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Dynamic interactions among selected world stock indices: a VAR approach

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Abstract. *The present study focused on examining the dynamic and causal relationships among selected world stock market indices. The growing importance of dynamic interactions among the stock indices have emerged as a focal point of research, driven by the recognition that financial markets are interconnected and interdependent. To achieve the above stated objective, multivariate vector autoregressive (VAR) approach is applied. For which the monthly time series data on the selected indices are obtained for the period 2010-2024. The required data was sourced from yahoofinance.com and the analysis was conducted using RStudio software version 2022.12.0+353 and MS Excel. We found that almost all the indices exhibit a positive and significant impact from their own past values on their future values and they are expected to increase over the next eight months. The impulse response function analysis reveals that only shocks in NSE are positively influenced by their own past values, along with the past values of other indices. Additionally, the FEVD test results indicate that most of the variance in each index is attributable to their own shocks, with the exception of TSX and DAX.*

Keywords: causality, forecasts, indices, shocks, stationarity.

JEL Classification: C51, C53, C58.

1. Introduction

The world of stock markets is a dynamic ecosystem where various indices represent the performance of different economies. Stock markets serve as critical indicators of economic health, reflecting the collective sentiments and expectations of investors worldwide. The interconnectedness of global financial markets has intensified with the advent of globalization, prompting analysts to closely monitor the behavior and interactions of various stock market indices across the world. Dynamic interactions among the stock indices have emerged as a focal point of research, driven by the recognition that financial markets are interconnected and interdependent. This interconnectedness gives rise to complex relationships, characterized by response loops, spillover effects, and contagion risks. Since the fluctuations in one market can swiftly spread across borders, impacting the performance of other markets. Such dynamics underscore the need for advanced analytical tools capable of capturing the details of these interactions. However, studying the dynamic interactions among world stock market indices is not without its challenges. A deeper understanding of the dynamic interactions among world stock market indices can enable investors to construct more resilient portfolios that are better equipped to weather market turbulence. Traditional econometric methods basically depend on linear models to analyze the relationships among variables. These methods, such as Ordinary Least Squares (OLS) regression, time series analysis, and panel data techniques, have been extensively used in financial econometrics to study the behavior of stock market indices. Furthermore, factors such as market volatility, investor behavior, and macroeconomic shocks further complicate the analysis. In this context, Vector Autoregression (VAR) emerges as a powerful technique for modeling the dynamic interactions among multiple time series variables. These models capture the lagged dependencies and endogenous interactions among these variables. Sadorsky (1999) utilized a VAR approach to investigate the relationship between the three-month U.S. Treasury rate, the S&P 500 stock index, stock returns, and oil prices. The study revealed empirical evidence indicating that increases in oil prices exerted a negative impact on actual stock prices. Alalaya et al. (2021), compared VAR model predicting accuracy to machine learning approaches like random forest and gradient boosting. Bohte and Rossini (2019), used Bayesian models with constant and time-varying volatility, including stochastic volatility and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model in forecasting the ability of four major cryptocurrencies. The results demonstrate that stochastic volatility outperforms the benchmark of VAR in both point and density forecasting, and that employing a student-t distribution for stochastic volatility errors is more effective than the standard normal approach. Catania et al. (2019), indicate significant improvements in point forecasting using combinations of univariate models and in density forecasting using the selection of multivariate models. The VAR model outperforms other traditional forecasting approaches in terms of forecasting accuracy (Chang et al. 2021). Hafner et al. (2021), noticed that the VAR model outperformed the traditional time-series models in terms of forecasting accuracy. Ibrahim et al. (2020), showed that the VAR models achieved better performance compared to the traditional autoregression models and the BVAR models. Li and Li (2020), conclude that VAR models are a suitable option for forecasting. Yang et al. (2020) found that the VAR model offered accurate forecasts and outperforms other forecasting models such as the ARIMA model. Adebiyi et al. (2009) employed the VAR methodology to assess the influence of oil prices, exchange rates, interest rates, and industrial production indices on the stock price index in Nigeria. Their findings echoed those of Sadorsky, demonstrating a negative correlation between world oil prices and the Nigerian stock price index. This suggests that as oil prices rise, the stock price index in Nigeria tends to decline. The VAR models have found extensive application in macroeconomic forecasting and analysis, serving as valuable tools for policymakers. While estimating the model is sufficient for one-period ahead forecasting, the interest often extends to multi-period forecasting scenarios. In such cases, two primary methods are commonly employed: the direct forecast method and the iterated forecast method. The debate over which method is superior for multi-period forecasting has spurred theoretical research by scholars such as Bhansali (1996, 1997), Clements and Hendry (1996), Kang (2003), Chevillon and Hendry (2005), Ing (2003), among others. The VAR model offers a flexible framework for understanding the evolving dynamics of stock market indices. Hence, an attempt has been made to investigate the dynamic interactions among selected world stock market indices using a Vector Autoregression approach. This study aims to unravel the complex relationships and interdependencies that characterize global financial markets.

