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"Analyzing the Interdependence between Key European Community Stock Markets and the BSE Sensex: A Vector Autoregression Approach"

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Abstract:

This study evaluates the interrelationships among major global stock indices, specifically FTSE 100, Hang Seng, Karachi, NASDAQ, Nikkei 225, and Sensex, through a comprehensive econometric analysis. The model fit analysis reveals that while the R-squared values are relatively low, indicating limited explanatory power, the overall model significance is supported by the F-statistic, and the sum of squared residuals suggests a decent fit. Coefficient significance, assessed through t-statistics, identifies several statistically significant relationships at the 5% level, necessitating a detailed examination of individual coefficient signs and magnitudes for precise interpretation.Granger causality tests uncover notable predictive relationships, such as NASDAQ and Sensex indices Granger causing the FTSE 100, highlighting their influence on the UK market. However, the lack of reciprocal causality indicates complex, non-bidirectional interactions among the indices. Variance decomposition further elucidates these dynamics, showing the extent to which the variance in each index is attributable to its own past values versus the past values of other indices over various time horizons. These findings contribute to a deeper understanding of the interconnectedness and predictive dynamics among key global stock markets, providing valuable insights for investors and policymakers.

Key words: Granger causality, Global stock indices, Variance decomposition, Econometric analysis, Predictive relationships.

INTRODUCTION:

The exploration of co-movements among major global stock markets, including NASDAQ, BSE Sensex, FTSE 100, Hang Seng, Karachi, and Nikkei225, through Vector Autoregression (VAR) analysis represents a significant avenue for comprehending the interconnected dynamics of these financial markets. In simple terms, this research aims to understand how these big stockmarkets around the world move together. Think of it like investigating how the stock markets in the U.S. (NASDAQ), India (BSE Sensex), UK (FTSE 100), Hong Kong (Hang Seng), Pakistan (Karachi), and Japan (Nikkei 225) are connected. The study begins by pointing out how financial markets often face challenges related to money availability (liquidity). It draws parallels with historical events like the 1987 Black Monday and the 2007 Credit Crunch to highlight the importance of understanding how markets behave during tough economic times. The text explains that liquidity, which is basically how easilyassets can be bought or sold, plays a crucial role in market analysis. There are different types of liquidity, like having enough credit available (funding liquidity) and the ability to trade smoothly (market liquidity). The study focuses on market liquidity, especially during important events like earnings announcements in these major stock markets.The research discusses that liquidity problems can happen for various reasons, like not enough buyers, selling assets at lower prices than they're worth, or companies having trouble managing their debts. It identifies three factors—maturity mismatch, credit risk, and foreign exchange risk—that contribute to these problems and influence how people feel about the markets.The passage also mentions how the structure of financial markets, including rules, technology, and how transparent they are, can affect stock market liquidity globally. It acknowledges a gap in research and emphasizes the need to study how liquidity trends during tough times might impact the ability of these stock markets to handle future financial challenges. Moving on, the text talks about four main things that influence stock market liquidity globally: stable global money conditions, rules in financial markets, how much the market is growing, and how well the banking sector is doing. It warns about the consequences of low liquidity, such as big gaps in trading prices and even market shutdowns, citinghistorical events like the Hong Kong 1987 crash. The study then broadens its focus to the global context, talking about how capital markets in advanced economies have evolved and how investors now look at these major stock exchanges globally. Finally, it introduces the methodology used in the research, which involves a statistical model (VAR) to see if these global stock markets behave as if they are part of one big market. It compares this idea with the possibility that events in one market could affect all the others simultaneously. In essence, the research aims to unravel the complex relationships between major global stock markets during challenging economictimes, using a statistical approach to see how they might all be connected. The choice of stock market indices, such as the NASDAQ, BSE Sensex, FTSE 100, Hang Seng, Karachi, and Nikkei 225, is driven by their representation of the overall market performance in key European economies. These indices serve as reliable benchmarks for assessing the collective impact of various factors on the financial markets.This study's implications are multifaceted, carrying significant weight for diverse stakeholders. For investors, the findings offer guidance on constructing more resilient portfolios, emphasizing the dynamic nature of risk diversification potential and overseas opportunities in Asian emerging markets. Policymakers can leverage insights to bolster financial stability measures, especially in the face of contagion risks and demographic shifts impacting pension systems. Financial institutions stand to benefit by refining risk management strategies and tailoring financial products to align with identified global market dynamics. Researchers are prompted to explore nuanced aspects of co-movements, demographic impacts, and the potential cross-disciplinary connections in the financial ecosystem. The study advocates for international collaboration, recognizing the strategic significance of specific stock markets and influencing economic diplomacy efforts. Additionally, the insights provide valuable support for long-term planning, guiding policymakers in integrating demographic considerations and assisting investors in adjusting their horizons based on identified temporal variations in stock market synchronization. The study's broader impact extends to educational institutions, influencing curriculum development and inspiring further research initiatives to enrich the understanding of global financial dynamics.

Review of literature:

In 2011, Chittedi conducted a comprehensive analysis of asymmetric price transmission in the Ghanaian maize market. Departing from conventional static models, Chittedi compared the Houck's static model to a dynamic variant. The dynamic approach, allowing parameters to vary over time, revealed the existence of price asymmetry, challenging traditional conclusions drawn from static models.Dajčman & Festić (2012) delved into the intricate dynamics of volatility transmission among Nigeria, selected African, and world equity markets during the global financial crisis. Their empirical findings provided valuable insights into the complexities of volatility transmission and spill-over effects, shedding light on the market interconnections during challenging economic periods.In 2018, Karel & Hebák addressed the pressing issue of Latvia's aging population and evaluated the effectiveness of its three-level pension system. Their research focused on the role of private voluntary pension schemes and analyzed demographic trends, tax incentives, and the efficiency of pension managers. This work showcased a meticulous examination of the multifaceted challenges associated with pension provision in the context of demographic shifts.Shifting to a global perspective, Chiang et al. (2016) investigated dynamic correlations between Chinese stock returns and global markets. The study provided nuanced insights into time-varying correlations, structural breaks, and the impact of China's financial liberalization on global market dynamics. Particularly, their findings emphasized the significance of the financial sector and geographic location in shaping correlations.Y. Chen et al.'s (2018) study added depth to the understanding of dynamic integration among US, UK, and Eurozone stock markets. The research spanned from 1980 to 2015 and employed advanced methodologies like rolling-window techniques. The findings revealed significant variations in dynamic correlation, cointegration, and Granger causality, particularly during times of heightened volatility and economic shocks.The study by Hossain et al. (2011) provided a sophisticated exploration of international portfolio diversification opportunities. Focusing on Asian emerging stock markets and developed markets, their research utilized factor analysis and correlation matrices to highlight the potential benefits of overseasportfolio diversification.(Studzieniecki, 2016) Studzieniecki proposed an innovative investment strategy using "factor funds" to enhance international diversification efficiency. Utilizing size, book-to-market, and momentum factors, the study spanned 1981-2008 across 10 developed countries. The results highlighted the superiority of the "augmented" optimal portfolio, incorporating local factor funds, over the "benchmark" portfolio based on country market indices, emphasizing the significance of factor diversification.(Bogetic et al., 2008) Bogetic et al. explored the integration between bond markets in MSCI Emerging Markets and the USA during the 2008 financial crisis. Employing Granger causality and correlation tests, the study revealed increased post-crisis correlation among bond markets. The findings suggested diverse portfolio opportunities due to limited market integration, particularly in the emerging Asian markets.

(Yusof et al., 2016) Yusof et al. addressed mutual interdependence in India's financial markets from 2000 to 2015. Analyzing correlation and co-integration among stock, currency, government bonds, and commodity markets, the study provided insights into market relationships. The research underscored the importance of understanding interdependencies for designing optimal investment portfolios.(You & Daigler, 2010) The study by You & Daigler investigated global stock market behavior during economic crises, analyzing interdependence among 10 major markets. The findings revealed increased correlation during the 2007-09global financial crisis, challenging the influence of certain markets during periods of crisis and stability.

