.844-853.https://jamanetwork.com/journals/jama/fullarticle/2762311

Wu, D., Wang, X., Su, J., Tang, B., & Wu, S. (2020). A labeling method for financial time series prediction based on trends. *Entropy*, *22*(10), 1162.https://www.mdpi.com/1099-4300/22/10/1162/pdf

www.statswork.com. (n.d.). *Quantaitive research – statswork*. [online] Available at: https://www.statswork.com/insights/sample-work/research-methodology/quantaitive-research/.

Zou, J., Zhao, Q., Jiao, Y., Cao, H., Liu, Y., Yan, Q., ... and Shi, J. Q. (2022). Stock market prediction via deep learning techniques: A survey. *arXiv preprint arXiv:2212.12717*.https://arxiv.org/pdf/2212.12717

Appendices

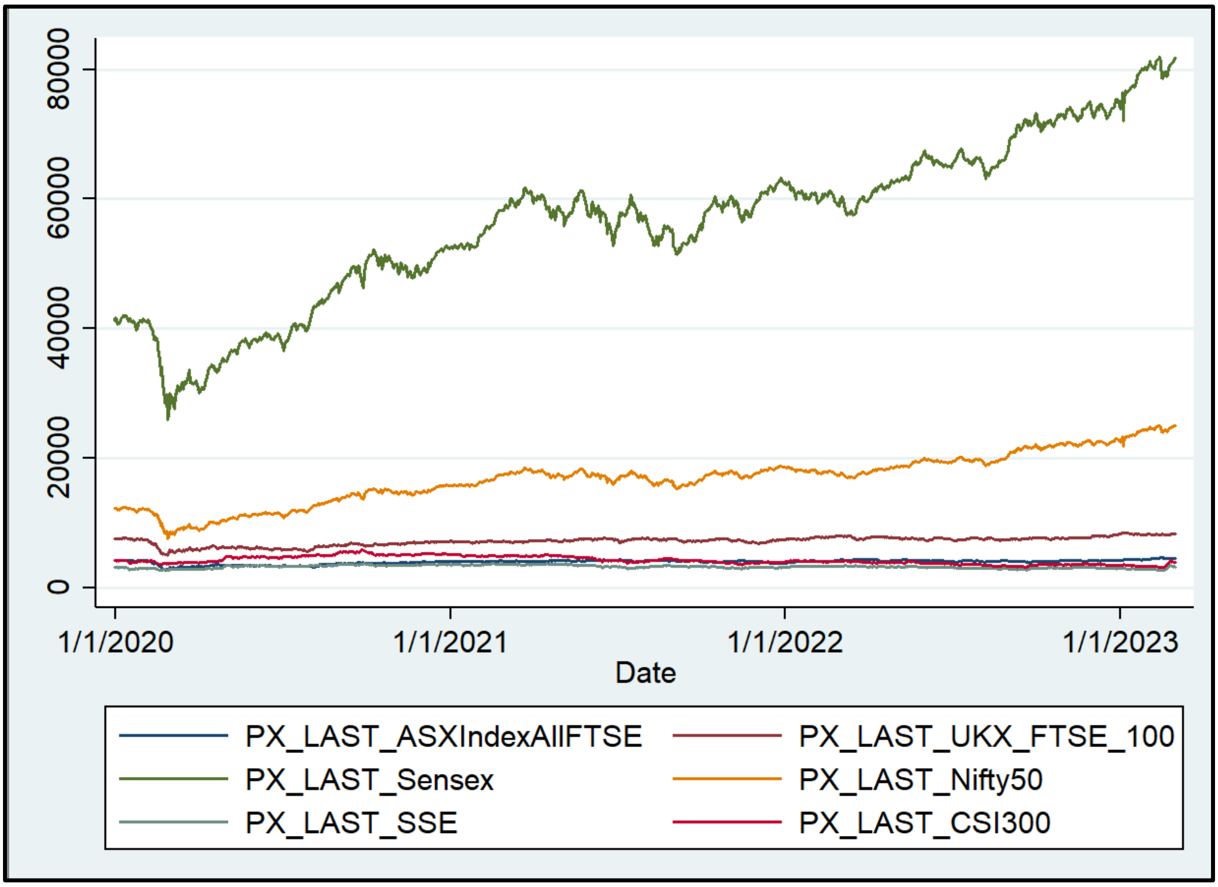
Appendix 1: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
PX_LAST_ASXIndexAll	1,157	3964.196	333.3783	2727.86	4596.71
PX_LAST_UKX_FTSE_100	1,157	7176.712	657.5429	4993.89	8445.8
PX_LAST_Sensex	1,157	56332.66	12321.47	25981.24	81867.55
PX_LAST_Nifty50	1,157	16802.51	3818.464	7610.25	25017.75
PX_LAST_SSE	1,157	3219.882	238.7823	2660.167	3715.372
PX_LAST_CSI300	1,157	4218.706	613.4274	3159.25	5807.72

