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FORECASTING SELECTED INTERNATIONAL STOCK INDICES RETURNS BY USING ARIMA MODEL

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ABSTRACT

This article investigates the application of Autoregressive Integrated Moving Average (ARIMA) models in forecasting returns for five major international stock indices: FTSE 100, HANG SENG, NIKKEI 225, NIFTY 50, and S&P 500. Grounded in a comprehensive methodology, the study begins by tracing the evolution of ARIMA models and their pivotal role in analysing complex temporal patterns across diverse sectors, including finance and economics. Methodologically, the research encompasses data collection from financial databases, preprocessing to ensure data quality and stationarity, ARIMA model specification through Box-Jenkins methodology, parameter estimation, and thorough validation against historical data. Results highlight varying model performances across indices, with the FTSE 100 and S&P 500 exhibiting lower prediction errors compared to the HANG SENG and NIKKEI 225, indicative of differing levels of market volatility and predictability. The analysis integrates unit root tests, ARIMA model specifications (e.g., ARIMA(2,0,1) for FTSE 100 and ARIMA(3,0,3) for S&P 500), forecast accuracy assessments, and residual diagnostics, providing insights into model adequacy and areas for further refinement. Author underscores the robustness of ARIMA models in capturing and forecasting the intricate dynamics of international stock markets, while acknowledging challenges posed by market volatility and non-linearities. The study's findings contribute to a nuanced understanding of each index's predictive behaviour, informing investment strategies and risk management practices in global financial markets. Future research directions could explore advanced time series techniques or hybrid models to enhance predictive accuracy, particularly for indices exhibiting higher volatility. Overall, this research underscores the pivotal role of ARIMA models in empirical finance, offering actionable insights for stakeholders navigating the complexities of international stock market forecasting.

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INTRODUCTION

In the dynamic landscape of time series forecasting, the Autoregressive Integrated Moving Average (ARIMA) model has emerged as a cornerstone tool, offering robust capabilities across a spectrum of disciplines. Developed to capture and predict patterns in sequential data, ARIMA has been extensively applied in fields ranging from finance and economics to environmental science and beyond. This introduction explores the evolution and application of ARIMA models, highlighting pivotal studies and their contributions to understanding complex temporal dynamics, including international stock indexes.The ARIMA model, first formalized by George Box and Gwilym Jenkins in the 1976, represents a synthesis of autoregressive (AR), differencing (I), and moving average (MA) components. Its inception marked a paradigm shift in time series analysis, providing a structured framework to discern and forecast trends in data characterized by sequential dependencies. Over the decades, ARIMA has evolved from its foundational roots to encompass diverse variants and hybrid approaches, catering to the multifaceted demands of contemporary forecasting challenges. Within financial markets, ARIMA has been pivotal in forecasting stock prices, volatility, economic indices, and international stock indexes. Stevenson (2007) pioneered its application in real estate market forecasting, underscoring the model's utility in navigating market fluctuations and informing strategic investment decisions. Sen et al. (2016) and Singh *et al.* (2012) extended its relevance to financial market analysis, demonstrating its efficacy in predicting stock returns and market behaviours. These studies underscore ARIMA's adaptability in capturing the intricacies of economic variables amidst evolving market conditions. Alnaa *et al*. (2011) exemplified ARIMA's role in macroeconomic forecasting, utilizing it to predict inflation trends in Ghana. Their findings not only highlighted the model's predictive accuracy but also its implications for policy formulation and economic stability. Similarly, Advani *et al.* (2024) delved into ARIMA's application alongside Vector Autoregression (VAR) models, emphasizing its efficacy in forecasting key economic indicators such as the Consumer Price Index (CPI) in India. These studies underscore ARIMA's capacity to inform critical policy decisions by providing timely and accurate economic forecasts, including insights into international market trends. Predicting international stock indexes requires a comprehensive understanding of various factors that influence global financial markets. Key requirements include access to high-quality and extensive historical data on stock prices, economic indicators, interest rates, and geopolitical events. Accurate data collection and preprocessing are essential to remove noise and ensure data integrity. Additionally, the prediction models need to account for different time zones, currency fluctuations, and varying market regulations across countries. This involves integrating economic theories and financial models that consider cross-market linkages and dependencies, such as the impact of one country's economic policies on another's stock market performance. Incorporating macroeconomic indicators like GDP growth rates, inflation rates, and employment statistics, as well as microeconomic factors such as corporate earnings and sectoral performance, is also crucial.

Another critical requirement is the deployment of advanced statistical and machine learning techniques to enhance prediction accuracy. Traditional time series models like ARIMA must be complemented with modern approaches such as Long Short-Term Memory (LSTM) networks, support vector machines, and hybrid models to capture the non-linearities and complexities inherent in international markets. The use of sentiment analysis tools to gauge investor sentiment from news articles and social media can provide additional predictive power. Furthermore, real-time data processing capabilities are vital to adapt to the rapidly changing market conditions and sudden economic shifts. Robust computational infrastructure and sophisticated software tools are necessary to handle large datasets and perform complex calculations. Continuous model validation and back testing against historical data ensure the reliability and robustness of predictions, providing investors with actionable insights for making informed decisions in the global financial landscape. In response to the increasing complexity of forecasting challenges, researchers have innovated hybrid models that integrate ARIMA with machine learning techniques. Abdoli et al. (2020) explored the synergies between ARIMA and Long Short-Term Memory (LSTM) networks, enhancing predictive accuracy in forecasting stock market movements in Iran. This hybrid approach not only improves forecasting precision but also addresses non-linearities and complex interactions inherent in financial data. Moreover, Abellana et al. (2020) proposed a hybrid Support Vector Regression (SVR) - Seasonal ARIMA (SARIMA) model for tourism demand forecasting in the Philippines, demonstrating its efficacy in capturing seasonal variations and long-term trends.