2. Data and Methodology

The study employed an empirical approach to construct multiple VAR models with Variance Decomposition for individual companies within the selected stock indices. This paper involves a comparative study of six major stock indices (listed in Table 1) to investigate the interrelationships among them. The study examined monthly time series data for the chosen indices over a period of 158 months, from 1st January 2010 to 1st February 2024. The required data were sourced from yahoofinance.com. The analysis was conducted using RStudio software version 2022.12.0+353 and MS Excel. Below are the randomly selected stock indices:

Table 1. *Selected indices*

Sl. No.	Index	Symbol	Country
1	Nifty 50	NSE	India
2	NYSE Composite (DJ)	NYSE	USA
3	SSE Composite Index	SSE	China
4	Nikkei 225	Nikkei	Japan
5	S&P/TSX Composite index	TSX	Canada
6	DAX Performance Index	DAX	Germany

The process of constructing VAR model involves several steps, outlined as follows:

2.1. Stationarity Test

The notion of stationarity holds considerable importance when analyzing time series data. This study employs the Augmented Dickey-Fuller (ADF) test to assess the stationarity of selected indices. The ADF test is an extension of the original Dickey-Fuller test, pioneered by David Dickey and Wayne Fuller in 1979. The null hypothesis of the test posits that the time series under examination possesses a unit root. The ADF test statistic is calculated as follows:

$$ADF = (Y_t - Y_{t-1}) - \lambda \times \Delta Y_{t-1}$$

Where: Y_t stands for the time series at time t, Y_{t-1} is the time series at time $t-1$, ΔY_{t-1}, represents the first difference of the time series at time $t-1$, and λ, indicates the coefficient.

2.2. Optimum Lag Selection

Constructing a VAR model requires a critical step of carefully selecting the optimal lag order. This process involves determining the most suitable number of lags for each variable in the VAR model. Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan-Quinn Criterion (HQ) are commonly used for this purpose. These criteria serve as measures of the relative goodness of fit of a statistical model, penalizing excessive complexity by accounting for the number of parameters and the sample size.

2.3. Estimation technique

The casual links among the selected indices will be examined using the Vector Autoregression (VAR) model, developed by Christopher Sims (1980), is a widely applied stochastic process for multivariate time series analysis. It proves vital in comprehending and forecasting economic and financial time series behavior (Campbell et al., 1996). The VAR model extends the univariate autoregression model to multivariate time series data, wherein each variable is expressed as a linear function of its own past lags as well as those of other variables. The general equation of the VAR model with p lags can be represented as follows:

$$Y_t = \alpha_i + \beta_1(X_{t-1}) + \beta_2(X_{t-1}) \dots \dots \dots . + \beta_p\left(X_{t-p}\right) + \varepsilon_t$$

Where: Y_t stands for vector of endogenous variables at time t, α_i is a constant terms, β_1, β_2, and β_p, are the coefficient corresponding to the lagged values of the endogenous, and ε_t is the error terms assumed to be white noise.

Below are the equations representing the VAR models corresponding to the results depicted in Table 5.

$$NSE_t = \alpha_i + \beta_1(NSE_{t-1}) + \beta_2(NYSE_{t-1}) + \beta_3(SSE_{t-1}) + \beta_4(Nikkei_{t-1}) + \beta_5(TSX_{t-1}) + \beta_6(DAX_{t-1}) + \varepsilon_t$$

$$NYSE_t = \alpha_i + \beta_1(NSE_{t-1}) + \beta_2(NYSE_{t-1}) + \beta_3(SSE_{t-1}) + \beta_4(Nikkei_{t-1}) + \beta_5(TSX_{t-1}) + \beta_6(DAX_{t-1}) + \varepsilon_t$$

$$SSE_t = \alpha_i + \beta_1(NSE_{t-1}) + \beta_2(NYSE_{t-1}) + \beta_3(SSE_{t-1}) + \beta_4(Nikkei_{t-1}) + \beta_5(TSX_{t-1}) + \beta_6(DAX_{t-1}) + \varepsilon_t$$

$$Nikkei_t = \alpha_i + \beta_1(NSE_{t-1}) + \beta_2(NYSE_{t-1}) + \beta_3(SSE_{t-1}) + \beta_4(Nikkei_{t-1}) + \beta_5(TSX_{t-1}) + \beta_6(DAX_{t-1}) + \varepsilon_t$$

$$TSX_t = \alpha_i + \beta_1(NSE_{t-1}) + \beta_2(NYSE_{t-1}) + \beta_3(SSE_{t-1}) + \beta_4(Nikkei_{t-1}) + \beta_5(TSX_{t-1}) + \beta_6(DAX_{t-1}) + \varepsilon_t$$

$$DAX_t = \alpha_i + \beta_1(NSE_{t-1}) + \beta_2(NYSE_{t-1}) + \beta_3(SSE_{t-1}) + \beta_4(Nikkei_{t-1}) + \beta_5(TSX_{t-1}) + \beta_6(DAX_{t-1}) + \varepsilon_t$$

This paper employs the VAR methodology due to its effectiveness in addressing endogeneity concerns, a significant challenge in econometric modeling using time series data. Additionally, the VAR approach allows for the generation of impulse response functions and the decomposition of forecast error variances, enhancing analytical insights. The VAR technique offers a flexible framework ideal for this study by treating all variables in the equation system as endogenous.

3. Results and Discussion

Table 2. *Descriptive statistics for the selected indices*

	NSE	NYSE	SSE	Nikkei	TSX	DAX
Mean	10602.025	11956.862	2926.736	20060.011	15821.680	11348.793
σ	4571.623	2741.678	512.240	6918.087	2780.737	2883.164
CV	0.431	0.229	0.175	0.345	0.176	0.254
CAGR	0.009	0.005	0.000	0.008	0.003	0.006
Kurtosis	-0.526	-0.897	0.167	-0.589	-0.745	-0.789
Skewness	0.733	0.238	0.016	0.114	0.556	-0.084
JB test	15.856	6.874	0.108	2.767	11.787	4.414
	*(0.000)******	*(0.032)**	*(0.947)*	*(0.251)*	*(0.003)****	*(0.110)*

Note: value in parentheses are p-values, σ represents the standard deviation, CV indicates the coefficient of variation, CAGR stands for the compound annual growth rate, and JB denotes the Jarque-Bera.
Source: Author(s) calculation.