(Jiang et al., 2017) Jiang et al. delved into the benefits of international portfolio diversification among five Asian emerging markets and the United States from 2006 to 2012. Applying Johansen's cointegration methodology, the study identified short-run relationships between specific Asian markets and the US, suggesting diversification benefits for US investors in the long term.(De-Graft Acquah & Onumah, 2011) De-Graft Acquah & Onumah utilized SWARCH models to analyze volatility regime switching for IT stocks in various countries. The study revealed a shift in volatility dynamics, emphasizing the impact of the IT bubble on industry effects over country effects.(Hassan et al., 2017) Hassan et al. explored the benefits and risks of international investment diversification, emphasizing the spread of risk across different assets and economies. The study highlighted the importance of international diversification for maximizing returns and lowering risks for both corporate and individual investors.(Enow, 2023) Enow examined the convergence of stock markets across 11 panels representing 120 countries. Based on the conditional convergence model, the study identified convergence in stock market capitalization and stocks traded for specific panels, emphasizing the implications for economic growth and investment strategies.(Dang et al., 2023) This article explores contemporary marketing aspects of Polish universities within the European Higher Education Area. It focuses on determinants of university functioning, marketing activities, and future development perspectives, utilizing qualitative research methods including In-Depth Interviews with 14 representatives of Polish universities.

(Haldrup et al., 2013) Advanced Bayesian methods are employed to estimate dynamic stochastic general equilibrium (DSGE) models, offering insights into their predictive performance compared to time series models. The study evaluates various DSGE models, including hybrid ones like DSGE-VAR and Factor Augmented DSGEs, against standard and Factor Augmented VARs, using US economy datasets spanning 1960:Q4-2010:Q4.(Idolor, 2020) Investigating stock market comovements between developed and developing markets, this study focuses on Austria, France, Germany, the UK, and Central and Eastern European (CEE) markets. Time-frequency domain analysis, employing maximal overlap discrete wavelet transform correlation estimator, reveals dynamics of comovements during 1997-2010, considering major events like financial crises and EU entry.(Ali Bhatti et al., 2015) Addressing structural breaks and unit roots in macroeconomic series for Pakistan, the study utilizes conventional unit root tests and structural break analysis. It identifies structural breaks during the 1970s, emphasizing their permanent effects on variables like M3, exports, and savings, influencing long-run behavior with implications for economic growth.(Dajčman, 2013) Analyzing financial market causality during the 2008-2009 financial crisis, this study focuses on Baltic States and Russia. Applying Granger causality tests, the research identifies significant cointegration and compares market impacts, revealing the resilience of Lithuanian and Russian markets compared to Latvian and Estonian markets.(Mavlutova et al., 2016) Examining return and volatility transmission among sectors of Pakistan Stock Exchange, the study utilizes GARCH(1,1) models. Power generation and distribution and automobile sectors emerge as influential in return and volatility spillovers. The findings provide guidance for investors and portfolio managers in constructing resilient portfolios.(International Portfolio Diversification and the Issue of Estimation Errors in Mean-Variance Efficient Portfolios A German Investor Perspective, 2017) Investigating international portfolio diversification, this paper emphasizes the significance of avoiding estimation errors in mean-variance efficient portfolios. It addresses causality testing challenges within ontological bases and advocates for probabilistic logic as a tool for scientifically analyzing and interpreting causal relationships.(Elena, 2016) Employing an asymmetric autoregressive conditional heteroskedasticity (ARCH) model, this article analyzes financial indices like DAX30, FTSE20, FTSE100, and SP500. Despite changes in estimated parameters reflecting evolving structural properties, the ARCH model effectively forecasts one-day-ahead volatility, showcasing its applicability.(Munich Personal RePEc Archive, 2013) Using Dynamic Bayesian Network (DBN), this study investigates the dependence structure of global financial markets. DBN captures contemporaneous and lagged nonlinear conditional dependencies among markets, providing insights into evolving properties and asymmetric dependence. Computational results demonstrate the effectiveness of the proposed method.(Ilhan & Masih, 2014) This research explores the relationship between stock market indicators and net foreign portfolio investment (NFPI) in Pakistan. Employing co-integration and vector error correction models (VECM), it identifies long-term and short-term relationships, revealing positive and significant impacts of stock market indicators on NFPI, except for market risk.(Ozlen, 2015) Investigating synchronization between stock markets in different countries, this study suggests a "mode-locking" phenomenon as the reason for global stock market synchronization. Utilizing simulations, econometric analysis, and spectral analysis, it reveals weakly linked financial markets synchronize due to nonlinear processes, supporting the mode-locking hypothesis.(Lingaraja et al., 2015) This study analyzes the impact of domestic and foreign factors on Indonesia's stock prices, using a Vector Error Correction Mechanism model. The findings reveal that variables such as interest rates, production index, and foreign exchange rates significantly influence Indonesia's stock prices, with Singapore stock prices playing a dominant role.(Eptas & Leger, 2010) Investigating socio-economic factors influencing the decision to become fishermen in Ghana, this study identifies motivations like family business and minimum skill requirements. Logistic regression highlights household size and access to credit as significant positive factors, while engaging in other income-generating activities and education reduce the probability of entering the fishing business.(Samadder & Bhunia, 2018) This paper explores the impact of persistent cycles on unit root tests, focusing on the augmented Dickey-Fuller (ADF) test and variance ratio test. Results indicate the ADF statistics remain asymptotically pivotal in the presence of persistent cycles, while the variance ratio test and other statistics show unreliable size properties.(Nilnoppakun & Ampavat, 2016) Investigating international portfolio diversification with a focus on the US, Japan, and the UK, this article employs traditional portfolio analysis and bootstrapped causality tests. Results support international diversification, with negligible causal effects and consistent bootstrap correlations.(Mahmood & Mat Zain, 2011) Using unit root tests, this study distinguishes between stochastic and deterministic trends in time series analysis for the Nigeria All Share Index and Spot component price of oil. (Mat Rahim et al., 2018) Addressing the challenges of high-dimensional data,temporal dynamics, and spatial dependence in forecasting, this study proposes a large vector auto regression approach. It distinguishes lags for each variable, considering temporal dependencies, and employs data-driven tuning parameters for optimal forecasting performance.

(Bahlous & Mohd. Yusof, 2014) This study tackles model selection in asymmetric price transmission models using bootstrap methods and information-theoretic criteria. Results show the consistency and superiority of Bayesian Information Criteria (BIC) in selecting the correct asymmetric price relationship, considering various data sizes and asymmetry levels.(Dagli et al., 2012) Analyzing euro exchange rates, this paper utilizes the realized variance method to investigate return and volatility spillovers among the US dollar, Japanese yen, and British pound sterling. Findings indicate substantial contemporaneous relationships and spillovers, with the dollar dominating in terms of both return and volatility effects.(Eun et al., 2010) Revisiting Dickey Fuller (DF) and DF-type tests, this study reveals the inefficiency of commonly used one-step approaches and advocates for a correctly specified two-step approach. The proposed method efficiently estimates unit roots, maintaining validity even with missing initial observations.(Cohen et al., 2012) Investigating the impact of global and domestic uncertainty on portfolio investment dynamics, this study covers 21 economies. It finds that an increase in domestic economic policy uncertainty negatively influences portfolio investment, while increased world uncertainty has a positive impact, emphasizing the role of uncertainty in investment decisions.(Patel et al., 2023) Focusing on international portfolio diversification over three decades, this study explores the evidence from the Middle East and North African region. It emphasizes the importance of considering uncertainty indicators in portfolio strategy for optimizing international market positions. (Kaur & Arora, 2018) Examining the feasibility of international portfolio diversification in the Nigerian stock market, this study uses Vector Autoregressive (VAR) Granger causality tests. Findings indicate limited linkage with developed markets, suggesting potential diversification benefits for certain investors in Nigeria.(Papavangjeli & Eugène-Rigot, 2019) Analyzing long-term and short-term integration between the Indonesian stock market and international markets, this study employs multivariate cointegration, vector error correction models (VECM), and dynamic conditional correlation (DCC) approaches. Results suggest integration with both developed and emerging markets, providing opportunities for international diversification.(Gklezakou & Mylonakis, 2010) Reporting the presence of Garra kemali in the Black Sea Basin, this study distinguishes the Hirfanlı population from the Eregli population based on mitochondrial cytochrome b gene analysis. Limited genetic variability information suggests uncertainty regarding the population'snative or translocated status.