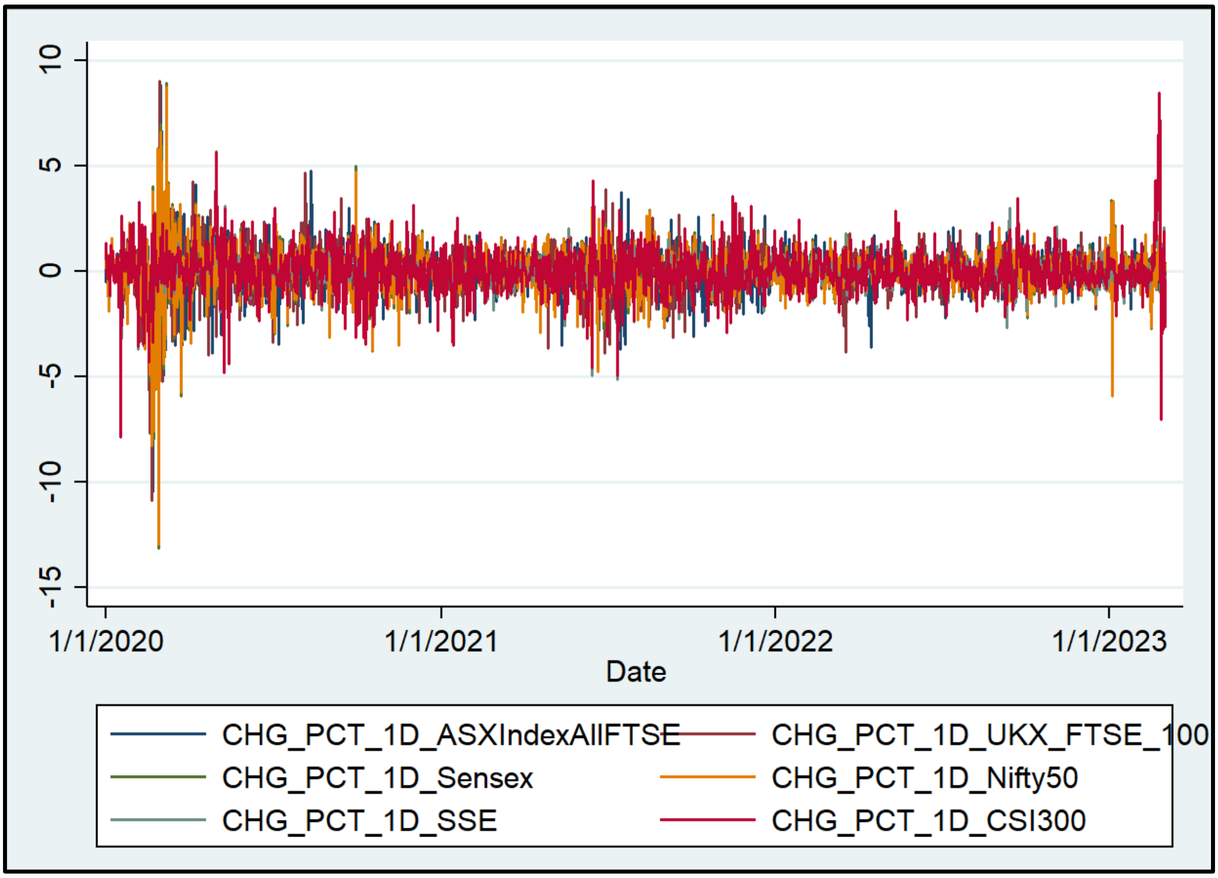
Variable	Observations	Mean	Std. Dev.	Min	Max
CHG_PCT_1D_ASXIndexAllFTSE	1,157	0.02108	1.113622	-10.49	8.86
CHG_PCT_1D_UKX_FTSE_100	1,157	0.014408	1.128179	-10.87	9.05
CHG_PCT_1D_Sensex	1,157	0.066992	1.24459	-13.15	8.97
CHG_PCT_1D_Nifty50	1,157	0.069905	1.225998	-12.98	8.76
CHG_PCT_1D_SSE	1,157	0.01008	1.085173	-7.725	8.064
CHG_PCT_1D_CSI300	1,157	0.002524	1.237301	-7.88	8.48

Variable	Observations	Mean	Std. Dev.	Min	Max
PX_VOLUME_ASXIndexAllFTSE	1,157	1.13E+09	4.74E+08	2	4.20E+09
PX_VOLUME_UKX_FTSE_100	1,157	7.10E+08	2.96E+08	1.23E+08	2.57E+09
PX_VOLUME_Sensex	1,187	1.33E+07	1.66E+07	1.84E+06	4.52E+08
PX_VOLUME_Nifty50	1,187	3.96E+08	2.03E+08	4.50E+07	1.81E+09
PX_VOLUME_SSE	1,157	3.08E+10	8.78E+09	1.37E+10	1.29E+11
PX_VOLUME_CSI300	1,157	1.43E+10	4.87E+09	6.48E+09	5.90E+10

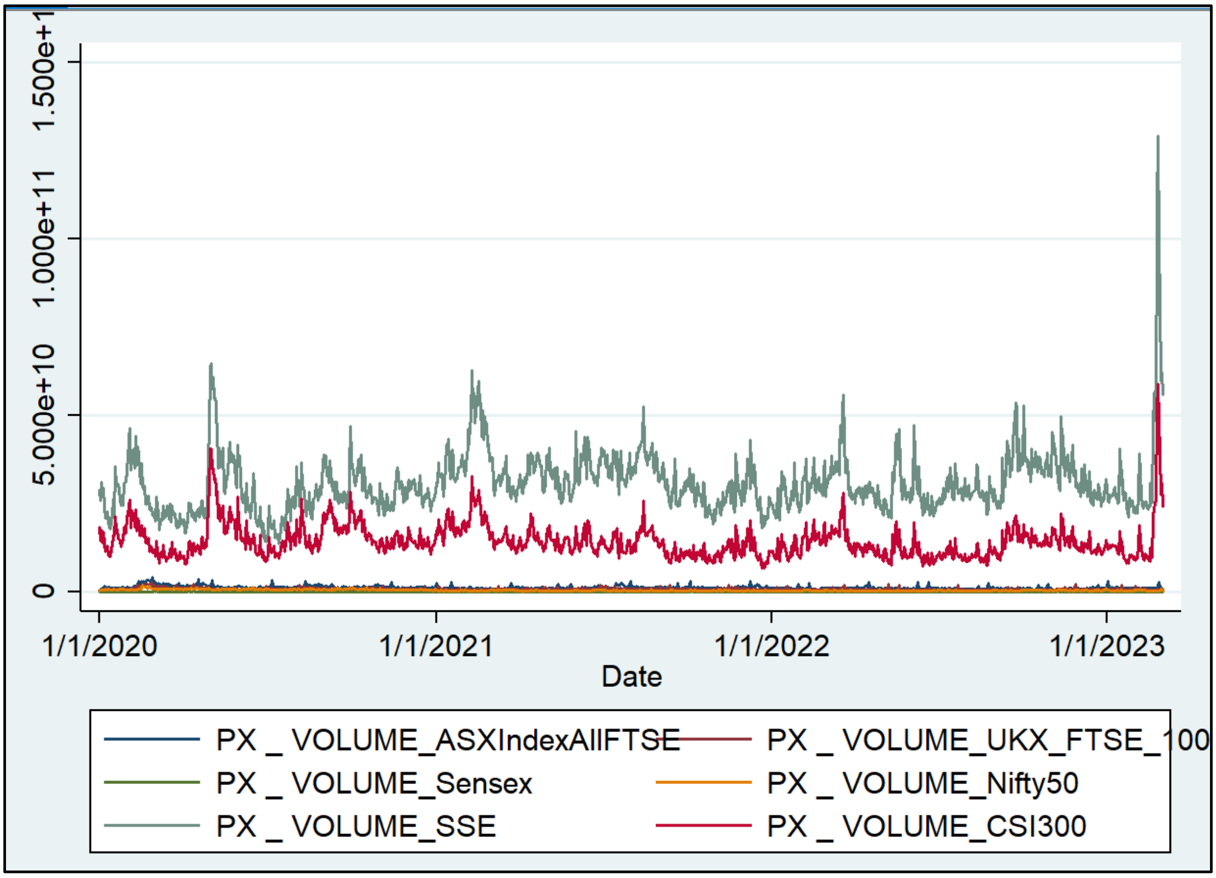
Appendix 2: Visualization for PX_LAST indexes