Figure 1. *Monthly time series plot for the actual (I(0)) data*

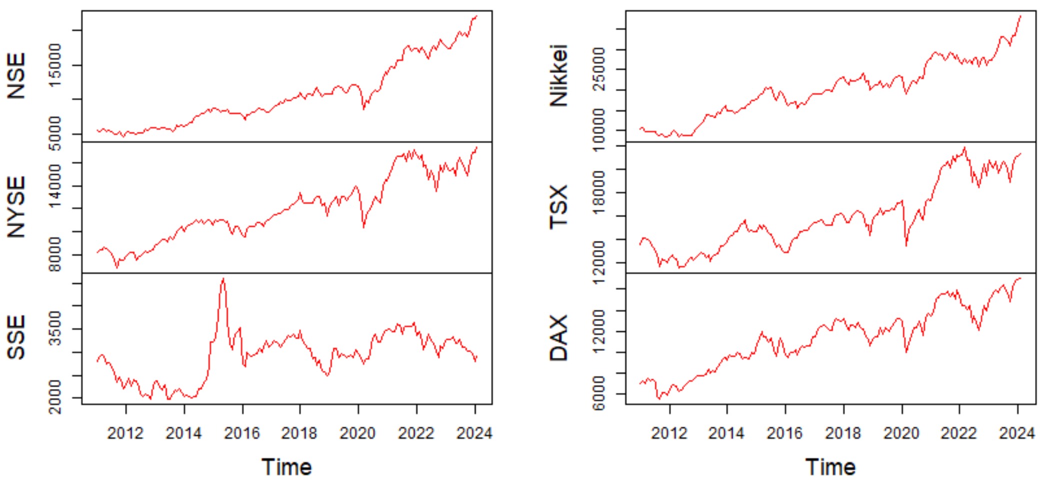
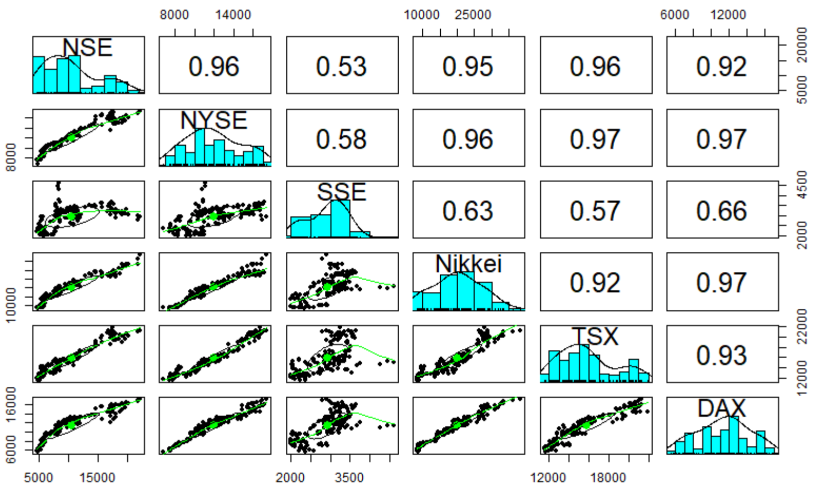


Table 2 presents significant descriptions of the behavior of the selected stock market indices for time series analysis. The mean values of the indices range between 2926.74 and 20060.01, with the SSE revealing the lowest mean and volatility, while the Nikkei has the highest mean and volatility. Almost all indices have coefficients of variation (CV) below 1, indicating stable performance relative to the mean. The NSE and Nikkei demonstrate stronger long-term growth potential, as evidenced by their higher compound annual growth rate (CAGR) values. The distributions of the majority of indices are flat and right-skewed. Additionally, half of the indices show deviations from normality, representing potential non-randomness in the series.

Figure 2. *Correlation matrix*



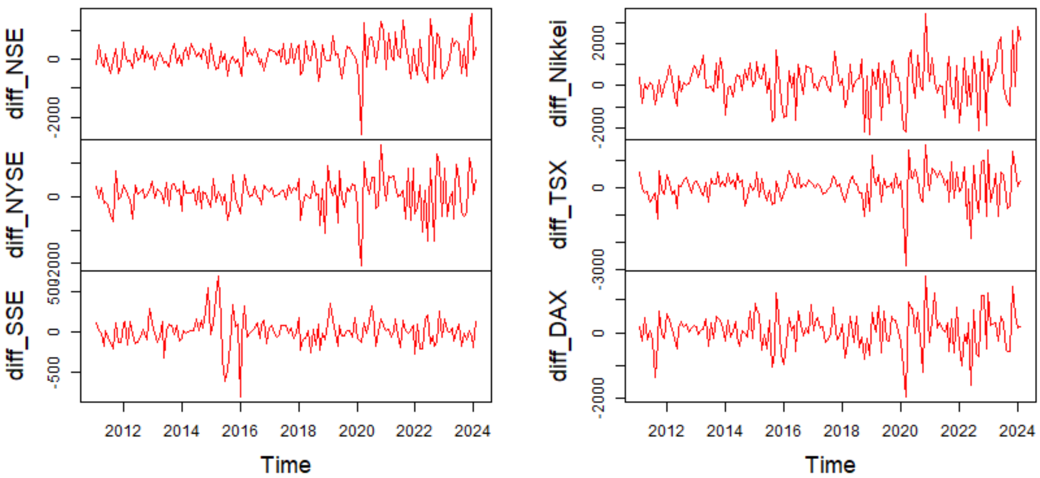
With the exception of SSE, all the other indices exhibit very high associations with each other, indicating strong degree of similarity in their movements in the global stock markets. On the other hand, SSE has moderate associations with the rest of the indices, ranging between 52.9% (between SSE and NSE) and 66.4% (between SSE and DAX).