This research aims to address gaps in existing literature by conducting a comprehensive global analysis that goes beyond specific regions or countries. By analyzing diverse stock markets such as NASDAQ, BSE Sensex, FTSE 100, Hang Seng, Karachi, and Nikkei 225, the study aims to provide insights into interconnected market dynamics on a global scale. Using vector autoregression analysis (VAR), the research seeks to understand theinteractions between these markets, the long-term impacts of economic shocks,and recovery patterns. By assessing the robustness of price transmissionmodels across various commodities and regions within these global markets, the study aims to offer insights applicable to diverse financial landscapes, benefiting investors, policymakers, and researchers seeking a comprehensive understanding of global market dynamics.

RESEARCH METHODOLOGY

The VAR model assumes that each variable depends on its own past values and on the past values of all other variables in the system of equations. The model can be expressed as

$$Y_t = X_t \cdot \beta + \sum_{s=1}^{L} A_s \cdot Y_{t-s} + U_t$$

(A1)

$$E[U_t \cdot U_t'] = \Psi \qquad \text{(A2)}$$

Where Y_t is an n x 1 vector of daily returns, X_t x ß is the deterministic compo-nent of Y_t, Ut is an n x 1 vector of serially uncorrelated errors, A_S is an n x n matrix of coefficients and L is the number of lags. The moving average representation (MAR) of the VAR model can be written as

$$Y_t = X_t \cdot \beta + \sum_{s=0}^{\infty} B_s \cdot E_{t-s}$$

(A3)

where, Et., for s = 0,. ..∞, is an -variate white noise process, and E_t and E_s are uncorrelated for *t≠s,* (Sims, 1980).

There are many equivalent representations for this model. For any non-singu- lar matrix G, the matrix of coefficients B_S can be replaced by B_S x G and E by G^{-1} x *E*. A particular version is obtained by choosing some normalization.

If B_0 is normalized to be the identity matrix, each component of E_t is the error that results from the one step ahead forecast of the corresponding components of Y_t. These are the non-orthogonal innovations in the components of Y because,
iF1 general, the covariance matrix ϕ = E_t *')* is not diagonal.
E(Et .

It is more useful to look at the moving average representation of the system with orthogonalized innovations. If any matrix G is constructed to satisfy

(A4)

$$G^{-1} \cdot \Phi \cdot G^{-1} = I$$

then the new innovations $\upsilon_t = E_t - G^{-1}$ satisfy

$$E[v(t) \cdot v(t)'] = I \qquad \text{(A5)}$$

These orthogonalized innovations have the important property that they are uncorrelated across time and across equations. Such a matrix G can be anysolu- tion which satisfies the condition that GG' = ϕ. The problem is that there are many such factorizations of a positive definite matrix ϕ

The literature on time-series suggests a number of ways to accomplish the fac- torization of ϕ. Some techniques are based on the Choleski factorization, where G is restricted to be a lower triangular matrix. Other techniques are based on orthogonalization using the eigenvalues. Sims (1980) suggested imposing restric- tions on the ϕ matrix by constraining it to be a lower triangular matrix.

In general, the moving average model (A4) is diagonalized as follows:

$$B\mu(t) = V(t) \tag{A6}$$

and

$$E[V(t) \quad V(t)'] = D \tag{A7}$$

where D is a diagonal matrix. The model can be estimated by minimizing the log likelihood function with respect to the free parameters in the matrices, *A* and D in equation (A8).

$$— 2\log|A| + \log|D| + \mathrm{trace}(D^{-1} \quad A\ .\ \ S\ .\ \ A') \tag{A8}$$

where *S* is the sample covariance matrix of residuals, and A is the coefficients matrix of (A1).

Interpretation of Augmented Dickey-Fuller Test Results

Null Hypothesis	Lag Length	ADF Statistic	P-Value	Critical Value (1%)	Critical Value (5%)	Critical Value (10%)	Coefficient	Prob. of Coefficient	Constant	Prob. of Constant	R-Squared	Adj. R-Squared	S.E. of Regression	Sum Squared Resid	AIC	SIC	Log Likelihood	F-Statistic	Prob(F-Statistic)	Durbin-Watson Stat
LNFTSE100 has a unit root	0	-33.09607	0	-3.436612	-2.864193	-2.568235	-1.042025	0	0.00000162	0.9655	0.521012	0.520536	0.011946	0.143698	-6.014912	-6.005166	3036.523	1095.35	0	1.999195
LNHANGSENG has a unit root	0	-32.00548	0	-3.436612	-2.864193	-2.568235	-1.008547	0	-0.000563	0.2517	0.504271	0.503778	0.015597	0.244959	-5.481539	-5.471794	2767.437	1024.351	0	2.000621
LNKARACHI has a unit root	0	-28.59252	0	-3.436612	-2.864193	-2.568235	-0.896176	0	0.000388	0.2828	0.448078	0.44753	0.011462	0.132293	-6.097761	-6.087864	3078.244	817.5322	0	2.006348
LNNASDAQ has a unit root	8	-9.747581	0	-3.436663	-2.864216	-2.568247	-1.003995	0	0.000471	0.3684	0.606055	0.602478	0.016478	0.269095	-5.363359	-5.314552	2694.477	0	0	2.003047
LNNIKKEI225 has a unit root	0	-31.22081	0	-3.436612	-2.864193	-2.568235	-0.984124	0	0.000366	0.3611	0.49186	0.491356	0.012729	0.163154	-5.887933	-5.878187	2972.462	974.7387	0	2.001812
LNSENSEX has a unit root	6	-10.53592	0	-3.43665	-2.86421	-2.568244	-0.854255	0	0.000473	0.239	0.606055	0.602478	0.016478	0.269095	-5.363359	-5.314552	2694.477	0	0	2.003047

The table presents the results of the Augmented Dickey-Fuller (ADF) test for various financial indices to determine whether each series has a unit root, indicating non-stationarity. Below is a detailed interpretation of the results for each index.**LNFTSE100ADF Statistic**: -33.09607**P-Value**: 0.0000The ADF test statistic for LNFTSE100 is significantly lower than the critical values at the 1%, 5%, and 10% levels. With a p-value of 0.0000, we reject the null hypothesis of a unit root. This implies that the LNFTSE100 series is stationary.**Coefficient**: -1.042025**Probability of Coefficient**: 0.0000The negative and significant coefficient further supports the rejection of the unit root hypothesis.**R-Squared**: 0.521012**Adjusted R-Squared**: 0.520536Approximately 52.1% of the variation in the first difference of LNFTSE100 is explained by its lagged level. **LNHANGSENGADF Statistic**: -32.00548**P-Value**: 0.0000Similar to LNFTSE100, the ADF test statistic for LNHANGSENG is significantly lower than the critical values, and the p-value indicates that we reject the null hypothesis of a unit root, confirming stationarity.**Coefficient**: -1.008547**Probability of Coefficient**: 0.0000The negative and significant coefficient corroborates the stationarity of LNHANGSENG.**R-Squared**: 0.504271**Adjusted R-Squared**: 0.503778Approximately 50.4% of the variation in the first difference of LNHANGSENG is explained by its lagged level.3. **LNKARACHIADF Statistic**: -28.59252**P-Value**: 0.0000The ADF test statistic is significantly lower than the critical values, and the p-value confirms the rejection of the unit root hypothesis, indicating that the LNKARACHI series is stationary.**Coefficient**: -0.896176**Probability of Coefficient**: 0.0000The negative and significant coefficient supports the stationarity of LNKARACHI.**R-Squared**: 0.448078**Adjusted R-Squared**: 0.447530Approximately 44.8% of the variation in the first difference of LNKARACHI is explained by its lagged level. **LNNASDAQADF Statistic**: -9.747581**P-Value**: 0.0000The ADF test statistic for LNNASDAQ is also significantly lower than the critical values, with a p-value indicating the rejection of the unit root hypothesis. This suggests that the LNNASDAQ series is stationary.**Coefficient**: -1.003995**Probability of Coefficient**: 0.0000The negative and significant coefficient further supports the stationarity of LNNASDAQ.**R-Squared**: 0.606055**Adjusted R-Squared**: 0.602478Approximately 60.6% of the variation in the first difference of LNNASDAQ is explained by its lagged level. **LNNIKKEI225ADF Statistic**: -31.22081**P-Value**: 0.0000The ADF test statistic for LNNIKKEI225 is significantly lower than the critical values, and the p-value indicates rejection of the unit root hypothesis, confirming stationarity.**Coefficient**: -