Appendix 3: Visualization for CHG_PCT_1D indexes



Appendix 4: Visualization for PX_VOLUME indexes



Appendix 5: Correlation analysis

Variable	PX_LAST_ASX IndexAllFTSE	PX_LAST_UK X_FTSE_100	PX_LAS T_Sensex	PX_LAST _Nifty50	PX_LA ST_SSE
PX_LAST_ASX IndexAllFTSE	1.0000 (--)				
PX_LAST_UK X_FTSE_100	0.9153* (0.0000)	1.0000 (--)			
PX_LAST_Sens ex	0.7932* (0.0000)	0.8620* (0.0000)	1.0000 (--)		
PX_LAST_Nifty 50	0.7889* (0.0000)	0.8589* (0.0000)	0.9993* (0.0000)	1.0000 (--)	
PX_LAST_SSE	-0.0053 (0.8563)	0	0	0	1.0000 (--)
PX_LAST_CSI3 00	0	0	0	0	0.8873* (0.0000)

Variable	CHG_PCT_1 D_ASXIndex AllFTSE	CHG_PCT_ 1D_UKX_F TSE_100	CHG_P CT_1D_ Sensex	CHG_P CT_1D_ Nifty50	CHG_P CT_1D _SSE	CHG_P CT_1D_ CSI300
CHG_PCT_1 D_ASXIndex AllFTSE	1.0000 (--)					
CHG_PCT_1 D_UKX_FTS E_100	-0.0474 (0.1073)	1.0000 (--)				
CHG_PCT_1 D_Sensex	0.0649* (0.0274)	0.1750* (0.0000)	1.0000 (- -)			
CHG_PCT_1 D_Nifty50	0.0664* (0.0238)	0.1745* (0.0000)	0.9966* (0.0000)	1.0000 (- -)		
CHG_PCT_1 D_SSE	0.0164 (0.5781)	-0.00078312	-0.0293 (0.3192)	-0.0297 (0.3134)	1.0000 (--)	
CHG_PCT_1 D_CSI300	0.0125 (0.6708)	-0.002472	-0.0287 (0.3288)	-0.0298 (0.3110)	0.9568* (0.0000)	1.0000 (- -)

Variable	PX_VOLUME_ASXIndexAllFTSE	PX_VOLUME_UKX_FTSE_100	PX_VOLUME_Sensex	PX_VOLUME_Nifty50	PX_VOLUME_SSE	PX_VOLUME_CSI300
PX_VOLUME_ASXIndexAllFTSE	1.0000 (--)					
PX_VOLUME_UKX_FTSE_100	0.4036* (0.0000)	1.0000 (--)				
PX_VOLUME_Sensex	0.0913* (0.0019)	0.1358* (0.0000)	1.0000 (--)			
PX_VOLUME_Nifty50	0.4334* (0.0000)	0.4353* (0.0000)	0.2841* (0.0000)	1.0000 (--)		
PX_VOLUME_SSE	-0.00001127	-0.00038272	-0.00116325	0	1.0000 (--)	
PX_VOLUME_CSI300	0.0243 (0.4093)	0.0126 (0.6691)	0.0122 (0.6792)	0.1415* (0.0000)	0.8472* (0.0000)	1.0000 (--)

Appendix 6: Augmented Dickey-Fuller (ADF) Test

Variable	Test Statistic (Z(t))	1% Critical Value	5% Critical Value	10% Critical Value	p-value
PX_LAST_ASXIndexAllFTSE	-2	-3.43E+00	-2.86E+00	-2.57	3.88E-01
PX_LAST_UKX_FTSE_100	-2	-3.43E+00	-2.86E+00	-2.57E+00	5.10E-01
PX_LAST_Sensex	0	-3.43E+00	-2.86E+00	-2.57E+00	9.69E-01
PX_LAST_Nifty50	0	-3.43E+00	-2.86E+00	-2.57E+00	9.81E-01
PX_LAST_SSE	-3	-3.43E+00	-2.86E+00	-2.57E+00	9.84E-02
PX_LAST_CSI300	-1	-3.43E+00	-2.86E+00	-2.57E+00	5.58E-01
CHG_PCT_1D_ASXIndexAllFTSE	-23	-3.43	-2.86	-2.57	0
CHG_PCT_1D_UKX_FTSE_100	-24	-3.43	-2.86	-2.57	0
CHG_PCT_1D_Sensex	-25	-3.43	-2.86	-2.57	0
CHG_PCT_1D_Nifty50	-24	-3.43	-2.86	-2.57	0
CHG_PCT_1D_SSE	-22	-3.43	-2.86	-2.57	0
CHG_PCT_1D_CSI300	-23	-3.43	-2.86	-2.57	0
PX_VOLUME_ASXIndexAllFTSE	-11	-3.43	-2.86	-2.57	0
PX_VOLUME_UKX_FTSE_100	-12	-3.43	-2.86	-2.57	0
PX_VOLUME_Sensex	-20	-3.43	-2.86	-2.57	0
PX_VOLUME_Nifty50	-7	-3.43	-2.86	-2.57	0
PX_VOLUME_SSE	-8	-3.43	-2.86	-2.57	0
PX_VOLUME_CSI300	-8	-3.43	-2.86	-2.57	0