Beyond finance, ARIMA models have found application in diverse sectors including real estate, energy, commodities forecasting, and international stock indexes. Cheng et al. (2023) compared univariate forecasting methods for crude oil prices, highlighting ARIMA's robust performance amidst volatile market conditions. Ismail et al. (2020) utilized a DS-ARIMA-GARCH model to predict natural gas consumption patterns in Egypt, showcasing its ability to capture complex seasonal fluctuations and volatility in energy demand. These sector-specific applications underscore ARIMA's versatility and reliability in addressing the forecasting needs of diverse industries. Historically, ARIMA models have played a crucial role in analysing and predicting market behaviours during significant economic events. Angabini et al. (2010) explored its application during the Malaysian financial crisis, revealing insights into market efficiency and volatility dynamics. Wahyudi et al. (2021) and Hendrawaty et al. (2023) focus on the COVID-19 pandemic underscore ARIMA's adaptability in modelling economic disruptions and forecasting inflationary trends amidst global uncertainties. In conclusion, the ARIMA model stands as a pivotal tool in time series forecasting, offering a structured framework to decipher complex temporal patterns across various domains. Through its evolution and application in diverse fields, ARIMA continues to empower researchers, policymakers, and practitioners with insights essential for informed decision-making in an increasingly interconnected global economy. As technological advancements and data availability expand, ARIMA's role in forecasting and strategic planning is poised to further evolve, continuing its legacy as a cornerstone of predictive analytics.

LITERATURE REVIEW

The application of the Autoregressive Integrated Moving Average (ARIMA) model in forecasting international stock index returns has garnered significant attention in the academic and financial communities. This literature review explores the diverse methodologies and contexts in which ARIMA models have been employed, highlighting their adaptability and effectiveness in various domains. From predicting stock prices and market volatility to analysing macroeconomic indicators and managing crisis scenarios, ARIMA's ability to model and forecast time series data is well-documented. Additionally, the review examines the advancements in hybrid models that combine ARIMA with other techniques, showcasing the continuous evolution and enhancement of forecasting methodologies to address the complexities of modern financial markets.

Model-Specific Analysis

ARIMA Models: The Autoregressive Integrated Moving Average (ARIMA) model is a prominent tool in time series forecasting, widely applied across various domains. The ARIMA model has been extensively utilized across various studies for time series forecasting, demonstrating its adaptability and robustness. For instance, Stevenson (2007) employed ARIMA models in real estate market forecasting, emphasizing the need for careful model specification to achieve accurate future predictions. Similarly, Alnaa et al. (2011) used the ARIMA model to predict inflation in Ghana, showcasing its effectiveness in macroeconomic forecasting. Sen et al. (2016), Kundu et al. (2020), Al-Shiab (2006) and Singh et al. (2012) further highlighted ARIMA's utility in financial market analysis, particularly in predicting stock prices, indices, and market returns. Fattah et al. (2018) focuses on demand forecasting in the food industry by employing a ARIMA model and predict future demand. In environmental and health-related forecasting, Kaur et al. (2023) reviewed the application of ARIMA models, noting their widespread use and the enhanced accuracy of hybrid variants. Similarly, Advani et al. (2024) utilized ARIMA and VAR models to forecast the unemployment rate and Consumer Price Index (CPI) in India, finding ARIMA more suitable for inflation forecasting. Meher et al. (2021) employs the ARIMA model to predict the share prices of pharmaceutical companies listed under NIFTY100 in India. Angabini et al. (2010). explore its application in assessing market efficiency in Malaysia during the 2007/2008 financial crisis, identifying changes in volatility dynamics using ARIMA and GARCH models. Wahyudi et al. (2021) utilize ARIMA to investigate inflation volatility in Indonesia before and during the COVID-19 pandemic, confirming its effectiveness in forecasting short-term inflationary trends. Similarly, Viswanatha Reddy (2019) demonstrates ARIMA's predictive capability for short-term stock market movements in India, emphasizing its utility in financial decision-making.

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Industry-Specific Analysis

Financial Markets: ARIMA models are extensively used in financial markets to predict stock prices, volatility, and indices. Rossetti et al. (2017) and Morina et al. (2024) focused on market volatility and financial performance, respectively, using these models to gain insights into market dynamics. Sen et al. (2016) and Singh et al. (2012) studies on stock price prediction and market returns further underscored the importance of these models in financial analysis. Mobarek et al. (2008) investigate the efficiency of the Dhaka Stock Exchange using ARIMA alongside non-parametric tests, finding evidence of market inefficiency. Mustapa et al. (2019) employ ARIMA-GARCH models to forecast S&P 500 prices, highlighting the model's ability to capture time series dynamics and volatility clustering. Additionally, Hendrawaty et al. (2023) research on aviation stock prices during COVID-19 confirms ARIMA's effectiveness in predicting stability in volatile markets.

Inflation, Energy and Commodities: Forecasting in the energy and commodities sectors has benefited from advanced time series models. Cheng et al. (2023) compared various univariate forecasting methods for crude oil prices, finding the grey forecast method particularly reliable. For predicting vegetable prices Mahmoud Sayed Agbo, H (2023) used ARIMA Models and found that ARIMA models (1,1,1), (2,1,2), (1,1,0), (1,1,2), (0,1,0), and (1,1,1) as most suitable for forecasting the prices of green beans, tomatoes, onions, oranges, grapes, and strawberries, respectively. Ismail et al. (2020) employed a DS-ARIMA-GARCH model to predict natural gas consumption in Egypt, highlighting the model's ability to capture complex seasonal patterns and volatility in energy consumption. Nochai et al. (2006) focus on forecasting oil palm prices in Thailand, identifying optimal ARIMA models for different price types with high accuracy. These applications demonstrate ARIMA's versatility in handling diverse economic indicators and commodity prices. ARIMA models are also applied in forecasting inflation. Kelikume et al. (2014) used ARIMA to predict inflation in Nigeria, providing valuable insights for policymakers in economic planning. The study emphasized the model's effectiveness in capturing short-term fluctuations and aiding in monetary policy decisions.