Table 3. *Augmented Dickey-Fuller (ADF) test*

Exogenous: Trend and Constant	ADF test (I(0))		ADF test (I(1))	
	t-stat	p-value	t-stat	p-value
NSE	-1.0973	0.92	-5.6514	0.01
NYSE	-3.2661	0.08	-5.4112	0.01
SSE	-2.9256	0.19	-4.5441	0.01
Nikkei	-2.2173	0.49	-5.2794	0.01
TSX	-3.0828	0.13	-5.6658	0.01
DAX	-3.2947	0.08	-5.9236	0.01

Note: (I(0)) indicates that the time series is integrated at order 0, while (I(1)) indicates that the time series is integrated at order 1.
Source: Author(s) calculation.

Figure 3. *Monthly time series plot for the first differenced (I(1)) data*



It is evident that for all the indices, the ADF test with first-order differencing (I(1)) results in t-statistics ranging from -4.5441 to -5.9236, with corresponding p-values of 0.01. This specifies that the indices are stationary after differencing once. Hence, they do not exhibit a unit root and are suitable for modeling using a VAR model.

Table 4. *Optimum lag order selection criteria*

Lag	Log L	LR	FPE	AIC	SC	HQ
0	-7261.764	NA	1.81E+35	98.213	98.335	98.262
1	-6418.015	1607.69	3.30E+30*	87.298*	88.148*	87.643*
2	-6398.503	35.60	4.13E+30	87.520	89.100	88.162
3	-6383.879	25.49	5.55E+30	87.809	90.118	88.747
4	-6356.847	44.93	6.33E+30	87.930	90.968	89.165
5	-6322.628	54.10	6.60E+30	87.954	91.721	89.485
6	-6287.730	52.35*	6.89E+30	87.969	92.465	89.796
7	-6265.787	31.13	8.65E+30	88.159	93.384	90.282
8	-6231.129	46.37	9.28E+30	88.177	94.131	90.596
9	-6208.084	28.96	1.18E+31	88.352	95.035	91.068
10	-6186.376	25.52	1.57E+31	88.546	95.958	91.557

Note: Log L represents the logarithm of the likelihood function, LR stands for the likelihood Ratio, FPE denotes the final prediction error, AIC indicates the Akaike information criterion, SC is the Schwarz Criterion, and HQ denotes to the Hannan-Quinn Criterion.
Source: Author(s) calculation.

Selection of optimum lag order is important in time series analysis, since it has direct impact on the accuracy and predictive power of the model. In this study, several criteria are used to evaluate different lag orders, as depicted in Table 4. FPE measures forecast error variance, with the lower values signify the better forecasting performance. It is evident that the lag order 1 has the minimum FPE value, suggesting that this lag order may offer the most accurate forecasts. In line with these findings, the low values of AIC, SC, and HQ also confirm that a lag order of 1 has the potential to be the preferred choice. Hence, the optimum lag order of 1 is used for the estimation of VAR model to capture the essence of interconnected global financial markets.

Table 5. *Vector autoregression (VAR) model estimates*

	NSE	NYSE	SSE	Nikkei	TSX	DAX
$NSE_{(t-1)}$	0.950	0.092	-0.008	0.251	0.137	0.105
	(0.000)***	(0.078).	(0.631)	(0.013)*	(0.017)*	(0.066).
$NYSE_{(t-1)}$	-0.115	0.890	-0.039	-0.264	0.172	0.040
	(0.332)	(0.000)***	(0.335)	(0.252)	(0.189)	(0.758)
$SSE_{(t-1)}$	-0.142	-0.094	0.880	-0.154	-0.012	0.023
	(0.246)	(0.442)	(0.000)***	(0.515)	(0.928)	(0.862)
$Nikkei_{(t-1)}$	0.088	0.027	-0.005	0.898	-0.029	0.017
	(0.036)*	(0.516)	(0.741)	(0.000)***	(0.533)	(0.716)
$TSX_{(t-1)}$	0.071	-0.133	0.023	-0.173	0.673	-0.159
	(0.464)	(0.174)	(0.491)	(0.360)	(0.000)***	(0.137)
$DAX_{(t-1)}$	-0.056	0.029	0.052	0.302	0.002	0.898
	(0.503)	(0.729)	(0.068).	(0.061).	(0.984)	(0.000)***
α	167.436	1909.606	54.329	2475.975	2299.343	1745.386
	(0.770)	(0.001)**	(0.780)	(0.027)*	(0.000)***	(0.006)**
Std. error	507.400	508.200	172.200	983.900	557.900	556.200
R^2	0.988	0.967	0.892	0.980	0.961	0.964
Adj. R^2	0.988	0.965	0.888	0.980	0.960	0.963
F-stat	2082.46	727.21	206.51	1251.88	622.35	668.23
p-value	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Log likelihood	-1197.19	-1197.43	-1027.51	-1301.17	-1212.08	-1211.61
AIC	15.340	15.343	13.178	16.665	15.530	15.524
SC	15.476	15.479	13.315	16.801	15.666	15.660

Note: value in parentheses are p-values.
Source: Author(s) calculation.