Variable	Test Statistic (Z(t))	1% Critical Value	5% Critical Value	10% Critical Value	p-value
D_ASXIndexAllFTSE	-23.573	-3.43	-2.86	-2.57	0
D_UKX_FTSE_100	-24.229	-3.43	-2.86	-2.57	0
D_SSE	-22.536	-3.43	-2.86	-2.57	0
D_CSI300	-22.74	-3.43	-2.86	-2.57	0

Appendix 7: Volatility

PX_LAST_ASXIndexAllFTSE

Variable	Coefficient	Standard Error	z-Statistic	P-Value	95% Confidence Interval
Constant (_cons)	4110.775	1.841445	2232.36	0	[4107.166, 4114.384]
ARCH (L1)	0.940805	0.135986	6.92	0	[0.6742775, 1.207333]
GARCH (L1)	0.043175	0.07259	0.59	0.552	[-0.0990993, 0.1854499]
Constant (_cons for ARCH/GARCH)	784.299	167.2474	4.69	0	[456.5, 1112.098]

PX_LAST_UKX_FTSE_100

Variable	Coefficient	Standard Error	z-Statistic	P-Value	95% Confidence Interval
Constant (_cons)	7474.841	3.935537	1899.32	0	[7467.127, 7482.554]
ARCH (L1)	0.921873	0.144211	6.39	0	[0.6392248, 1.204521]
GARCH (L1)	0.065633	0.056013	1.17	0.241	[-0.0441513, 0.1754167]
Constant (_cons for ARCH/GARCH)	3069.722	446.0813	6.88	0	[2195.418, 3944.025]

PX_LAST_Sensex

Variable	Coefficient	Standard Error	z-Statistic	P-Value	95% Confidence Interval
Constant (_cons)	59645.32	53.15833	1122.03	0	[59541.14, 59749.51]
ARCH (L1)	0.974763	0.203013	4.8	0	[0.5768644, 1.372661]
GARCH (L1)	0.02015	0.100314	0.2	0.841	[-0.1764614, 0.2167619]
Constant (_cons for ARCH/GARCH)	238687.2	73824.06	3.23	0.001	[93994.75, 383379.7]

PX_LAST_Nifty50

Variable	Coefficient	Standard Error	z-Statistic	P-Value	95% Confidence Interval
Constant (_cons)	17684.73	16.17347	1093.44	0	[17653.03, 17716.43]
ARCH (L1)	1.010228	0.212176	4.76	0	[0.5943701, 1.426086]
GARCH (L1)	-0.01727	0.1004	-0.17	0.863	[-0.2140531, 0.1795069]
Constant (_cons for ARCH/GARCH)	23358.03	5820.155	4.01	0	[11950.74, 34765.33]

PX_LAST_SSE Variable	Coefficient	Standard Error	z-Statistic	P-Value	95% Confidence Interval
Constant (_cons)	3250.677	2.371675	1370.63	0	[3246.029, 3255.326]
ARCH (L1)	0.933959	0.186823	5	0	[0.5677932, 1.300126]
GARCH (L1)	0.06416	0.077748	0.83	0.409	[-0.0882238, 0.2165445]
Constant (_cons for ARCH/GARCH)	664.572	149.9926	4.43	0	[370.592, 958.552]

PX_LAST_CSI300 Variable	Coefficient	Standard Error	z-Statistic	P-Value	95% Confidence Interval
Constant (_cons)	3964.816	3.654392	1084.95	0	[3957.654, 3971.978]
ARCH (L1)	0.838519	0.160026	5.24	0	[0.5248729, 1.152164]
GARCH (L1)	0.174854	0.052227	3.35	0.001	[0.0724905, 0.2772182]
Constant (_cons for ARCH/GARCH)	993.7741	247.6608	4.01	0	[508.3678, 1479.18]

CHG_PCT_1D_ASXIndexAllFTSE

Variable	Coefficient	Standard Error	z-Statistic	P-Value	95% Confidence Interval
Constant (_cons)	0.043682	0.026475	1.65	0.099	[-0.0082082, 0.0955723]
ARCH (L1)	0.143079	0.018433	7.76	0	[0.1069508, 0.1792071]
GARCH (L1)	0.797206	0.025241	31.58	0	[0.747734, 0.8466779]
Constant (_cons for ARCH/GARCH)	0.059928	0.010391	5.77	0	[0.0395627, 0.0802926]

CHG_PCT_1D_UKX_FTSE_100

Variable	Coefficient	Standard Error	z-Statistic	P-Value	95% Confidence Interval
Constant (_cons)	0.034045	0.026804	1.27	0.204	[-0.0184902, 0.0865794]
ARCH (L1)	0.139374	0.017032	8.18	0	[0.105993, 0.1727553]
GARCH (L1)	0.80715	0.022607	35.7	0	[0.7628406, 0.8514596]
Constant (_cons for ARCH/GARCH)	0.056664	0.009799	5.78	0	[0.0374581, 0.0758696]

CHG_PCT_1D_Sensex

Variable	Coefficient	Standard Error	z-Statistic	P-Value	95% Confidence Interval
Constant (_cons)	0.095492	0.023324	4.09	0	[0.0497786, 0.1412063]
ARCH (L1)	0.13857	0.013838	10.01	0	[0.111449, 0.1656916]
GARCH (L1)	0.834106	0.016744	49.81	0	[0.8012881, 0.8669242]
Constant (_cons for ARCH/GARCH)	0.037214	0.008455	4.4	0	[0.0206437, 0.0537849]

CHG_PCT_1D_Nifty50					
Variable	Coefficient	Standard Error	z-Statistic	P-Value	95% Confidence Interval
Constant (_cons)	0.094988	0.023753	4	0	[0.0484337, 0.141543]
ARCH (L1)	0.140561	0.013585	10.35	0	[0.1139354, 0.1671855]
GARCH (L1)	0.830006	0.016773	49.48	0	[0.7971316, 0.8628803]
Constant (_cons for ARCH/GARCH)	0.038871	0.008545	4.55	0	[0.0221238, 0.0556186]

CHG_PCT_1D_SSE

Variable	Coefficient	Standard Error	z-Statistic	P-Value	95% Confidence Interval
Constant (_cons)	0.000994	0.027997	0.04	0.972	[-0.0538798, 0.055868]
ARCH (L1)	0.159175	0.012576	12.66	0	[0.1345259, 0.1838241]
GARCH (L1)	0.749714	0.025615	29.27	0	[0.6995092, 0.7999197]
Constant (_cons for ARCH/GARCH)	0.10699	0.0187	5.72	0	[0.0703387, 0.1436412]