Other Sectors: Tourism demand forecasting, as demonstrated by Abellana et al. (2020), utilized hybrid models to achieve high accuracy in predicting long-term trends. This study underscored the importance of incorporating multiple forecasting techniques to capture the nuances of tourism demand. In the energy sector, ARIMA models are employed for short-term load and price forecasting. Contreras et al. (2003) apply ARIMA to predict electricity prices, proving its relevance in competitive electric power markets. Cheng et al. (2023) combine the lifting scheme with ARIMA for load forecasting, achieving superior accuracy compared to traditional methods. These studies underscore ARIMA's utility in managing energy demand and pricing. In the real estate sector, Stevenson (2007) applied ARIMA models to forecast market trends, demonstrating the model's applicability in assessing market fluctuations and informing investment decisions. Jadevicius et al. (2015) also employed ARIMA models to investigate house price changes in Lithuania, providing valuable insights for stakeholders in the housing market.

Period-Specific Analysis

Calendar Specific: Many studies focused on the early 2000s to 2010s period, leveraging the availability of extensive historical data. For example, Rossetti et al. (2017) analyzed fixed income market volatility from 2000 to 2011, while Alnaa et al. (2011) predicted inflation in Ghana using data from 2000 to 2010. These studies highlight the importance of historical data in developing robust forecasting models. Research in the post-2010 period has continued to explore advanced forecasting techniques. Sen et al. (2016) study on stock price prediction in India's FMCG sector from 2010 to 2016 and Ismail et al. (2020) work on natural gas consumption from 2010 onwards exemplify the ongoing efforts to refine forecasting models with more recent data.Recent studies, such as Morina et al. (2024) and Bhatia et al. (2024), have focused on the 2020s, incorporating the latest data and addressing contemporary challenges. These studies demonstrate the evolving nature of forecasting models and their application to current economic and market conditions.

Financial Crises Specific: During financial crises, ARIMA models serve as indispensable tools for analyzing and predicting market behavior amidst heightened volatility and uncertainty. Researchers like Amir Angabini et al. (2010) and O (2012) have extensively utilized ARIMA models to study the impacts of crises on financial markets. For instance, Angabini et al. (2010) examined the Malaysian financial market during the 2007/2008 global financial crisis, employing ARIMA models to identify shifts in volatility dynamics and market efficiency. Their findings revealed increased sensitivity to external shocks and highlighted ARIMA's capability to capture sudden changes in market sentiment, providing critical insights for policymakers and financial institutions navigating turbulent economic environments. Similarly, Chowdhury (2022) research focused on the COVID-19 pandemic's impact on stock market volatility, employing ARIMA models to assess the effects of unprecedented global disruptions on market stability. Chowdhury's study underscored ARIMA's adaptability in modeling complex economic shocks and its role in forecasting short-term fluctuations amidst evolving crisis scenarios. By analyzing historical data and incorporating real-time market indicators, ARIMA models offer predictive accuracy crucial for anticipating market reactions and formulating proactive risk management strategies during financial crises. These studies collectively highlight ARIMA's versatility and reliability as a foundational tool in crisis management and financial forecasting, aiding stakeholders in mitigating risks and seizing opportunities in volatile market conditions.

Long- and Short-Term Trends Specific: In economic forecasting, ARIMA models serve as versatile tools capable of analyzing both long-term trends and short-term fluctuations across various sectors. For instance, Lwaho et al. (2023) demonstrate ARIMA's effectiveness in predicting long-term agricultural production trends, such as maize output in Tanzania, by leveraging historical data to identify underlying patterns and seasonal fluctuations crucial for policy and planning decisions. Conversely, ARIMA models, exemplified in studies like Viswanatha Reddy (2019) analysis of short-term stock market movements in India, excel in capturing immediate market dynamics and rapid changes in financial indicators. By integrating real-time data and adjusting model parameters dynamically, ARIMA enhances accuracy in short-term trend analysis, facilitating timely decision-making for investors and stakeholders navigating volatile economic landscapes. ARIMA model can provide valuable insights for investors seeking to make informed decisions based on short-term forecasts of stock prices (Wadi et al., 2018). ARIMA model is effective in short-term prediction, demonstrating its competitive edge against other established techniques in stock price forecasting (Adebiyi et al. 2014). McGough et al. (1995) focuses on short-term forecasting of commercial rental values in the UK using ARIMA models. These capabilities underscore ARIMA's comprehensive utility in providing insights into both enduring economic trajectories and transient market conditions, supporting strategic planning and informed decision-making across industries.

Pandemic Impact Specific: During the COVID-19 period, ARIMA models have proven essential in forecasting economic indicators and market behaviours amid unprecedented volatility. Wahyudi et al. (2021) utilized ARIMA to analyze inflation volatility in Indonesia before and during the pandemic, confirming its effectiveness in forecasting short-term inflationary trends. Similarly, Hendrawaty et al (2023) demonstrated ARIMA's predictive capability for short-term stock market movements in India, emphasizing its utility in financial decision-making during the pandemic. These models provided crucial insights for policymakers and investors, aiding in navigating the economic uncertainties induced by COVID-19. The adaptability of ARIMA models in responding to rapidly changing conditions underscored their value in maintaining financial stability and informing strategic decisions during crises. Furthermore, hybrid models combining ARIMA with machine learning techniques exhibited enhanced predictive performance, effectively capturing the complex and nonlinear patterns that emerged during the pandemic. Pai et al. (2005) and Wang et al. (2023) highlighted the superior accuracy of these hybrid models in financial markets, particularly in forecasting stock prices and market volatility. The integration of ARIMA with advanced methods improved the reliability of predictions, providing a robust framework for managing both short-term economic disruptions and longer-term trends. Overall, the extensive application of ARIMA and its hybrid variants during the COVID-19 period highlighted their critical role in time series analysis, offering a comprehensive tool for economic and market forecasting.