The estimated results of the VAR model among various stock market indices, namely NSE, NYSE, SSE, Nikkei, TSX, and DAX, are presented in Table 5. Except for the models using NSE and SSE as response variables, all other models exhibit positive and significant intercept values. However, the intercept values for the models with NYSE, Nikkei, TSX, and DAX as response variables, are higher than those for NSE and SSE. Almost all the indices experience positive and significant impact of their own past value (lag 1) on their future value, indicating strong autoregressive behavior, where its own past value is a good predictor of future values. The cross-market influences are also evident, notably for NSE influenced by Nikkei's past value and TSX influenced by NSE's past value. Furthermore, the F-statistics with associated p-values validate the overall significance of the models and their predictive power is extremely high, ranging from 89% to 99% across all the indices.

Table 6. *Forecasts for the selected indices using VAR model*

Month	NSE	NYSE	SSE	Nikkei	TSX	DAX
1/3/2024	22721.49	17871.50	2938.34	39031.07	21529.04	17438.47
1/4/2024	23283.27	18324.00	2961.24	39616.04	21858.91	17797.17
1/5/2024	23816.74	18758.45	2982.35	40210.79	22219.38	18154.09
1/6/2024	24328.79	19170.54	3003.38	40806.45	22593.21	18500.98
1/7/2024	24824.66	19558.77	3025.17	41398.13	22969.22	18833.63
1/8/2024	25308.40	19923.39	3048.02	41983.70	23340.46	19150.43
1/9/2024	25783.19	20265.81	3071.94	42562.83	23702.89	19451.47
1/10/2024	26251.57	20588.08	3096.74	43136.41	24054.48	19737.84

Source: Author(s) calculation.

The predictions for selected stock market indices using VAR model are presented in Table 6. It is noticed that the prices of all the indices are expected to increase over the next eight months. NSE and NYSE are expected to grow by roughly 2.10% per month, while all other indices, except SSE, are forecasted to increase by more than 1% and less than 2% per month.

Table 7. *Granger Causality test*

Sl. No.	Pairs	P-value	Pairs	P-value	Causality
1	NSE/NYSE	0.862	NYSE/NSE	0.019*	Uni-directional
2	NSE/SSE	0.638	SSE/NSE	0.382	No Causality
3	NSE/Nikkei	0.195	Nikkei/NSE	0.097.	No Causality
4	NSE/TSX	0.405	TSX/NSE	0.001***	Uni-directional
5	NSE/DAX	0.870	DAX/NSE	0.056.	No Causality
6	NYSE/SSE	0.550	SSE/NYSE	0.266	No Causality
7	NYSE/Nikkei	0.005**	Nikkei/NYSE	0.368	Uni-directional
8	NYSE/TSX	0.281	TSX/NYSE	0.025*	Uni-directional
9	NYSE/DAX	0.247	DAX/NYSE	0.686	No Causality
10	SSE/Nikkei	0.288	Nikkei/SSE	0.373	No Causality
11	SSE/TSX	0.271	TSX/SSE	0.653	No Causality
12	SSE/DAX	0.122	DAX/SSE	0.593	No Causality
13	Nikkei/TSX	0.855	TSX/Nikkei	0.017*	Uni-directional
14	Nikkei/DAX	0.933	DAX/Nikkei	0.018*	Uni-directional
15	TSX/DAX	0.115	DAX/TSX	0.925	No Causality

Source: Author(s) calculation.

Table 7 presents the results of the Granger Causality test conducted on various pairs of stock market indices. Majority of the pairs showing no causality between each other imply that there is no significant directional influence between those particular indices. Therefore, the movements or behaviors of these indices are basically independent of each other. The presence of unidirectional causality is noticed from NYSE, TSX and DAX to Nikkei, and from NYSE, TSX to NSE. Hence, it is evident that the past movements in these indices influence changes in the Nikkei and NSE, but not vice versa. Similarly, NYSE also exhibits unidirectional causality only from TSX.

In order to examine the interconnectedness and dynamics of global financial markets, the impulse response analysis is conducted, and its coefficients for various stock exchanges are presented in Table A1. These coefficients represent the response of each stock exchange to one-unit shock in itself and other exchanges. The shocks in NSE are positively influenced by its own past values along with the past values of other indices. Notably, the impact of Nikkei on NSE shocks shows an increasing trend from lag 1 to 11. Furthermore, NSE is the most responsive index, as it is responded by the shocks of all indices. The NYSE exhibits high responsiveness to the shocks resulting from the past five values of all the other indices (including its own previous values), with the exception of NSE. However, as the lag order increases, the magnitude of this effect begins to decrease. SSE, Nikkei, and TSX are extremely responsive to the shocks resulting from their own previous values compared to those of other indices. Interestingly, there is an upward trend in the coefficients with the increase in lag order for all the indices (except for their own past values) in affecting the shocks of Nikkei.