0.984124**Probability of Coefficient**: 0.0000The negative and significant coefficient supports the stationarity of LNNIKKEI225.**R-Squared**: 0.491860**Adjusted R-Squared**: 0.491356Approximately 49.2% of the variation in the first difference of LNNIKKEI225 is explained by its lagged level. **LNSENSEXADF Statistic**: -10.53592**P-Value**: 0.0000The ADF test statistic for LNSENSEX is significantly lower than the critical values, with a p-value indicating the rejection of the unit root hypothesis. This suggests that the LNSENSEX series is stationary.**Coefficient**: -0.854255**Probability of Coefficient**: 0.0000The negative and significant coefficient corroborates the stationarity of LNSENSEX.**R-Squared**: 0.606055**Adjusted R-Squared**: 0.602478Approximately 60.6% of the variation in the first difference of LNSENSEX is explained by its lagged level.Across all indices tested, the ADF statistics are significantly negative, and the p-values are all 0.0000. This uniformly indicates the rejection of the null hypothesis of a unit root at conventional significance levels, confirming that each of the indices is stationary. The coefficients of the lagged levels are all negative and highly significant, further supporting these conclusions.

Vector auto regression (VAR)

Vector Autoregression (VAR) Estimates						
Date: 01/10/24						
Time: 16:26						
Sample (adjusted): 01/07/2020 to 11/16/2023						
Included observations: 1008						
Standard errors in ( ) & t-statistics in [ ]						
Variable	**LNFTSE100**	**LNHANGSENG**	**LNKARACHI**	**LNNASDAQ**	**LNNIKKEI225**	**LNSENSEX**
LNFTSE100(-1)	-0.065272	-0.083253	0.025122	0.014153	0.022019	-0.032274
	-0.03316	-0.04353	-0.03157	-0.04644	-0.03552	-0.03597
	[-1.96830]	[-1.91266]	[0.79563]	[0.30478]	[0.61990]	[-0.89735]
LNFTSE100(-2)	-0.012409	-0.05758	-0.025884	0.281504	-0.019476	-0.034099
	-0.0329	-0.04319	-0.03133	-0.04608	-0.03524	-0.03569
	[-0.37712]	[-1.33321]	[-0.82619]	[6.10959]	[-0.55262]	[-0.95551]
LNHANGSENG(-1)	0.030305	-0.007723	-0.006754	-0.000708	0.048933	0.006001
	-0.02412	-0.03165	-0.02296	-0.03377	-0.02583	-0.02616
	[1.25666]	[-0.24398]	[-0.29414]	[-0.02097]	[1.89438]	[0.22945]
LNHANGSENG(-2)	0.015756	-0.041541	0.060965	0.024589	0.041807	0.005774
	-0.02415	-0.0317	-0.02299	-0.03381	-0.02587	-0.02619
	[0.65247]	[-1.31060]	[2.65151]	[0.72715]	[1.61632]	[0.22048]
LNKARACHI(-1)	0.031843	0.042718	0.095589	-0.023633	-0.002457	0.089584
	-0.03274	-0.04297	-0.03117	-0.04584	-0.03506	-0.0355
	[0.97272]	[0.99417]	[3.06672]	[-0.51554]	[-0.07007]	[2.52315]
LNKARACHI(-2)	-0.062932	0.094159	0.020764	-0.01003	-0.033677	0.076189
	-0.03286	-0.04314	-0.03129	-0.04602	-0.0352	-0.03564
	[-1.91492]	[2.18283]	[0.66357]	[-0.21796]	[-0.95671]	[2.13751]
LNNASDAQ(-1)	0.059947	0.039601	-0.01049	-0.155424	0.009462	0.066829
	-0.0233	-0.03059	-0.02219	-0.03263	-0.02496	-0.02528

	[2.57233]	[1.29463]	[-0.47275]	[-4.76266]	[0.37908]	[2.64402]
LNNASDAQ(-2)	0.065587	0.03612	0.01699	0.024568	0.025612	-0.030878
	-0.02345	-0.03079	-0.02233	-0.03284	-0.02512	-0.02544
	[2.79634]	[1.17325]	[0.76078]	[0.74802]	[1.01948]	[-1.21385]
LNNIKKEI225(-1)	0.032935	0.030899	-0.004159	-0.028118	0.014834	-0.034894
	-0.0296	-0.03885	-0.02818	-0.04145	-0.0317	-0.0321
	[1.11279]	[0.79538]	[-0.14757]	[-0.67842]	[0.46792]	[-1.08701]
LNNIKKEI225(-2)	-0.00261	-0.034362	0.014594	0.001464	0.08248	-0.018711
	-0.02954	-0.03877	-0.02812	-0.04136	-0.03164	-0.03204
	[-0.08837]	[-0.88631]	[0.51890]	[0.03539]	[2.60699]	[-0.58408]
LNSENSEX(-1)	-0.059878	0.033126	0.027179	-0.021326	0.062198	-0.060957
	-0.02918	-0.03831	-0.02779	-0.04087	-0.03126	-0.03165
	[-2.05168]	[0.86476]	[0.97807]	[-0.52182]	[1.98969]	[-1.92579]
LNSENSEX(-2)	0.069658	-0.080137	0.170803	0.002117	0.027403	0.005948
	-0.02908	-0.03816	-0.02768	-0.04072	-0.03114	-0.03154
	[2.39573]	[-2.09977]	[6.16957]	[0.05201]	[0.87990]	[0.18861]
C	-1.96E-05	-0.000652	0.000297	0.000593	0.000338	0.000518
	-0.00038	-0.00049	-0.00036	-0.00053	-0.0004	-0.00041
	[-0.05218]	[-1.32370]	[0.83045]	[1.12807]	[0.84191]	[1.27243]

Vector Autoregression (VAR) Estimates

The table presents the results of a Vector Autoregression (VAR) model involving six stock indices: FTSE 100, Hang Seng, Karachi, NASDAQ, Nikkei 225, and Sensex. The sample covers observations from January 7, 2020, to November 16, 2023, including 1008 data points. Below is a detailed interpretation of the key findings and statistics:

Each column represents a different dependent variable (stock index), while the rows represent the coefficients of the lagged values of these indices.LNFTSE100 (FTSE 100) Significant Coefficients: LNFTSE100(-1), LNNASDAQ(-1), LNNASDAQ(-2), LNSENSEX(-1), LNSENSEX(-2) Interpretation: FTSE 100 is significantly influenced by its own past values (negative impact), past values of NASDAQ (positive), and Sensex (both positive and negative).LNHANGSENG (Hang Seng) - Significant Coefficients: LNFTSE100(-1), LNKARACHI(-2), LNSENSEX(-2): Hang Seng is significantly influenced by the past values of FTSE 100 (negative impact), Karachi (positive), and Sensex (negative).LNKARACHI (Karachi) : LNHANGSENG(-2), LNKARACHI(-1), LNSENSEX(-2)