Summary: The literature on ARIMA models demonstrates their critical role in forecasting international stock index returns and other economic indicators. The extensive use of ARIMA in various studies underscores its robustness and flexibility in handling different types of time series data. Furthermore, the development of hybrid models that integrate ARIMA with advanced machine learning techniques reflects the ongoing efforts to improve forecasting accuracy and manage the intricacies of financial data. As global markets become increasingly interconnected and volatile, the insights gained from these studies provide valuable guidance for future research and practical applications, reinforcing the importance of ARIMA models in financial forecasting and strategic decision-making.

METHODOLOGY

The methodology for forecasting international stock index returns using the ARIMA model begins with data collection, focusing on major international stock indexes such as the S&P 500, FTSE 100, Nikkei 225, HANGSENG, and NIFTY50. Historical daily closing prices for these indexes are obtained from financial databases like Yahoo Finance, covering a substantial time frame (10years) to capture various market conditions and trends. Data preprocessing involves cleaning and transforming the collected data to ensure its quality and suitability for modelling. Missing values are addressed through interpolation or imputation techniques, and data consistency is maintained by standardizing formats and frequencies. Transformations like log transformation may be applied to stabilize variance, and normalization or standardization is performed to facilitate better model performance. Stationarity, a critical requirement for ARIMA modelling, is assessed using the Augmented Dickey-Fuller (ADF) test, and non-stationary series are differenced until stationarity is achieved. The ARIMA model is specified using the Box-Jenkins methodology, which involves identifying the model parameters (p,d,q). Here, p represents the autoregressive order, d denotes the degree of differencing, and q signifies the moving average order. These parameters are determined through the analysis of Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. Model estimation follows, with the ARIMA model being fitted to the historical stock index data using statistical software like Gretl. Parameters are estimated through Maximum Likelihood Estimation (MLE) or other suitable methods. In-sample validation involves assessing the model fit by examining residuals for autocorrelation using the Ljung-Box test, checking residuals' normality with Q-Q plots, and calculating performance metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Out-of-sample testing entails dividing the data into training and testing sets (typically 80% training, 20% testing) and evaluating the model's predictive accuracy on the test set using metrics like MAE, RMSE, and Mean Absolute Percentage Error (MAPE). The model with the best performance metrics is selected. Forecast generation uses the chosen ARIMA model to predict future returns of the selected international stock indexes, providing point forecasts and confidence intervals. The ARIMA model equation is given by:

$$Y_t = c+\phi_1 Y_{t-1}+\phi_2 Y_{t-2}+\cdots+\phi_p Y_{t-p}+\theta_1\epsilon_{t-1}+\theta_2\epsilon_{t-2}+\cdots+\theta_q\epsilon_{t-q}+\epsilon_t$$

where Y_t is the differenced series,
ϕrepresents the autoregressive coefficients,
θdenotes the moving average coefficients,
and ϵ_t is the white noise error term.

In the implementation phase, the forecasting model is deployed in a real-time environment, continuously updating it with new data and using automated systems for data fetching, preprocessing, and forecast generation. Performance monitoring is conducted regularly to recalibrate the model as necessary, tracking actual returns against forecasts and adjusting model parameters to improve accuracy. Finally, dashboards and visualizations are developed to present forecasted returns and confidence intervals, providing actionable insights and recommendations to stakeholders and decision-makers. This comprehensive methodology ensures the effective utilization of the ARIMA model for forecasting international stock index returns, aiding investors, policymakers, and financial analysts in making informed decisions.

RESULTS DISCUSSION

Table 1. Unit Root Test of Selected International Indices Returns

Indexes	ADF Test (12 lag)	ADF GLS Test (12 lag)	KPSS Test (4 lag)
FTSE 100	-11.8093* (0.0000)	-8.40228* (0.0000)	0.0464513 (>0.1000)
HANG SENG	-11.6921* (0.0000)	-8.58538* (0.0000)	0.0474445 (>0.1000)
NIKKEI 225	-11.3212* (0.0000)	-5.08264* (0.0000)	0.0325168 (>0.1000)
NIFTY 50	-11.2318* (0.0000)	-8.62505* (0.0000)	0.0445953 (>0.1000)
S&P 500	-9.43711* (0.0000)	-8.98395* (0.0000)	0.0436445 (>0.1000)

(Source: Author's calculations)(* 5 percent level of significance) (Probabilities in parenthesis)

The Table 1 presents the results of unit root tests conducted on the returns of five international stock indexes: FTSE 100, HANG SENG, NIKKEI 225, NIFTY 50, and S&P 500. The tests used include the Augmented Dickey-Fuller (ADF) Test, the ADF-GLS Test, and the KPSS Test. For the ADF test with 12 lags, all indexes show highly significant test statistics with values of -11.8093 (FTSE 100), -11.6921 (HANG SENG), -11.3212 (NIKKEI 225), -11.2318 (NIFTY 50), and -9.43711 (S&P 500), all with p-values of 0.0000, indicating strong evidence against the null hypothesis of a unit root and suggesting stationarity. Similarly, the ADF-GLS test results, with test statistics of -8.40228 (FTSE 100), -8.58538 (HANG SENG), -5.08264 (NIKKEI 225), -8.62505 (NIFTY 50), and -8.98395 (S&P 500), all significant at the 5% level with p-values of 0.0000, further confirm the stationarity of these indexes. The KPSS test, which assesses the null hypothesis of stationarity around a deterministic trend, yields test statistics of 0.0464513 (FTSE 100), 0.0474445 (HANG SENG), 0.0325168 (NIKKEI 225), 0.0445953 (NIFTY 50), and 0.0436445 (S&P 500), all above the 0.1000 threshold. This indicates that the null hypothesis of stationarity cannot be rejected, supporting the results of the ADF and ADF-GLS tests. Thus, the KPSS test corroborates the finding that the returns of these international stock indexes are stationary. The consistent results across all three tests provide robust evidence that the returns of FTSE 100, HANG SENG, NIKKEI 225, NIFTY 50, and S&P 500 are stationary, making them suitable for further time series modelling and forecasting.