It can be observed from Table A2 that 100% of the variance in NSE is explained by its own shocks in the immediate period. As the lag increases, the proportion of variance explained by NSE's own shocks gradually decreases, while the contributions from other stock exchanges increase. However, by lag 10, around 85% of the variance in NSE is still explained by its own shocks, while the remaining 15% is attributed to the shocks from other exchanges. Similarly, for NYSE, 57.1% of the variance is explained by its own shocks, while 42.9% is attributed to the shocks from NSE at lag 1. With the increase in lag order, the proportion of variance explained by NYSE's own shocks decreases gradually, while the contributions from NSE and other stock exchanges increase. On an average, 78% of the movements in SSE are primarily driven by its own shocks, while NYSE, NSE and DAX contribute relatively lower proportions at 13%, 5% and 4%, respectively. More than half of the variance in Nikkei is described by its own shocks remains relatively stable around 49-52%, while the contributions from NSE range between 29-41%. Around 88% of the variance in TSX movements is described by shocks from NSE and NYSE, while only 10% is attributed to its own past shocks. Apart from the previous shocks from NSE, NYSE, and DAX, none of the other indices contribute at least 10% to the variations in DAX.

4. Conclusion

This study aims to explore the dynamic interactions among selected world stock market indices, namely the NSE, NYSE, SSE, Nikkei, TSX, and DAX, using the VAR approach. Monthly time series data spanning a period of 158 months, from 2010 to 2024, are studied. The results indicate that almost all the indices have strong associations with each other, except for the SSE, which shows moderate associations with the rest of the indices. Also, the results of the ADF test reveal that the indices become stationary at the first difference. An optimum lag order of one is chosen for estimating the VAR model to capture the essence of interconnected global financial markets, as indicated by the low values of FPE, AIC, SC, and HQ. The estimated results from the VAR model depict that almost all the indices exhibit a positive and significant impact from their own past values on their future values. Additionally, cross-market influences are observed between NSE and Nikkei, along with TSX and NSE. The predictive power of the model is extremely high across all indices. Moreover, the F-statistics and associated p-values confirm the overall significance of the models. The findings of forecast series suggest that the prices of all the indices are expected to increase over the next eight months. From the empirical results of the Granger causality test, the study found statistically significant evidence to conclude that the majority of pairs exhibit no significant directional influence between the particular indices. Unidirectional causality is observed only from NYSE, TSX, and DAX to Nikkei, from TSX to NYSE, and from NYSE and TSX to NSE. Empirical results from the impulse response function analysis reveal that only shocks in NSE are positively influenced by its own past values, along with the past values of other indices. With the exception of TSX and DAX, the forecast error variance decomposition (FEVD) test results indicate that most of the variance in each index is attributable to its own shocks.

While this study provides valuable insights, it is not without limitations. Its scope is constrained in terms of wider applicability, as it focuses solely on six major stock indices across the world. Consequently, the results may not be readily generalizable. As a future direction for research, it is recommended that other researchers expand the scope of the study to include additional stock indices.