CHG_PCT_1D_CSI300

Variable	Coefficient	Standard Error	z-Statistic	P-Value	95% Confidence Interval
Constant (_cons)	-0.0098	0.031998	-0.31	0.759	[-0.0725131, 0.0529152]
ARCH (L1)	0.115527	0.010909	10.59	0	[0.0941448, 0.1369085]
GARCH (L1)	0.83752	0.019394	43.18	0	[0.7995085, 0.8755308]
Constant (_cons for ARCH/GARCH)	0.074753	0.016257	4.6	0	[0.0428907, 0.106616]

PX_VOLUME_CSI300

Variable	Coefficient	Standard Error	z-Statistic	P-Value	95% Confidence Interval
Constant (_cons)	13,10,00,00,000	8.00E+07	1.64E+02	0	[1.29e+10, 1.32e+10]
ARCH (L1)	1	6.07E-02	1.00E+01	0.00E+00	[0.4890337, 0.7269202]
GARCH (L1)	0	2.60E-02	1.11E+01	0.00E+00	[0.2382473, 0.3402465]
ARCH _cons	22,20,00,00,00,00,00,00,000	-	-	-	-

PX_VOLUME_SSE

Variable	Coefficient	Standard Error	z-Statistic	P-Value	95% Confidence Interval
PX_VOLUME_SSE (_cons)	28,90,00,00,000	1.38E+08	2.09E+02	0	[2.87e+10, 2.92e+10]
ARCH (L1)	1	6.18E-02	9.82E+00	0.00E+00	[0.4858678, 0.7282155]
GARCH (L1)	0	2.81E-02	9.56E+00	0.00E+00	[0.2132692, 0.3233384]
ARCH _cons	78,00,00,00,00,00,00,00,000	-	-	-	-

PX_VOLUME_Nifty50

Variable	Coefficient	Standard Error	z-Statistic	P-Value	95% Confidence Interval
PX_VOLUME_Nifty50 (_cons)	29,30,00,000	1.91E+06	1.53E+02	0	[2.89e+08, 2.96e+08]
ARCH (L1)	0	3.23E-02	1.07E+01	0.00E+00	[0.2810589, 0.4078208]
GARCH (L1)	1	1.58E-02	3.98E+01	0.00E+00	[0.5980476, 0.6600903]
ARCH _cons	98,90,00,00,00,00,000	-	-	-	-

PX_VOLUME_ASXIndexAllFTSE

Variable	Coefficient	Standard Error	z-Statistic	P-Value	95% Confidence Interval
PX_VOLUME_ASXIndexAllFTSE (_cons)	1,02,00,00,000	9.62E+06	1.06E+02	0	[1.01e+09, 1.04e+09]
ARCH (L1)	1	6.68E-02	9.95E+00	0.00E+00	[0.5341285, 0.7960474]
GARCH (L1)	0	1.57E-02	3.36E+00	1.00E-03	[0.0219279, 0.0833729]
ARCH _cons	87,90,00,00,00,00,00,000	-	-	-	-

PX_VOLUME_UKX_FTSE_100

Variable	Coefficient	Standard Error	z-Statistic	P-Value	95% Confidence Interval
PX_VOLUME_UKX_FTSE_100 (_cons)	65,70,00,000	6.06E+06	1.09E+02	0	[6.45e+08, 6.69e+08]
ARCH (L1)	1	5.82E-02	1.01E+01	0.00E+00	[0.4712624, 0.6994708]
GARCH (L1)	0	1.66E-02	8.30E-01	4.05E-01	[-0.0187625, 0.0465015]
ARCH _cons	41,60,00,00,00,00,00,000	-	-	-	-

Appendix 8: Johansen Test

Rank	Parms	Log Likelihood (LL)	Eigenvalue	Trace Statistic	Critical Value (5%)
0	6	-39,354.77	-	4,867.77	94.15
1	17	-3.88E+04	5.95E-01	3,823.64	6.85E+01
2	26	-3.84E+04	5.27E-01	2.96E+03	4.72E+01
3	33	-3.80E+04	5.06E-01	2.14E+03	2.97E+01
4	38	-3.76E+04	4.88E-01	1.37E+03	1.54E+01
5	41	-3.72E+04	4.66E-01	6.48E+02	3.76E+00
6	42	-3.69E+04	4.29E-01	-	-

```
. vecrank D_ASXIndexAllFTSE D_UKX_FTSE_100 D_SSE D_CSI300 D_Sensex D_Nifty50, lags(1)

                       Johansen tests for cointegration
Trend: constant                                         Number of obs =    1155
Sample:  1/3/2020 - 3/2/2023                                     Lags =       1
-------------------------------------------------------------------------------
                                                        5%
maximum                                      trace    critical
  rank    parms      LL        eigenvalue  statistic    value
    0       6    -39354.766         .      4867.7650    94.15
    1      17    -38832.705     0.59505    3823.6412    68.52
    2      26    -38400.409     0.52695    2959.0495    47.21
    3      33    -37993.095     0.50604    2144.4215    29.68
    4      38    -37607.026     0.48753    1372.2836    15.41
    5      41    -37244.903     0.46584     648.0385     3.76
    6      42    -36920.884     0.42940
-------------------------------------------------------------------------------
```

Appendix 9: Johansen Test

Rank	Parms	Log Likelihood (LL)	Eigenvalue	Trace Statistic	Critical Value (5%)
0	6	-8,956.89	-	4,953.05	94.15
1	17	-8.39E+03	6.25E-01	3,820.22	6.85E+01
2	26	-7.94E+03	5.44E-01	2.91E+03	4.72E+01
3	33	-7.53E+03	5.05E-01	2.10E+03	2.97E+01
4	38	-7.15E+03	4.85E-01	1.33E+03	1.54E+01
5	41	-6.79E+03	4.62E-01	6.17E+02	3.76E+00
6	42	-6.48E+03	4.14E-01	-	-