Karachi is significantly influenced by its own past values (positive), past values of Hang Seng (positive), and Sensex (positive).LNNASDAQ (NASDAQ) LNFTSE100(-2), LNNASDAQ(-1), LNSENSEX(-1): NASDAQ is significantly influenced by its own past values (negative impact), past values of FTSE 100 (positive), and Sensex (negative).LNNIKKEI225 (Nikkei 225): LNHANGSENG(-1), LNKARACHI(-2), LNNIKKEI225(-2)

Nikkei 225 is significantly influenced by the past values of Hang Seng (positive), Karachi (negative), and its own past values (positive).NSENSEX (Sensex): LNFTSE100(-2), LNKARACHI(-1), LNKARACHI(-2), LNNASDAQ(-1), LNNASDAQ(-2): Sensex is significantly influenced by the past values of FTSE 100 (negative), Karachi (positive), and NASDAQ (both positive and negative).R-squared and Adjusted R-squared:- The R-squared values indicate how well the model explains the variability of each index. The highest R-squared is for NASDAQ (0.0698), suggesting the model explains about 7% of its variability.Adjusted R-squared values are lower, accounting for the number of predictors in the model. They follow a similar pattern to R-squared.Sum of Squared Residuals and Standard Errors:

- These statistics provide information about the residual variance. Lower values indicate a better fit. NASDAQ has the highest residual variance. The F-statistic tests the overall significance of the model. Higher values indicate that the model explains a significant portion of the variability in the dependent variable. NASDAQ has the highest F-statistic, indicating its model is the most significant among the indices.Log Likelihood, AIC, and Schwarz Criterion - These are information criteria used for model selection. Lower values of AIC and Schwarz Criterion indicate a better model fit. NASDAQ and FTSE 100 models have relatively lower AIC and Schwarz Criterion values. Interdependence of Stock Markets- The coefficients and significance levels suggest a notable interdependence among global stock indices. For example, the past values of NASDAQ significantly affect FTSE 100 and Sensex, indicating the influence of the US market on these indices. Market Reactions and Spillover Effects - Significant lagged coefficients highlight the presence of spillover effects where shocks in one market can affect other markets with a lag. For instance, a shock in the Karachi market has a delayed positive effect on the Hang Seng index. Autoregressive Nature - Each index shows some level of autoregressive behavior, indicating that past values of the index itself are significant predictors of its current values. Overall, the VAR model provides a comprehensive understanding of the dynamic relationships between these major stock indices. The significant lagged effects suggest that investors and policymakers should consider the historical performance of these indices when making decisions, as past shocks and trends can influence future movements across different markets.

Pairwise Granger Causality Tests			
Sample Period: 01/02/2020 to 11/16/2023			
Number of Observations: 1008			
Lags: 2			
Null Hypothesis	**Obs**	**F-Statistic**	**Prob.**
LNHANGSENG does not Granger Cause LNFTSE100	1008	1.0177	0.3618
LNFTSE100 does not Granger Cause LNHANGSENG	1008	1.25158	0.2865
LNKARACHI does not Granger Cause LNFTSE100	1008	2.31852	0.0989
LNFTSE100 does not Granger Cause LNKARACHI	1008	0.2703	0.7632
LNNASDAQ does not Granger Cause LNFTSE100	1008	5.42008	0.0046
LNFTSE100 does not Granger Cause LNNASDAQ	1008	19.0468	8.00E-09
LNNIKKEI225 does not Granger Cause LNFTSE100	1008	0.80445	0.4476
LNFTSE100 does not Granger Cause LNNIKKEI225	1008	0.47385	0.6227
LNSENSEX does not Granger Cause LNFTSE100	1008	5.51172	0.0042
LNFTSE100 does not Granger Cause LNSENSEX	1008	0.78132	0.4581

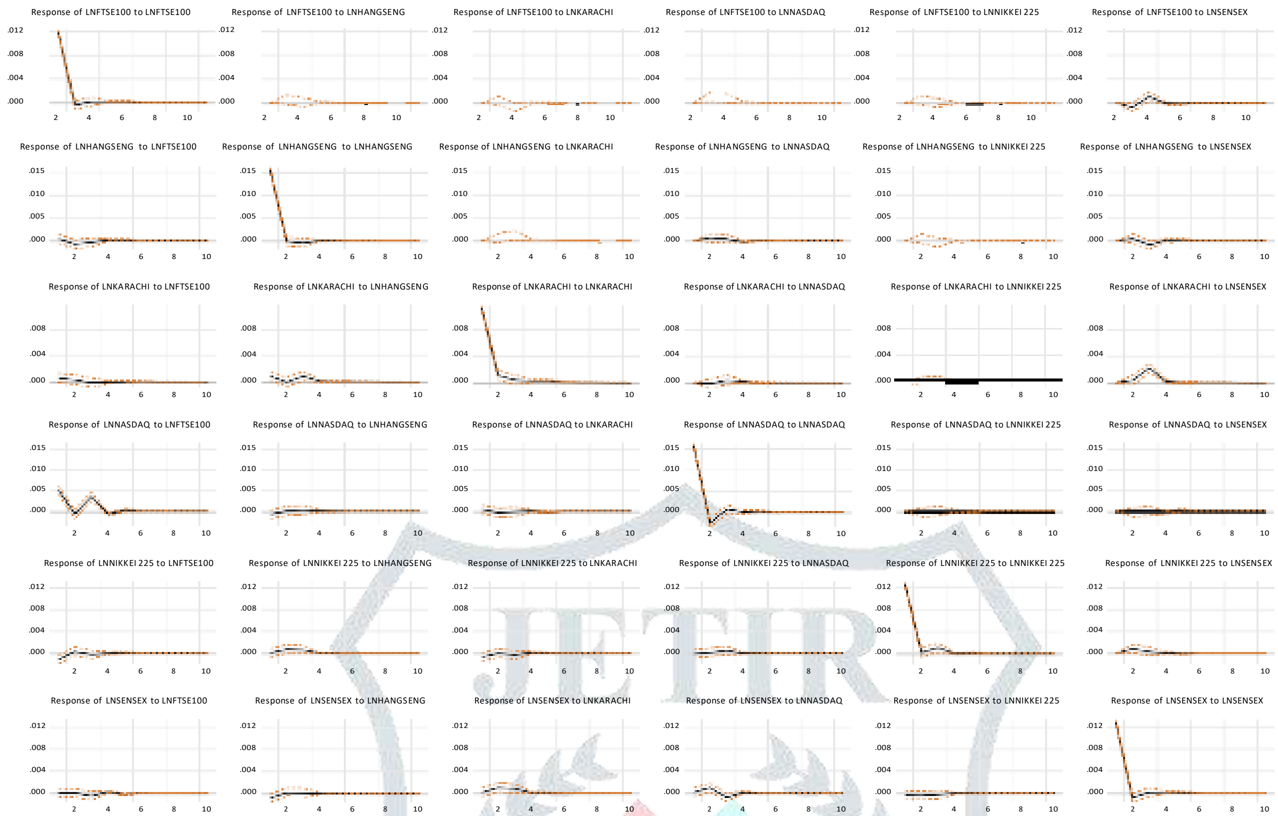
LNKARACHI does not Granger Cause LNHANGSENG	1008	2.93621	0.0535
LNHANGSENG does not Granger Cause LNKARACHI	1008	2.5851	0.0759
LNNASDAQ does not Granger Cause LNHANGSENG	1008	0.56474	0.5687
LNHANGSENG does not Granger Cause LNNASDAQ	1008	0.45762	0.6329
LNNIKKEI225 does not Granger Cause LNHANGSENG	1008	0.69421	0.4997
LNHANGSENG does not Granger Cause LNNIKKEI225	1008	2.83352	0.0593
LNSENSEX does not Granger Cause LNHANGSENG	1008	2.53485	0.0798
LNHANGSENG does not Granger Cause LNSENSEX	1008	0.10028	0.9046
LNNASDAQ does not Granger Cause LNKARACHI	1008	0.21062	0.8101
LNKARACHI does not Granger Cause LNNASDAQ	1008	0.06329	0.9387
LNNIKKEI225 does not Granger Cause LNKARACHI	1008	0.09202	0.9121
LNKARACHI does not Granger Cause LNNIKKEI225	1008	0.18828	0.8284
LNSENSEX does not Granger Cause LNKARACHI	1008	18.0399	2.00E-08
LNKARACHI does not Granger Cause LNSENSEX	1008	6.11492	0.0023