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Appendix

Table A1. *Impulse Response Analysis*

	Impulse Response of Stock Market Indices to NSE Shocks						Impulse Response of Stock Market Indices to NYSE Shocks					
Lag	NSE	NYSE	SSE	Nikkei	TSX	DAX	NSE	NYSE	SSE	Nikkei	TSX	DAX
1	507.38	333.03	31.93	529.30	356.52	329.00	0.00	383.82	53.15	418.91	354.09	318.45
2	492.92	316.40	33.49	547.70	351.83	314.82	-7.37	310.11	54.39	301.76	292.48	253.34
3	482.95	300.84	34.70	561.28	343.26	300.99	-17.15	246.84	54.19	204.93	240.50	199.01
4	476.47	287.07	35.49	572.21	333.02	288.51	-28.33	192.37	53.02	124.79	195.94	153.31
5	472.70	275.44	35.85	581.92	322.52	277.90	-40.20	145.41	51.21	58.45	157.26	114.62
6	471.12	266.07	35.82	591.33	312.64	269.35	-52.26	104.92	48.97	3.56	123.34	81.75
7	471.30	258.90	35.45	600.99	303.87	262.85	-64.16	70.06	46.47	-41.81	93.42	53.77
8	472.94	253.81	34.83	611.21	296.47	258.29	-75.66	40.12	43.81	-79.24	66.93	29.94
9	475.79	250.62	34.02	622.14	290.54	255.49	-86.62	14.49	41.07	-110.05	43.41	9.66
10	479.69	249.12	33.07	633.84	286.09	254.25	-96.96	-7.37	38.31	-135.36	22.55	-7.57
11	484.49	249.10	32.04	646.25	283.04	254.36	-106.62	-25.92	35.57	-156.08	4.05	-22.17
	Impulse Response of Stock Market Indices to SSE Shocks						Impulse Response of Stock Market Indices to Nikkei Shocks					
Lag	NSE	NYSE	SSE	Nikkei	TSX	DAX	NSE	NYSE	SSE	Nikkei	TSX	DAX
1	0.00	0.00	160.62	101.85	-5.29	34.17	0.00	0.00	0.00	708.58	-46.66	103.59
2	-16.09	-10.66	142.53	77.96	-8.37	36.97	53.40	28.35	0.98	676.00	-51.47	112.20
3	-30.07	-20.08	127.35	59.45	-13.57	37.04	97.03	58.39	0.78	655.91	-41.59	126.91
4	-42.11	-28.12	114.44	45.07	-19.89	35.43	133.17	87.70	0.14	643.64	-23.20	143.98
5	-52.42	-34.77	103.33	33.85	-26.61	32.86	163.49	114.88	-0.51	636.00	-0.44	161.13
6	-61.19	-40.07	93.67	25.04	-33.24	29.84	189.26	139.18	-0.95	630.92	23.97	177.04
7	-68.63	-44.14	85.18	18.05	-39.45	26.67	211.41	160.29	-1.11	627.05	48.29	191.03
8	-74.91	-47.09	77.66	12.41	-45.05	23.56	230.65	178.19	-0.96	623.59	71.46	202.82
9	-80.18	-49.09	70.95	7.73	-49.94	20.61	247.54	193.05	-0.53	620.13	92.89	212.42
10	-84.61	-50.29	64.92	3.72	-54.09	17.87	262.50	205.11	0.12	616.45	112.30	219.94
11	-88.32	-50.83	59.48	0.14	-57.51	15.35	275.87	214.71	0.94	612.53	129.60	225.62
	Impulse Response of Stock Market Indices to TSX Shocks						Impulse Response of Stock Market Indices to DAX Shocks					
Lag	NSE	NYSE	SSE	Nikkei	TSX	DAX	NSE	NYSE	SSE	Nikkei	TSX	DAX
1	0.00	0.00	0.00	0.00	237.77	44.33	0.00	0.00	0.00	0.00	0.00	292.98
2	14.46	-30.24	7.69	-27.68	160.17	2.04	-16.26	8.41	15.13	88.58	0.52	263.16
3	24.99	-48.23	11.70	-41.48	105.31	-23.60	-25.33	14.45	26.31	150.42	-2.66	236.74
4	32.80	-57.49	13.33	-45.38	67.01	-37.67	-29.54	19.29	34.27	192.94	-6.96	214.09
5	38.77	-60.60	13.49	-42.37	40.77	-43.80	-30.53	23.53	39.66	221.48	-10.95	195.08
6	43.51	-59.45	12.76	-34.68	23.28	-44.58	-29.43	27.46	43.04	239.86	-13.95	179.31
7	47.47	-55.41	11.57	-24.00	12.13	-41.85	-27.04	31.18	44.88	250.84	-15.74	166.27
8	50.93	-49.50	10.16	-11.53	5.58	-36.90	-23.90	34.70	45.57	256.39	-16.33	155.47
9	54.09	-42.45	8.72	1.81	2.33	-30.64	-20.37	37.98	45.42	257.98	-15.89	146.44
10	57.08	-34.77	7.33	15.41	1.44	-23.71	-16.70	40.96	44.66	256.64	-14.60	138.78
11	59.99	-26.85	6.06	28.81	2.21	-16.52	-13.05	43.58	43.49	253.14	-12.68	132.16

Source: Author(s) calculation.