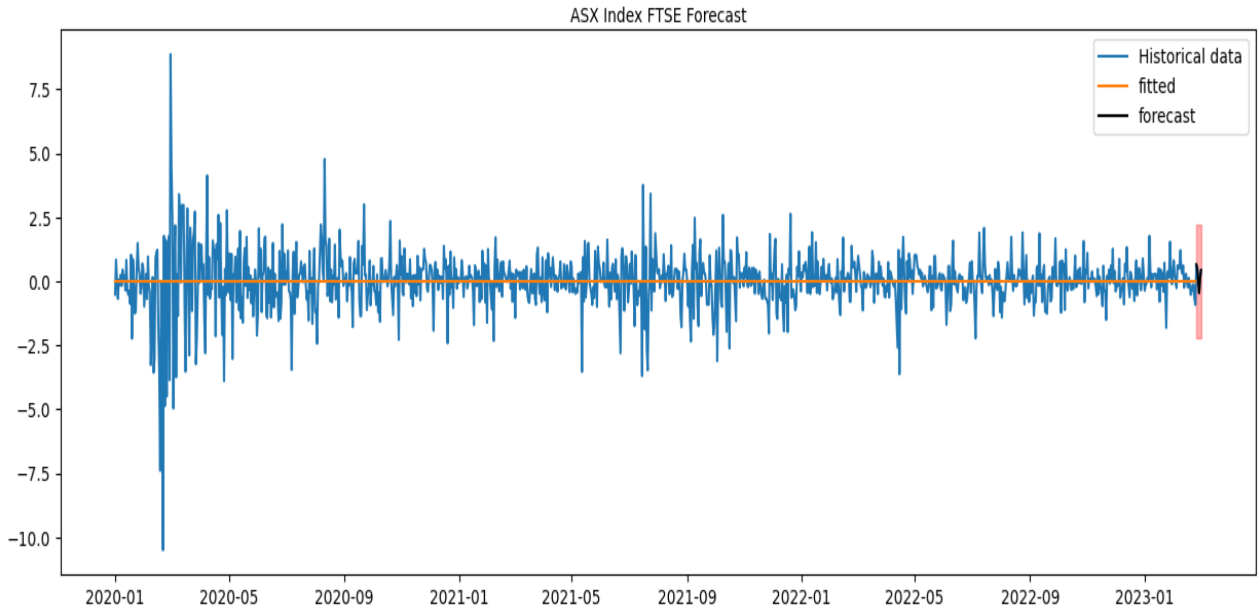
```
.
. vecrank CHG_PCT_1D_ASXIndexAllFTSE CHG_PCT_1D_UKX_FTSE_100 CHG_PCT_1D_Sensex CHG_PCT_1D_Nifty50 CHG_PCT_1D_SSE CHG_PCT_1D_CSI300, lags(1)

                       Johansen tests for cointegration
Trend: constant                                         Number of obs =    1156
Sample:  1/2/2020 - 3/2/2023                                     Lags =       1
-------------------------------------------------------------------------------
                                                          5%
maximum                                        trace    critical
  rank    parms       LL       eigenvalue  statistic     value
    0       6    -8956.8884           .    4953.0452     94.15
    1      17    -8390.4765     0.62467    3820.2213     68.52
    2      26    -7936.7333     0.54389    2912.7348     47.21
    3      33    -7530.6793     0.50466    2100.6269     29.68
    4      38    -7147.3174     0.48483    1333.9031     15.41
    5      41    -6789.0351     0.46198     617.3386      3.76
    6      42    -6480.3658     0.41376
-------------------------------------------------------------------------------
```

Appendix 10: Johansen Test

Rank	Parms	Log Likelihood (LL)	Eigenvalue	Trace Statistic	Critical Value (5%)
0	6	-1,46,056.30	-	1,947.45	94.15
1	17	-1.46E+05	4.88E-01	1,174.05	6.85E+01
2	26	-1.45E+05	3.74E-01	6.33E+02	4.72E+01
3	33	-1.45E+05	2.69E-01	2.71E+02	2.97E+01
4	38	-1.45E+05	1.17E-01	1.27E+02	1.54E+01
5	41	-1.45E+05	7.51E-02	3.69E+01	3.76E+00
6	42	-1.45E+05	3.14E-02	-	-

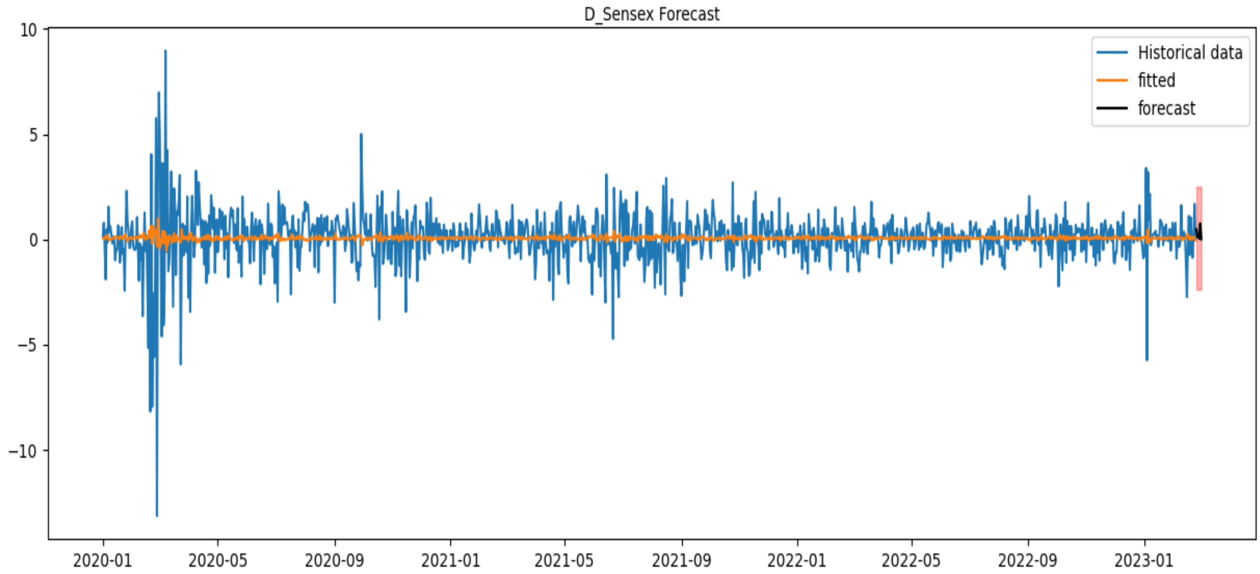
```
.
. vecrank PX_VOLUME_ASXIndexAllFTSE PX_VOLUME_UKX_FTSE_100 PX_VOLUME_Sensex PX_VOLUME_Nifty50 PX_VOLUME_SSE PX_VOLUME_CSI300, lags(1)

                     Johansen tests for cointegration
Trend: constant                                          Number of obs =    1156
Sample:  1/2/2020 - 3/2/2023                                      Lags =       1
-------------------------------------------------------------------------------
                                                         5%
maximum                                       trace    critical
  rank    parms       LL       eigenvalue  statistic    value
    0       6     -146056.3           .    1947.4510    94.15
    1      17     -145669.6     0.48779    1174.0533    68.52
    2      26    -145399.21     0.37362     633.2797    47.21
    3      33    -145218.14     0.26895     271.1303    29.68
    4      38    -145146.14     0.11712     127.1284    15.41
    5      41    -145101.01     0.07511      36.8646     3.76
    6      42    -145082.57     0.03139
-------------------------------------------------------------------------------
```