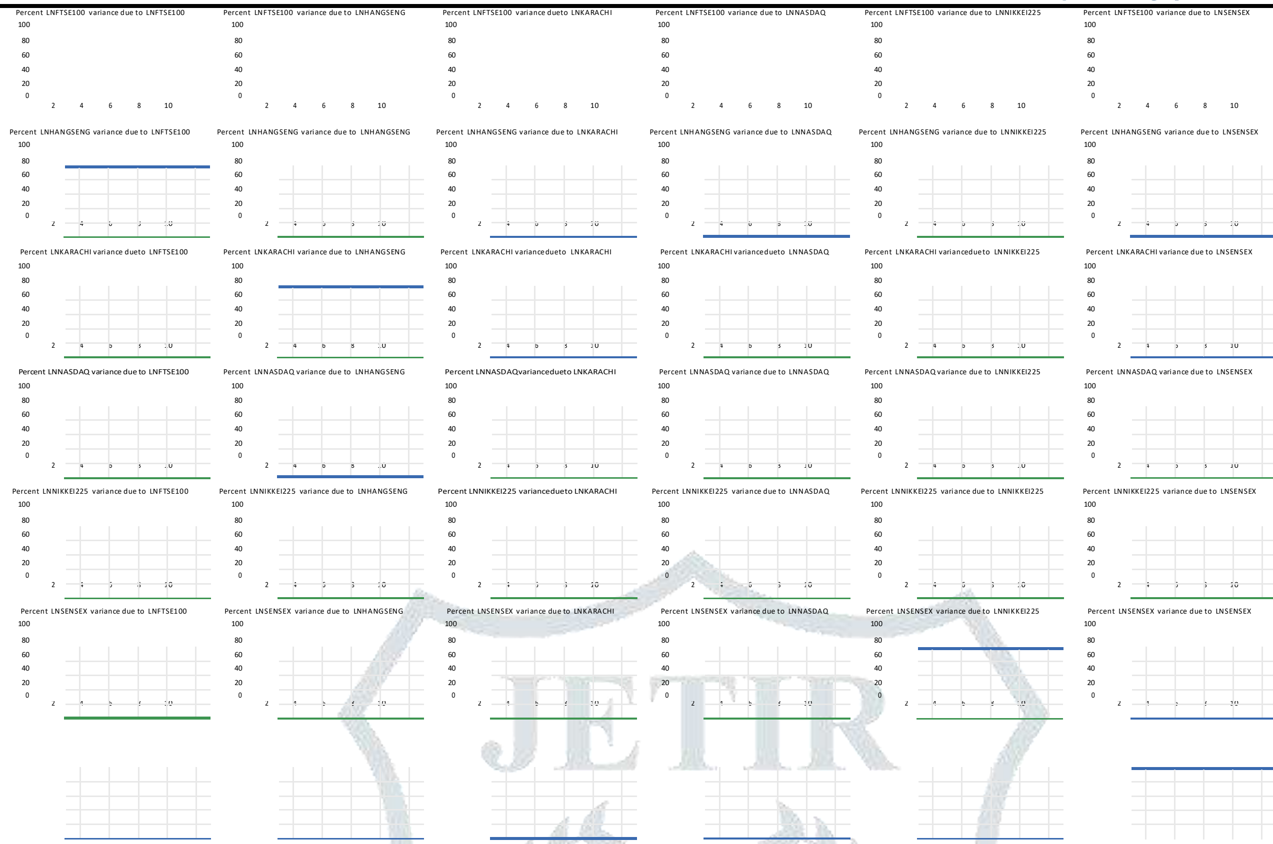
LNNIKKEI225 does not Granger Cause LNNASDAQ	1008	0.17133	0.8426
LNNASDAQ does not Granger Cause LNNIKKEI225	1008	0.62597	0.535
LNSENSEX does not Granger Cause LNNASDAQ	1008	0.21545	0.8062
LNNASDAQ does not Granger Cause LNSENSEX	1008	5.46258	0.0044
LNSENSEX does not Granger Cause LNNIKKEI225	1008	2.12266	0.1202
LNNIKKEI225 does not Granger Cause LNSENSEX	1008	0.98894	0.3723

Interpretation of Granger Causality Results:

LNNASDAQ → LNFTSE100 and LNFTSE100 → LNNASDAQ: There is bidirectional Granger causality between NASDAQ and FTSE 100, suggesting that past values of each index can help predict the other.LNSENSEX → LNFTSE100: Sensex Granger causes FTSE 100, indicating that past values of Sensex have predictive power over FTSE 100.LNFTSE100 → LNSENSEX: There is no reverse causality from FTSE 100 to Sensex.LNSENSEX → LNKARACHI and LNKARACHI → LNSENSEX: There is bidirectional Granger causality between Sensex and Karachi, indicating mutual predictive influences.LNNASDAQ → LNSENSEX: NASDAQ Granger causes Sensex, suggesting that past values of NASDAQ help in predicting Sensex movements.Non-significant Relationships:LNHANGSENG and LNFTSE100: No Granger causality detected in either direction.LNNIKKEI225 and other indices (except Sensex in one direction): No Granger causality detected.LNNASDAQ and LNHANGSENG: No Granger causality detected.LNKARACHI and LNHANGSENG: No strong evidence of Granger causality.LNNASDAQ and LNKARACHI: No Granger causality detected.The Granger causality tests reveal significant predictive relationships primarily involving NASDAQ, FTSE 100, Sensex, and Karachi indices. The bidirectional causality between NASDAQ and FTSE 100, as well as between Sensex and Karachi, highlights strong interdependencies among these markets. Understanding these relationships can be crucial for investors and policymakers to anticipate market movements and devise strategies accordingly.

Response to Cholesky One S.D. (d.f. adjusted) Innovations ± 2 S.E.





Variance Decomposition of LNFTSE100							
Period	S.E.	LNFTSE100	LNHANGSENG	LNKARACHI	LNNASDAQ	LNNIKKEI225	LNSENSEX
1	0.011837	100	0	0	0	0	0
2	0.011932	98.58422	0.177447	0.087678	0.603694	0.133902	0.413059
3	0.012025	97.08152	0.17786	0.443794	1.031802	0.134973	1.130054
4	0.012026	97.07333	0.179397	0.443816	1.031562	0.134942	1.136959
5	0.012028	97.05096	0.179952	0.446627	1.032044	0.135348	1.155066
6	0.012028	97.05046	0.179952	0.446784	1.032251	0.135407	1.155142
7	0.012028	97.04965	0.179961	0.447054	1.032402	0.135407	1.155526
8	0.012028	97.04963	0.179961	0.447054	1.032402	0.135407	1.155542
9	0.012028	97.04962	0.179962	0.447055	1.032402	0.135407	1.155555
10	0.012028	97.04962	0.179962	0.447055	1.032402	0.135407	1.155555
Variance Decomposition of LNHANGSENG							
Period	S.E.	LNFTSE100	LNHANGSENG	LNKARACHI	LNNASDAQ	LNNIKKEI225	LNSENSEX
1	0.015537	0.074433	99.92557	0	0	0	0
2	0.015589	0.335223	99.27569	0.09576	0.160613	0.058644	0.074065