Chart 1 depicts the ACF and PACF plots of selected international stock indices.The ACF and PACF plots for the FTSE 100 index reveal significant spikes at several lags, indicating strong autocorrelation and potential seasonality. The ACF shows notable autocorrelations at early lags, with several values exceeding the confidence intervals, while the PACF plot highlights significant partial autocorrelations at various lags, suggesting specific lagged dependencies. Conversely, the HANG SENG index displays a more dispersed pattern, with fewer significant spikes in the ACF and a gradual decline in autocorrelation, whereas the PACF shows

(Source: Author's Calculations)

Chart 1. ACF and PACF Plots Selected International Indices Returns (20 lag)

Table 2: Different ARIMA ModelParametersof Selected InternationalStock Indices Returns

S. No	Index	ARIMA Model	Constant	ϕ_1	ϕ_2	ϕ_3	θ_1	θ_2	θ_3	AIC	SC	RMSE	MAE	MPE	MAPE
1	FTSE 100	(1,0,1)	0.11120 (0.6757)	0.43182 (0.6028)			−0.53207 (0.4956)			650.8944	662.0443	3.5244	2.6928	94.049	98.747
		(2,0,1)	0.10109 (0.7149)	−0.9819* (0.0000)	−0.2070* (0.0230)		1.0000* (0.0000)			641.0942	655.0316	3.3135	2.4994	39.075	134.61
		(2,0,2)	0.10274 (0.7253)	−1.3204* (0.0007)	−0.4835 (0.1209)		1.3590* (0.0017)	0.35902 (0.4054)		642.5638	659.2888	3.3029	2.5015	38.037	136.94
2	HS	(1,0,1)	−0.1931 (0.3165)	0.9464* (0.0000)			−0.9999* (0.0000)			767.935	779.085	5.7052	4.3493	60.532	139.12
		(2,0,1)	−0.2353 (0.4915)	0.01151* (0.0003)	0.0181 (0.8623)		−0.9035* (0.0000)			770.1976	784.135	5.7448	4.3689	70.322	139.00
		(2,0,2)	−0.1942 (0.3223)	0.0792 (0.6686)	0.8264* (0.0000)		−0.1644 (0.4056)	−0.8355* (0.0000)		771.3474	788.0724	5.692	4.3283	78.666	139.44
3	NIKKEI 225	(1,0,1)	0.5842* (0.0000)	0.84283* (0.0000)			−1.0000* (0.0000)			712.679	723.829	4.5138	3.4163	81.01	146.64
		(2,0,1)	0.6044 (0.1209)	−0.8460* (0.0000)	−0.1425 (0.1374)		0.8392* (0.0000)			717.524	731.4615	4.6106	3.526	114.77	158.8
		(2,0,2)	0.6077 (0.0968)	−0.4853 (0.6100)	0.1586 (0.8449)		0.4787 (0.6058)	−0.3291 (0.6986)		719.5291	736.254	4.6109	3.538	115.65	166.78
4	NIFTY 50	(1,0,1)	0.93108* (0.0000)	0.8878* (0.0000)			−1.0000* (0.0000)			719.8563	731.0063	4.6571	3.3703	135.65	164.75
		(2,0,1)	1.02803* (0.0102)	−0.5120 (0.4276)	−0.0853 (0.3538)		0.4641 (0.4702)			725.9827	739.9201	4.7792	3.5121	134.4	173.96
		(2,0,2)	1.0394* (0.0108)	−0.449* (0.0000)	−0.9558* (0.0000)		0.37208* (0.0000)	0.95073* (0.0000)		721.2204	737.9454	4.6262	3.4158	68.857	179.26
5	S&P 500	(1,0,1)	0.78046* (0.0033)	0.33783 (0.1878)			−0.55050* (0.0130)			696.4166	707.5666	4.2596	3.2066	-393	577.44
		(2,0,1)	0.77813* (0.0038)	0.10276 (0.8197)	−0.11638 (0.3786)		−0.29993 (0.5051)			697.7166	711.6541	4.2468	3.1918	-331.2	514.52
		(3,0,3)	0.77867* (0.01590	0.4210* (0.000)	0.43797* (0.0000)	−0.839* (0.0000)	−0.5646* (0.0000)	−0.5646* (0.0000)	1.000* (0.0000)	694.5013	716.8013	3.9894	3.0547	-360.7	536.08

(Source: Author's calculations)(* 5 percent level of significance) (Probabilities in parenthesis)

Table 3. Actual, Estimation and Error of SelectedInternational Stock Indices Returns