Figure A1. *Graphical representation of Impulse Response Analysis*

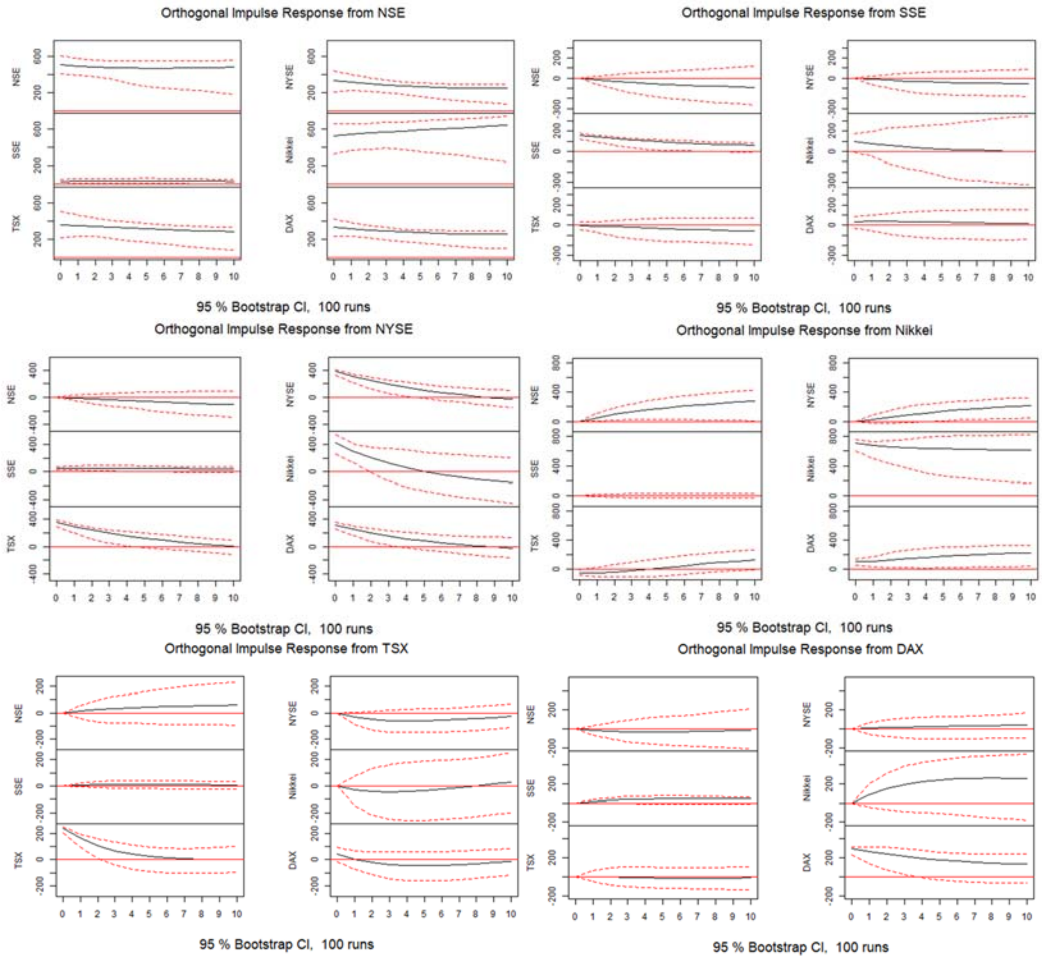

Table A2. *Forecast Error Variance Decomposition (FEVD) Analysis*

Variance Decomposition of NSE							Variance Decomposition of NYSE					
Lag	NSE	NYSE	SSE	Nikkei	TSX	DAX	NSE	NYSE	SSE	Nikkei	TSX	DAX
1	1.000	0.000	0.000	0.000	0.000	0.000	0.429	0.571	0.000	0.000	0.000	0.000
2	0.993	0.000	0.001	0.006	0.000	0.001	0.462	0.533	0.000	0.002	0.002	0.000
3	0.979	0.000	0.002	0.016	0.001	0.001	0.491	0.496	0.001	0.007	0.005	0.000
4	0.962	0.001	0.003	0.030	0.002	0.002	0.515	0.458	0.002	0.016	0.009	0.001
5	0.943	0.002	0.005	0.045	0.003	0.002	0.534	0.421	0.003	0.029	0.012	0.001
6	0.924	0.004	0.006	0.061	0.003	0.002	0.548	0.386	0.004	0.046	0.014	0.002
7	0.904	0.005	0.008	0.076	0.004	0.002	0.557	0.353	0.006	0.065	0.016	0.003
8	0.885	0.007	0.009	0.091	0.005	0.002	0.563	0.323	0.007	0.087	0.016	0.004
9	0.867	0.010	0.011	0.105	0.005	0.002	0.566	0.297	0.008	0.109	0.016	0.004
10	0.850	0.012	0.012	0.118	0.006	0.002	0.566	0.273	0.010	0.130	0.016	0.005
Variance Decomposition of SSE							Variance Decomposition of Nikkei					
Lag	NSE	NYSE	SSE	Nikkei	TSX	DAX	NSE	NYSE	SSE	Nikkei	TSX	DAX
1	0.034	0.095	0.870	0.000	0.000	0.000	0.289	0.181	0.011	0.519	0.000	0.000
2	0.039	0.106	0.849	0.000	0.001	0.004	0.317	0.146	0.009	0.524	0.000	0.004
3	0.044	0.115	0.825	0.000	0.003	0.012	0.338	0.117	0.008	0.525	0.001	0.012
4	0.049	0.123	0.802	0.000	0.004	0.022	0.355	0.094	0.006	0.524	0.001	0.020
5	0.053	0.128	0.780	0.000	0.005	0.033	0.368	0.077	0.005	0.520	0.001	0.028
6	0.057	0.133	0.760	0.000	0.006	0.044	0.378	0.065	0.005	0.516	0.001	0.035
7	0.061	0.136	0.742	0.000	0.006	0.055	0.387	0.056	0.004	0.511	0.001	0.040
8	0.065	0.138	0.726	0.000	0.006	0.064	0.395	0.050	0.004	0.505	0.001	0.045
9	0.068	0.140	0.712	0.000	0.006	0.073	0.401	0.046	0.003	0.499	0.001	0.049
10	0.071	0.142	0.700	0.000	0.006	0.081	0.408	0.043	0.003	0.493	0.001	0.052
Variance Decomposition of TSX							Variance Decomposition of DAX					
Lag	NSE	NYSE	SSE	Nikkei	TSX	DAX	NSE	NYSE	SSE	Nikkei	TSX	DAX
1	0.408	0.403	0.000	0.007	0.182	0.000	0.350	0.328	0.004	0.035	0.006	0.277
2	0.457	0.384	0.000	0.009	0.150	0.000	0.373	0.298	0.005	0.042	0.004	0.279
3	0.500	0.364	0.000	0.009	0.126	0.000	0.392	0.270	0.005	0.052	0.003	0.278
4	0.537	0.344	0.001	0.008	0.110	0.000	0.407	0.244	0.006	0.064	0.004	0.275
5	0.570	0.324	0.001	0.007	0.097	0.000	0.419	0.221	0.006	0.079	0.005	0.270
6	0.598	0.305	0.002	0.007	0.088	0.000	0.429	0.201	0.006	0.095	0.006	0.264
7	0.622	0.286	0.003	0.008	0.080	0.000	0.436	0.182	0.006	0.112	0.007	0.258
8	0.641	0.268	0.005	0.011	0.075	0.001	0.441	0.167	0.006	0.129	0.007	0.251
9	0.656	0.251	0.006	0.016	0.069	0.001	0.445	0.153	0.005	0.146	0.007	0.243
10	0.667	0.236	0.007	0.024	0.065	0.001	0.448	0.142	0.005	0.162	0.007	0.236

Source: Author(s) calculation.

Figure A2. *Graphical representation of Forecast Error Variance Decomposition (FEVD)*