Appendix 11: Forecasting for ASX Index



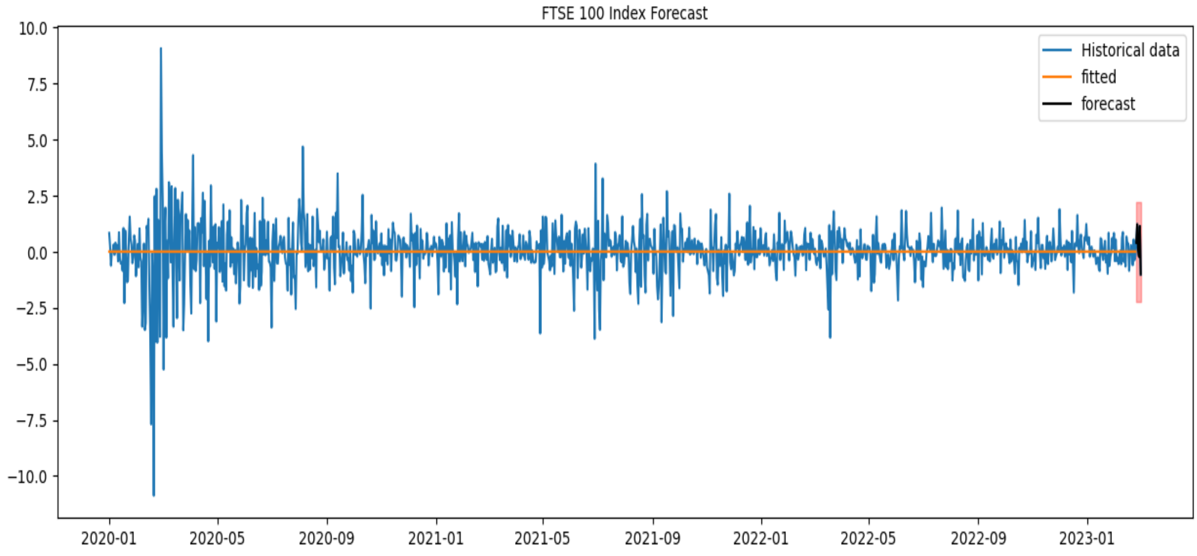
Variable	Coefficient	Standard Error	p-value	95% Confidence Interval
D_ASXIndexAllFTSE (Constant)	0.280111	1.251039	0.823	[-2.171881, 2.732104]
ARMA (AR L1)	0.001205	0.019362	0.95	[-0.0367439, 0.0391534]

Appendix 12: Forecasting for Sensex Index



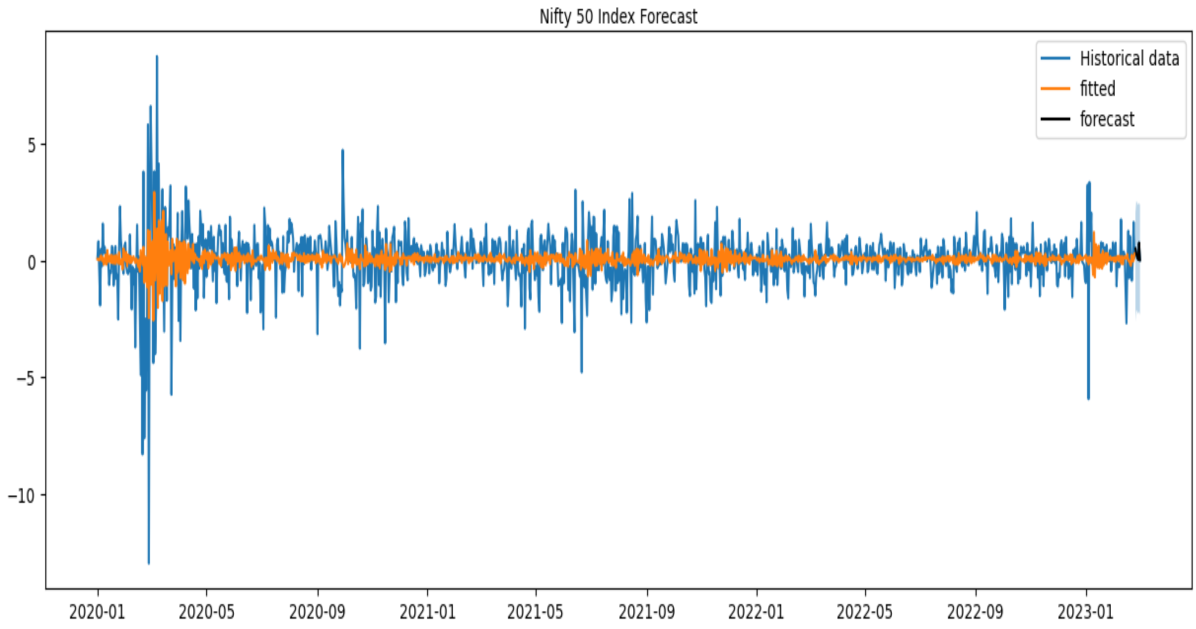
Variable	Coefficient	Standard Error	p-value	95% Confidence Interval
D_Sensex (Constant)	34.91734	17.39958	0.045	[0.8147941, 69.01988]
ARMA (AR L1)	-0.04334	0.01915	0.024	[-0.0808736, -0.0058074]