Month	FTSE 100			HANG SENG			NIKKEI 225			NIFTY 50			S&P 500		
	Actual	Forecast	Error	Actual	Forecast	Error	Actual	Forecast	Error	Actual	Forecast	Error	Actual	Forecast	Error
Jan-24	-1.337	1.606	-2.943	-9.612	0.792	-10.404	8.098	-0.441	8.539	-0.026	-0.148	0.121	1.577	0.724	0.853
Feb-24	-0.007	1.036	-1.043	6.418	0.739	5.678	7.636	-0.280	7.916	1.176	-0.027	1.203	5.043	1.298	3.745
Mar-24	4.141	-0.463	4.605	0.181	0.690	-0.508	3.026	-0.144	3.170	1.553	0.081	1.473	3.055	-0.705	3.760
Apr-24	2.380	0.462	1.918	7.125	0.642	6.483	-4.987	-0.030	-4.957	1.237	0.176	1.061	-4.251	0.427	-4.678
May-24	1.599	-0.136	1.735	1.767	0.598	1.169	0.214	0.067	0.147	-0.329	0.261	-0.589	4.690	-0.455	5.145
Jun-24	-1.354	0.259	-1.613	-2.017	0.555	-2.572	2.806	0.148	2.658	6.362	0.336	6.026	3.408	1.350	2.058

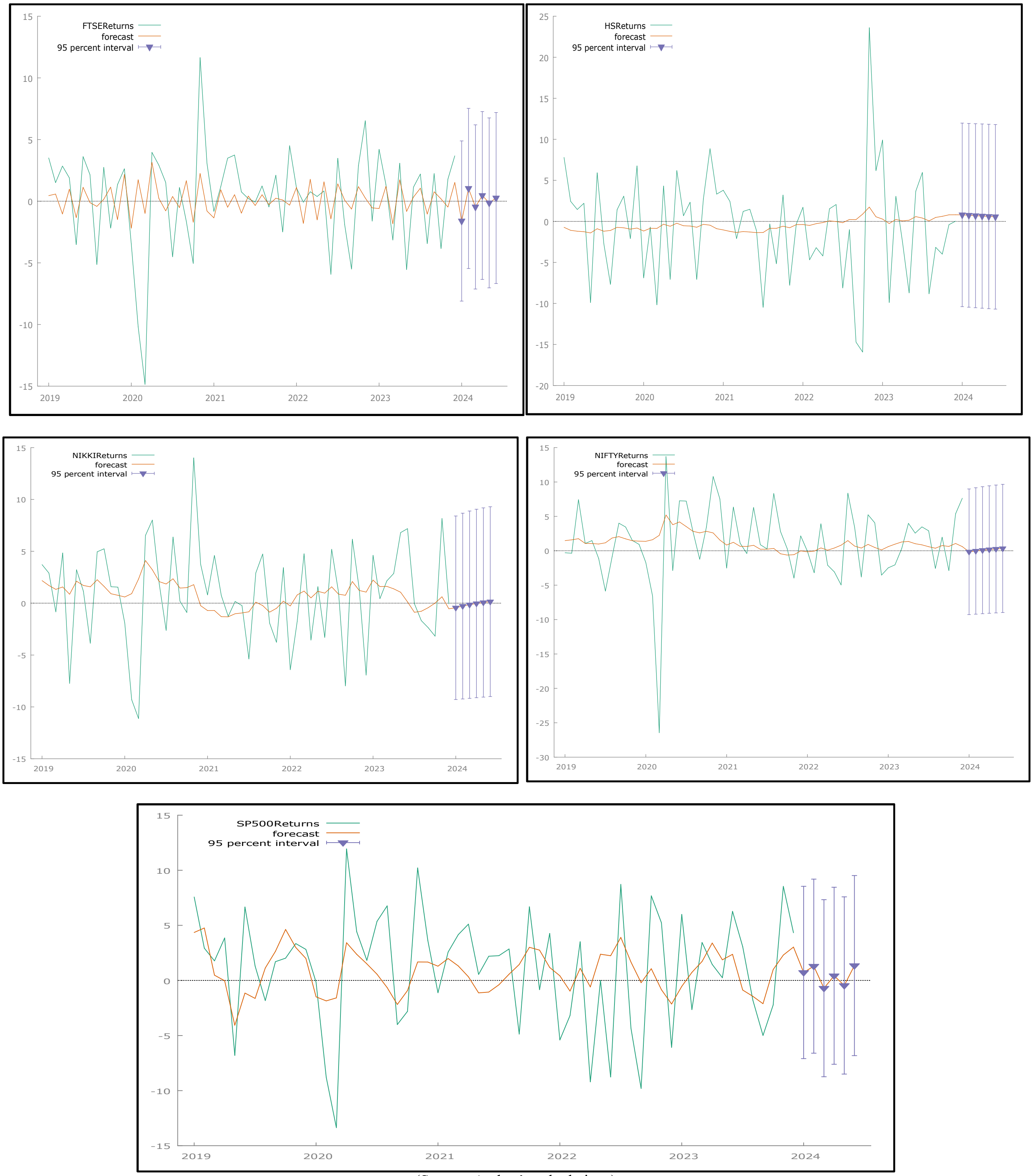
(Source: Author's calculations)

significant partial autocorrelations at early lags, tapering off later.For the NIKKEI 225, the ACF plot shows significant autocorrelations at various lags, suggesting non-randomness and influence from past values. The PACF plot's significant spike at the first lag indicates an AR(1) model may be appropriate. The NIFTY 50 also exhibits significant autocorrelations at multiple lags in the ACF, with the PACF showing a prominent spike at lag 1, supporting an AR(1) process. Similarly, the S&P 500's ACF plot indicates persistent patterns, and the PACF plot shows a significant spike at lag 1, both suggesting serial dependencies suitable for ARIMA modelling.