3	0.015685	0.389453	98.18191	0.603506	0.227869	0.147205	0.45006
4	0.015689	0.398462	98.12916	0.604138	0.265802	0.147162	0.455276
5	0.015691	0.405547	98.10798	0.604028	0.267177	0.14732	0.46795
6	0.015691	0.40816	98.10484	0.604101	0.267553	0.147317	0.46803
7	0.015691	0.408179	98.10473	0.604143	0.267554	0.147347	0.468048
8	0.015691	0.408186	98.10466	0.604174	0.267569	0.147347	0.468062
9	0.015691	0.408186	98.10466	0.604174	0.26757	0.147347	0.468065
10	0.015691	0.408186	98.10466	0.604174	0.26757	0.147347	0.468067
Variance Decomposition of LNKARACHI							
Period	**S.E.**	**LNFTSE100**	**LNHANGSENG**	**LNKARACHI**	**LNNASDAQ**	**LNNIKKEI225**	**LNSENSEX**
1	0.011271	0.250575	0.581144	99.16828	0	0	0
2	0.011333	0.318489	0.575854	98.98855	0.019763	0.003011	0.094336
3	0.011584	0.324161	1.064207	94.8639	0.112693	0.013009	3.622032
4	0.01159	0.329303	1.070524	94.81048	0.134283	0.016046	3.639361
5	0.011593	0.331052	1.070488	94.80402	0.138536	0.018676	3.637225
6	0.011594	0.331806	1.070513	94.80235	0.138538	0.018739	3.638054
7	0.011594	0.332142	1.070658	94.80058	0.138549	0.018744	3.639327
8	0.011594	0.332145	1.070665	94.80043	0.13856	0.018751	3.639448
9	0.011594	0.332148	1.070665	94.80042	0.138565	0.018753	3.639447
10	0.011594	0.332148	1.070665	94.80042	0.138565	0.018753	3.639448
Variance Decomposition of LNNASDAQ							
Period	**S.E.**	**LNFTSE100**	**LNHANGSENG**	**LNKARACHI**	**LNNASDAQ**	**LNNIKKEI225**	**LNSENSEX**
1	0.016576	9.534275	0.207488	0.083531	90.17471	0	0
2	0.016776	9.440459	0.206152	0.118775	90.1654	0.042709	0.026505
3	0.017164	13.25432	0.232215	0.116445	86.32788	0.043151	0.02599
4	0.017181	13.39229	0.232745	0.118374	86.16031	0.045448	0.050831
5	0.017187	13.39985	0.23258	0.132195	86.112		
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Variance Decomposition Results

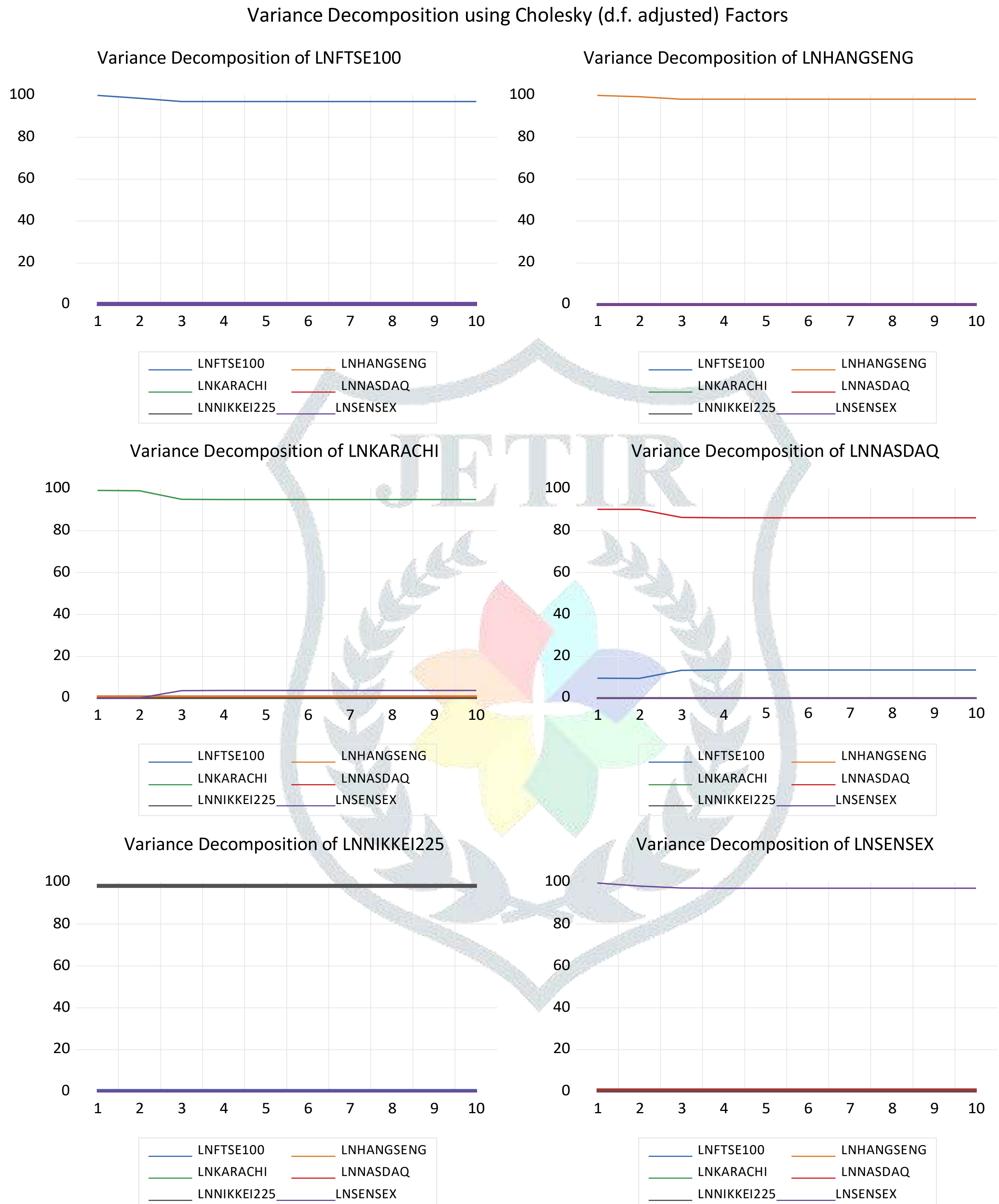
ariance Decomposition of LNFTSE100 Period 1 All the forecast error variance of LNFTSE100 is attributed to itself (100%), indicating complete own variance.Period 2-10: The percentage of variance attributed to LNFTSE100 decreases gradually from 98.58% to 97.05%. This indicates that while LNFTSE100 is still the dominant factor, other indices start to contribute marginally to its variance. LNNASDAQ shows a gradual increase in contribution, reaching about 1.03% by Period 10.LNSENSEX also increases its contribution, up to approximately 1.15% by Period 10.Other indices (LNHANGSENG, LNKARACHI, LNNIKKEI225) have minimal impact, each contributing less than 0.5%. Variance Decomposition of LNHANGSENG Period 1:LNHANGSENG largely explains its own variance (99.93%).Period 2-10:The self-explanatory power decreases slightly to about 98.10% by Period 10.LNFTSE100 increases its contribution to approximately 0.41%.LNKARACHI and LNNASDAQ also start to contribute slightly, each around 0.60%.LNSENSEX contributes around 0.47% by Period 10, while LNNIKKEI225 has a negligible impact.

Variance Decomposition of LNKARACHI Period 1: LNKARACHI explains 99.17% of its own variance.

Period 2-10:Its self-explanatory power decreases significantly to about 94.80%. LNFTSE100 and LNHANGSENG gradually increase their contributions to around 0.33% and 1.07%, respectively.