Appendix 13: Forecasting for FTSE 100 Index



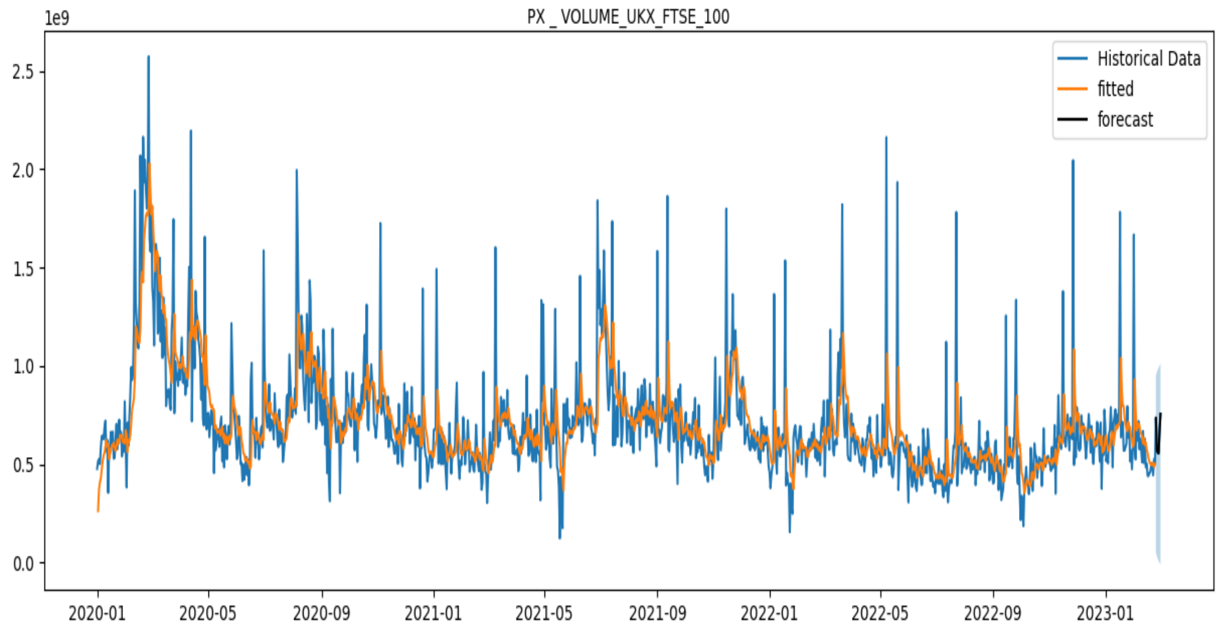
Variable	Coefficient	Standard Error	p-value	95% Confidence Interval
D_UKX_FTSE_100 (Constant)	0.589281	2.250165	0.793	[-3.82096, 4.999523]
ARMA (AR L1)	-0.02709	0.019099	0.156	[-0.0645206, 0.0103444]

Appendix 14: Forecasting for Nifty 50 Index



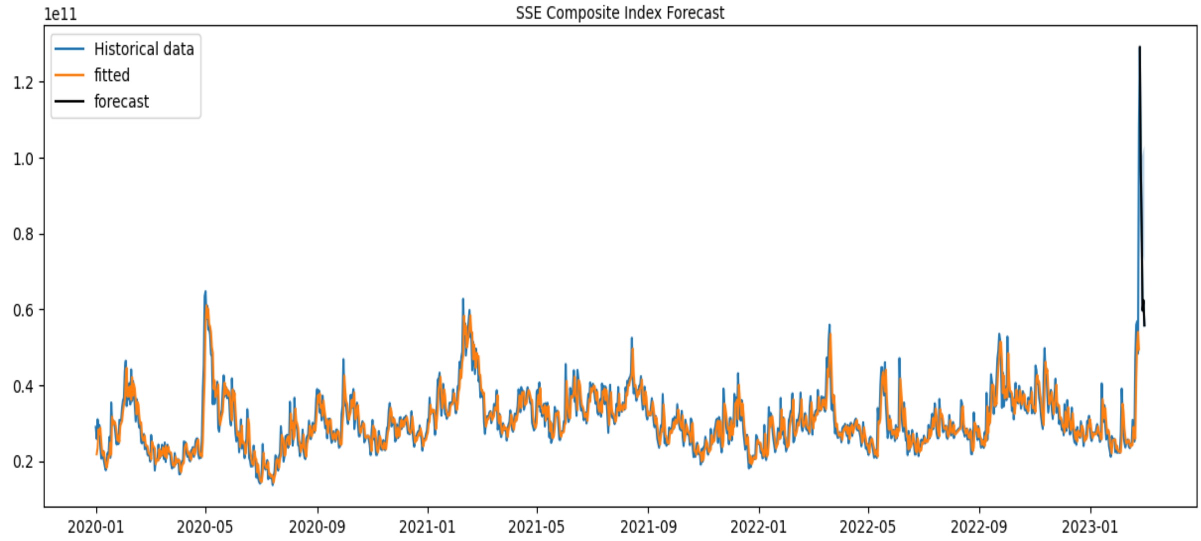
Variable	Coefficient	Standard Error	P-value	95% Confidence Interval
D_Nifty50 (Constant)	11.10292	5.195489	0.033	[0.9199509, 21.28589]
ARMA (AR L1)	-0.04566	0.018829	0.015	[-0.0825633, -0.0087533]

Appendix 15: Forecasting for PX_VOLUME_UKX_FTSE_100



Variable	Coefficient	Standard Error	z-value	p-value	95% Confidence Interval
PX_VOLUME_UKX_FTSE_100 (Constant)	7.10E+08	2.54E+07	27.92	0	[6.60e+08, 7.60e+08]
ARMA (AR L1)	0.5668	0.0166	34.06	0	[0.5342, 0.5995]

Appendix 16: Forecasting for SSE index



Variable	Coefficient	Standard Error	z-value	p-value	95% Confidence Interval
PX_VOLUME_SSE (Constant)	3.09E+10	1.15E+09	26.79	0	[2.86e+10, 3.31e+10]
ARMA (AR L1)	8.60E-01	0	129.46	0	[0.8465, 0.8725]