The ACF and PACF plots across the indices indicate significant autocorrelations and partial autocorrelations, suggesting the presence of temporal dependencies and non-randomness in the time series data. These patterns highlight the suitability of ARIMA models for capturing the relationships in the FTSE 100, HANG SENG, NIKKEI 225, NIFTY 50, and S&P 500 indices. Overall, AR(1) models appear particularly appropriate given the significant spikes at early lags in the PACF plots. The table 2 provides the ARIMA model specifications and their statistical outcomes for five international indices: FTSE 100, Hang Seng, NIKKEI 225, NIFTY 50, and S&P 500. The NIKKEI 225 index, ARIMA(1,0,1) model shows a significant constant term (0.5842) and significant autoregressive ($\phi1 = 0.84283$) and moving average ($\theta1 = -1.0000$) parameters. This model has an AIC of 712.679 and SC of 723.829, with RMSE and MAE values of 4.5138 and 3.4163, respectively. The MPE and MAPE values of 81.01 and 146.64 indicate substantial prediction errors. The ARIMA(2,0,1) and ARIMA(2,0,2) models, with higher AIC and SC values, do not significantly improve the fit or reduce prediction errors, suggesting that increased model complexity does not enhance predictive performance for the NIKKEI 225. For the FTSE 100, three models are assessed: ARIMA(1,0,1), (2,0,1), and (2,0,2). The ARIMA(2,0,1) model stands out with the lowest AIC (641.0942) and RMSE (3.3135), indicating the best fit among the models tested. This model features significant parameters ($\phi1 = -0.9819$, $\phi2 = -0.2070$, $\theta1 = 1.0000$), suggesting a balanced and accurate model with relatively low prediction errors (MPE = 39.075, MAPE = 134.61). The other models, although close, do not outperform the ARIMA(2,0,1) model in terms of these performance metrics.

The HS index models include ARIMA(1,0,1), (2,0,1), and (2,0,2). The ARIMA(1,0,1) model, with significant parameters ($\phi1 = 0.9464$ and $\theta1 = -0.9999$), exhibits an AIC of 767.935 and an RMSE of 5.7052. Despite having the lowest AIC among the models tested for this index, the HS index models exhibit high MPE and MAPE values (60.532 and 139.12), indicating significant prediction challenges. The more complex models (2,0,1) and (2,0,2) do not provide significant improvements, reflected in their higher AIC and RMSE values. The NIFTY 50 index's ARIMA(1,0,1) model, with significant parameters ($\phi1 = 0.8878$, $\theta1 = -1.0000$), shows an AIC of 719.8563 and RMSE of 4.6571. The high MPE and MAPE values (135.65 and 164.75) reflect considerable prediction difficulties. The ARIMA(2,0,2) model, despite having significant parameters, does not improve the fit substantially, with AIC and RMSE values remaining high. This suggests that, similar to the NIKKEI 225, increasing model complexity does not necessarily lead to better predictive performance. For the S&P 500, the ARIMA(3,0,3) model includes significant parameters ($\phi1 = 0.4210$, $\phi2 = 0.43797$, $\theta1 = -0.839$, $\theta2 = -0.5646$, $\theta3 = 1.000$) and shows the lowest AIC (694.5013) and RMSE (3.9894) among its evaluated models, indicating a better fit. However, the high MPE and MAPE values (-360.7 and 536.08) highlight significant prediction errors, likely due to the index's high volatility. Despite these challenges, the S&P 500's ARIMA(3,0,3) model demonstrates a relatively better fit compared to the other indices, showcasing the importance of carefully balancing model complexity and predictive accuracy. When comparing the indices, the FTSE 100 and S&P 500 models demonstrate relatively lower prediction errors. The FTSE 100's ARIMA(2,0,1) model has the lowest AIC (641.0942) and RMSE (3.3135) among all indices, suggesting a better fit. The S&P 500's ARIMA(3,0,3) model shows a comprehensive inclusion of parameters, with significant autoregressive and moving average terms, resulting in the lowest RMSE (3.9894) among its evaluated models. However, the S&P 500 exhibits extremely high MPE and MAPE values, indicating challenges in prediction accuracy, possibly due to its volatile nature. In contrast, the HS index models reveal higher AIC and RMSE values, indicating a relatively less accurate fit. The NIFTY 50's ARIMA (1,0,1) model provides a balanced trade-off with moderate AIC and RMSE values, but exhibits high prediction errors, similar to the NIKKEI 225. The table 3 presents actual, forecasted, and error values for the FTSE 100, Hang Seng, NIKKEI 225, NIFTY 50, and S&P 500 indices from January to June 2024. The forecasts are derived from ARIMA models, and the error is calculated as the difference between the actual and forecasted values. This analysis focuses on evaluating the forecast accuracy and identifying patterns in forecast performance across different indices. For the FTSE 100, the forecast errors fluctuate, with significant overestimations in January and March (errors of -2.943 and 4.605, respectively) and more accurate predictions in April and May (errors of 1.918 and 1.735, respectively). The Hang Seng index forecasts exhibit considerable errors throughout the period, with substantial underestimations in January (-10.404) and March (-0.508), and overestimations in February and April (errors of 5.678 and 6.483, respectively). These results indicate that the ARIMA model struggles to capture the volatility of the Hang Seng index. The NIKKEI 225 index shows a mix of overestimations and underestimations. The model significantly underestimates the index in January and February (errors of 8.539 and 7.916, respectively) but performs better in May and June (errors of 0.147 and 2.658, respectively). The NIFTY 50 forecasts are relatively accurate, with smaller errors in February, April, and June (errors of 1.203, 1.061, and 6.026, respectively). However, there are notable deviations in March and May (errors of 1.473 and -0.589, respectively). The S&P 500 forecasts demonstrate a high degree of accuracy in April and June (errors of -4.678 and 2.058, respectively) but show larger discrepancies in January and May (errors of 0.853 and 5.145, respectively). Overall, the ARIMA models provide varying degrees of accuracy across different indices. The FTSE 100 and NIFTY 50 show more consistent forecast performance with relatively smaller errors, suggesting these indices' historical patterns are more predictable. In contrast, the Hang Seng and NIKKEI 225 indices exhibit larger and more erratic errors, reflecting their higher volatility and the challenges in modeling their returns accurately. The S&P 500 forecasts also vary, but the model tends to perform better in capturing major movements compared to the Hang Seng and NIKKEI 225 indices.