LNSENSEX shows a noticeable increase in its contribution, reaching 3.64% by Period 10.- Contributions from LNNASDAQ and LNNIKKEI225 remain minimal. Variance Decomposition of LNNASDAQ

Period 1: LNNASDAQ explains 90.17% of its own variance. Period 2-10: The self-explanatory power remains high but slightly decreases to about 86.11% by Period 10.LNFTSE100 shows a significant contribution, increasing to about 13.40%.LNHANGSENG, LNKARACHI, LNNIKKEI225, LNSENSEX remain very low, each less than 1%.Variance Decomposition of LNNIKKEI225 Period 1: LNNIKKEI225 explains 98.80% of its own variance.Period 2-10: The self-explanatory power decreases marginally to about 97.50%.LNFTSE100** and **LNHANGSENG** increase their contributions to about 0.96% and 0.54%, respectively.LNKARACHI contributes around 0.37%.LNSENSEX contributes about 0.45%.LNNASDAQ** has minimal impact. Variance Decomposition of LNSENSEX Period 1:** LNSENSEX explains 99.51% of its own variance.Period 2-10: The self-explanatory power decreases slightly to about 97.03%.LNKARACHI and LNNASDAQ contributions increase noticeably to about 1.11% each.LNFTSE100 and LNHANGSENG** have minor contributions, each less than 0.40%. Contributions from **LNNIKKEI225** remain minimal.In conclusion, while each market predominantly explains its own variance, the gradual increase in cross-market contributions reflects the importance of considering international market dynamics in both investment strategies and policy-making decisions.


Variance Decomposition using Cholesky (d.f. adjusted) Factors
Variance Decomposition of LNFTSE100
Variance Decomposition of LNHANGSENG
Variance Decomposition of LNKARACHI
Variance Decomposition of LNNASDAQ
Variance Decomposition of LNNIKKEI225
Variance Decomposition of LNSENSEX
0
20
40
60
80
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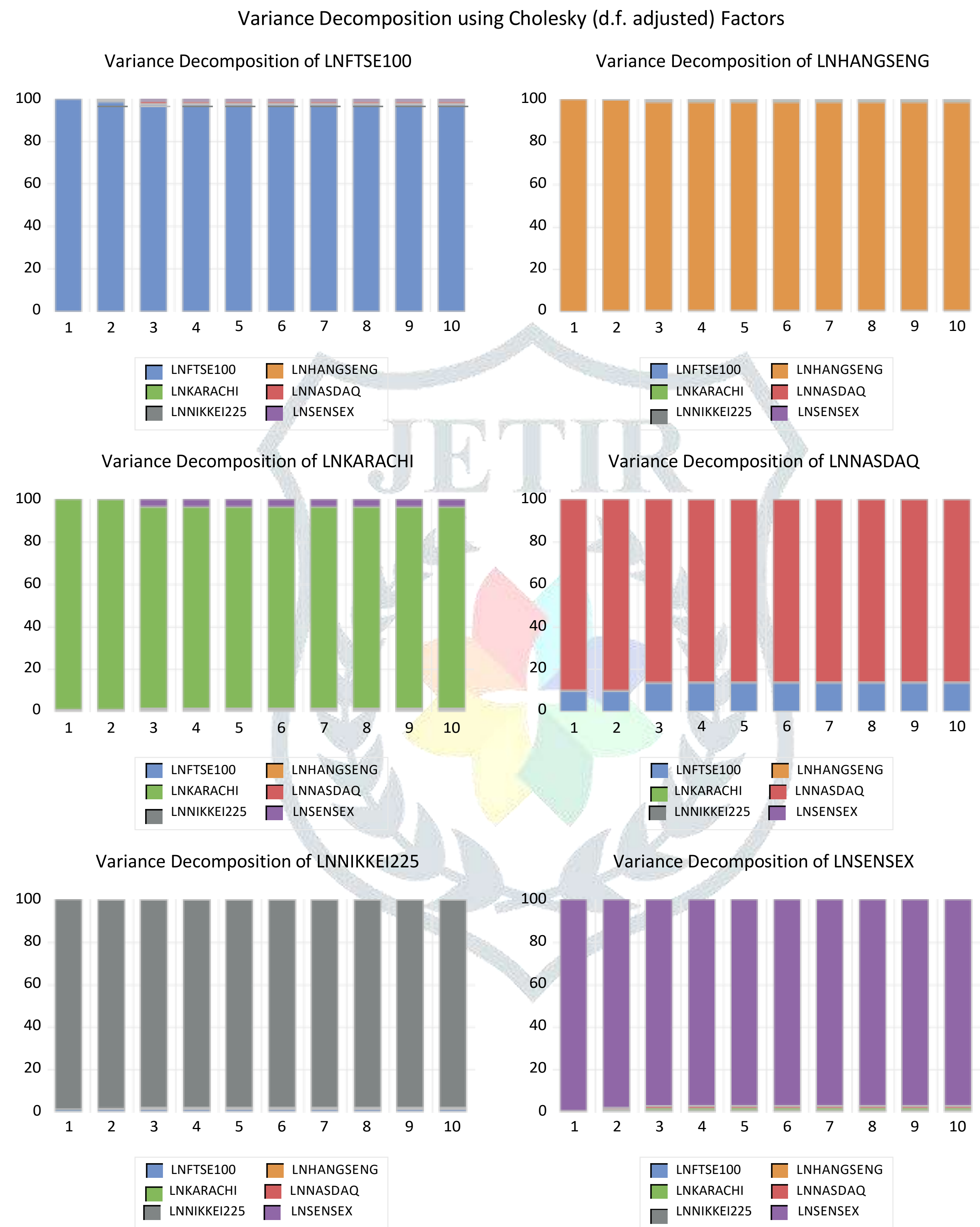
1 2 3 4 5 6 7 8 9 10
LNFTSE100
LNHANGSENG
LNKARACHI
LNNASDAQ
LNNIKKEI225
LNSENSEX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Variance Decomposition of LNKARACHI
Variance Decomposition of LNNASDAQ
Variance Decomposition of LNNIKKEI225
Variance Decomposition of LNSENSEX
100
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0
1 2 3 4 5 6 7 8 9 10
LNFTSE100
LNHANGSENG
LNKARACHI
LNNASDAQ
LNNIKKEI225
LNSENSEX

IMPLICATIONS&LIMITATIONS

Based on the analysis here are some potential implications for investors & Policymakers:

Investors:Portfolio Diversification:Identify indices with weak Granger causality relationships. These markets might offer diversification benefits as their movements are less interconnected.Analyze variance decomposition tables to see which markets' fluctuationsre primarily driven by their own past performance. These could be good candidates for standalone investments.Hedging Strategies:If Granger causality is strong between two indices (e.g., LNNASDAQ andLNFTSE100), investors might use options or futures contracts to hedge against potential losses in one market based on movements in the other.Trading Signals (with Caution):Analyze significant coefficient signs in the results table to potentially identify leading indicators for short-term price movements (be aware of model limitations and potential for false signals).Policymakers:Market Regulation:If the model identifies excessive interconnectedness between markets, policymakers might consider regulations to promote individual market stability and reduce systemic risk.Monetary Policy:Analyze how past monetary policy decisions have impacted differentmarkets through VAR to assess the effectiveness of interventions.International Cooperation:Identify markets with strong causal relationships to facilitate coordinatedpolicy responses to global economic events.

CONCLUSION

The evaluation of the model fit indicates that it explains only a small portion of the variability in the dependent variables, as suggested by the relatively low R-squared values. Nonetheless, the F-statistic implies that the overall model is significant, and the sum of squared residuals is reasonably low, indicating a decent fit. The significance of the coefficients is determined using t-statistics, where coefficients with |t-stat| > 1.96 are statistically significant at the 5% level. Detailed examination of the specific results table is necessary to interpret the individual coefficient signs and magnitudes. The Granger causality analysis uncovers intriguing relationships among the indices, such as LNNASDAQ and LNSENSEX Granger causing LNFTSE100, suggesting that their past values have predictive power for the UK market. However, there is no evidence of reciprocal causality, indicating complex directional relationships. The variance decomposition tables show the extent to which the variance in each index can be explained by its own past values and the past values of other indices over different time horizons, highlighting the varying degrees of influence among the indices.

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