Chart 2 depicts the actual and forecastedreturns of selected international stock indices, including the S&P 500, Nifty 50, FTSE 100, Hang Seng Index, and Nikkei Index. Each analysis notes significant volatility in the actual returns, particularly during periods of economic turbulence such as early 2021 and late 2023 for the Nikkei and early 2023 for the Hang Seng. The forecasts for all indices predict a general trend towards stabilization, albeit with increasing uncertainty as indicated by widening error bars. This growing uncertainty suggests that while the models attempt to smooth out extreme fluctuations observed in the actual data, there is still a broad range of potential outcomes as the forecast horizon extends into 2024. Comparing the paragraphs, it is evident that the analyses for each index follow a similar structure, emphasizing the contrast between historical volatility and predicted stabilization. The forecasts for all indices show less pronounced peaks and troughs compared to the actual data, reflecting a more moderated outlook. However, the error bars consistently indicate a cautionary note on the reliability of these predictions. Despite differences in regional and economic contexts, the overall trend across all indices suggests a move towards reduced volatility, though with a significant degree of uncertainty about future market behaviour. The table 4 presents the residual tests of selected international stock indices returns, analysing four key aspects: normality, autocorrelation, ARCH effects, and collinearity. Normality is assessed using a statistical test, where all indices show significant values at the 5 percent level, indicating non-normality in residuals. Notably, the NIFTY 50 index has the highest normality statistic (43.574) and the smallest p-value (0.0000), implying the strongest deviation from normality among the indices.



(Source: Author's calculations)

Chart 2. Selected International Stock Indices Actual and Forecasted Returns

Table 4. Residual Tests of Selected International Stock Indices Returns

Index	Normality		Auto Correlation		ARCH Effect		Collinearity	
	statistic	Prob	Ljung-Box	Prob	LM statistic	Prob	Belsley-Kuh-Welsch	
FTSE 100	18.341	0.0001*	5.1311	0.8227	20.1765	0.0638	0.2131	No Collinearity
HANGSENG	11.317	0.0034*	9.2603	0.5076	18.0565	0.1139	0.8314	No Collinearity
NIKKEI 225	8.221	0.0164*	14.943	0.1341	10.5415	0.5685	0.9773	No Collinearity
NIFTY 50	43.574	0.0000*	14.629	0.1462	3.49048	0.9909	0.8250	No Collinearity
S&P 500	6.097	0.0474*	8.9562	0.1761	7.9548	0.7886	0.1387	No Collinearity

(Source: Author's calculations)(* 5 percent level of significance)

In contrast, the S&P 500 has the lowest normality statistic (6.097) and a p-value (0.0474) just meeting the significance threshold, suggesting the least deviation from normality among the indices analysed. For autocorrelation, assessed using the Ljung-Box test, none of the indices show significant p-values, indicating no significant autocorrelation in residuals for any of the indices. ARCH effects, indicating volatility clustering, show mixed results. The FTSE 100 and HANGSENG indices have p-values close to significance at 0.0638 and 0.1139, respectively, suggesting potential ARCH effects, while the other indices, particularly the NIFTY 50 with a high p-value (0.9909), show no significant ARCH effects. Lastly, collinearity assessed using the Belsley-Kuh-Welsch test shows no collinearity issues across all indices, as all values are below the threshold indicating collinearity. The S&P 500 has the lowest collinearity value (0.1387), reaffirming that collinearity is not a concern in these residuals. This comprehensive analysis highlights the variation in statistical properties and potential issues within the residuals of these international stock indices returns.

CONCLUSION

In conclusion, the comprehensive analysis of selected international stock indices—FTSE 100, HANG SENG, NIKKEI 225, NIFTY 50, and S&P 500—reveals several key insights regarding their time series characteristics and modelling suitability. Firstly, all indices demonstrate stationarity based on robust evidence from unit root tests using the ADF and ADF-GLS methods, supported by non-rejection of the stationarity hypothesis in the KPSS test. This foundational finding underscores the potential for employing time series models like ARIMA to capture and forecast their returns effectively.Secondly, the ARIMA modelling results highlight varying degrees of model performance across indices. The FTSE 100 and S&P 500 exhibit more stable and lower prediction errors, particularly with well-fitted ARIMA specifications (e.g., ARIMA(2,0,1) for FTSE 100 and ARIMA(3,0,3) for S&P 500), despite challenges such as high volatility in the S&P 500. In contrast, the HANG SENG and NIKKEI 225 indices display higher prediction errors, indicating greater difficulty in capturing their volatile and less predictable market behaviours. The NIFTY 50 index shows moderate predictive performance, reflecting a balance between model complexity and accuracy. Lastly, the residual analysis provides insights into the statistical properties of the models' errors. While all indices exhibit non-normality in residuals, suggesting potential for further model refinement, autocorrelation tests indicate no significant serial correlation, except for marginal evidence of ARCH effects in some indices like FTSE 100 and HANG SENG. Importantly, collinearity is not a concern across any of the indices, ensuring the reliability of parameter estimates in the ARIMA models.In summary, while ARIMA models offer a viable framework for forecasting these international stock indices' returns, careful consideration of each index's volatility and non-random patterns is crucial. Future research could explore more advanced time series techniques or alternative models to further enhance predictive accuracy, especially for indices with higher inherent volatility like HANG SENG and NIKKEI 225. Overall, this analysis provides a solid foundation for understanding and predicting the dynamics of these key international stock markets, contributing to informed investment decisions and risk management strategies in global financial markets.

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