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BEYOND BORDERS: STOCK MARKET RETURNS ACROSS DIFFERENT TIME ZONES

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Abstract

The global stock market operates as a complex network influenced by diverse international forces and time zone dynamics. This study investigates the interdependence and interactions among 15 major stock market indices spanning various time zones, with a focus on NIFTY50's impact and influence. Utilizing daily log returns data from January 2018 to December 2023, including Close-Close (CC), Open-Close (OC), and Close-Open (CO) data, we employ time series analysis techniques. Cointegration analysis reveals a long-term relationship between NIFTY50 and the other 14 indices. Granger Causality analysis is employed to discern directional causality effects among markets. Notably, significant impacts from key indices such as the S&P 500 and Nifty 50 on global economic sentiment are identified. Moreover, market disparities attributable to regional time differences are observed. Through the Ljung-Box test for autocorrelation and the GARCH model for univariate forecasting, insights into market trends and volatility patterns are gained, facilitating informed decision-making and risk management strategies. This study contributes to the understanding of global market dynamics and informs strategies for navigating interconnected financial ecosystems.

Keywords: Nifty 50, GARCH, Ljung-Box Test, Granger Causality.

JEL Codes: G1, G2, F6.

1. INTRODUCTION

The international stock market is driven by a wide range of international forces and functions as a dynamic, networked ecosystem. The fact that financial hubs are spread over a wide range of time zones greatly adds to the complexity of stock market dynamics. Time zones have a profound effect on the stock market, influencing the ebbs and flows of financial activity. Global markets are predictors of each other's performance across the zones. Post-fast-paced globalization, the impact of an event in one corner of the world is visible across the other. There is a wide array of factors affecting the international stock market as it is a very dynamic and liquid ecosystem. One particular factor that adds a great deal of complexity is the impact of time zones. This is due to many pieces of information traveling across borders, influencing financial activity in the stock markets. Every trader can slightly predict the opening hours and volatility of the next trading day based on what happened in the market that closed before their time or opened before theirs did.

For example, in the financial world, if on a Friday night US markets open positively then it is likely that on Monday mornings the Indian market will open positively. This can be explained by the fact that macro factors affect markets similarly. Although, when long-term returns are considered these effects seem to fade out across different markets. This paper aims to study how over five years across 15 markets, daily returns vary and which markets can be considered leading and which markets can be considered lagging.

The mechanism for the transmission of price and volatility spillovers among the stock exchanges is now regarded as one of the most actively studied fields in economics and finance. The financial community largely believes that the American stock market provides the early signals to anticipate global spillovers. Numerous studies have documented price and volatility spillovers from the United States to the rest of the world. The complex network of relationships between global stock exchanges has become a focus of intensive investigation in the fields of economics and finance. The spread of price and volatility spillovers across several markets demonstrates not only the global financial system's interconnection but also the possibility of contagion and systemic danger. While various research has been conducted on these phenomena, gaps remain, particularly in understanding the function of emerging markets like the Indian Stock Exchange and their impact on global spillovers.

This study aims to add to the ahead corpus of research by conducting an in-depth Granger Causality analysis on price and volatility spillovers between the Indian Stock Exchange and 14 other major stock exchanges around the world. This is done to see whether the opening and closing of markets at different times affect each other and if so, how significantly. Moreover, gaps in current literature are identified and an attempt to fill these gaps is made specifically to include the influence of global indices on NIFTY50, India's leading index.

Cointegration analysis of each of the 14 indices along with NIFTY50 is done to determine the long-term relationship between them. The existence of cointegration comes from the Efficient Market Hypothesis, according to which any new information is reflected in the prices, this may not be consistent across markets. Therefore cointegration is necessary to investigate the variations in prices in one market over the other. Furthermore, the Ljung box test and GARCH models are used to analyze time series patterns, and volatility and improve your understanding of market trends for informed decision-making and risk management.

Table 1: Operating Hours of different stock exchanges as per IST

Stock Exchange Timings					
Sr. No	**Country**	**Stock Exchange**	**Symbol**	**Opening Time**	**Closing Time**
1	Australia	Australian Security Exchange	ASX	5:30 AM	11:30 AM
2	Japan	Japan Exchange Group	JPX	5:30 AM	11:30 AM
3	South Korea	Korea Exchange	KRX	5:30 AM	11:30 AM
4	Taiwan	Taiwan Stock Exchange	TWSE	6:30 AM	11:00 AM
5	Singapore	Singapore Stock Exchange	SGX	6:30 AM	11:30 PM
6	Hong Kong	Hong Kong Stock Exchange	HKEX	6:45 AM	1:30 PM
7	China	Shanghai Stock Exchange	SSE	7:00 AM	12:30 PM
8	China	Shenzhen Stock Exchange	SZSE	7:00 AM	12:30 PM
9	India	National Stock Exchange of India	NSE	9:15 AM	3:30 PM
10	India	Bombay Stock Exchange	BSE	9:15 AM	3:30 PM
11	Pakistan	Pakistan Stock Exchange	PSX	10:00 AM	4:45 PM
12	Saudi Arabia	Saudi Exchange	-	10:30 AM	3:30 PM
13	United Arab Emirates	Abu Dhabi Securities Exchange	ADX	11:30 AM	4:14 PM
14	United Arab Emirates	Dubai Financial Market	DFM	11:30 AM	4:14 PM
15	European Union	Euronext	ENXB	12:30 PM	9:00 PM
16	Germany	Deutsche Borse	DB1	12:30 PM	9:00 PM
17	France	Euronext Paris	-	2:30 PM	9:30 PM
18	UK	London Stock Exchange	LSE	1:30 PM	10:00 PM
19	Switzerland	SIX Swiss Exchange	SIX	1:30 PM	10:00 PM
20	Spain	BME Spanish Exchange	BME	1:30 PM	10:00 PM
21	US	NASDAQ	COMP	7:00 PM	1:30 AM
22	US	NYSE	NYX	7:00 PM	1:30 AM
23	Brazil	Brasil, Bolsa, Balcão	B3	7:00 PM	1:30 AM
24	Canada	TMX Group	TSXV	8:00 PM	2:30 AM
All Times are in Indian Standard Time (IST)					

Table 2: List of Bellwether indexes from major stock exchanges in the world

Bell Weather Indexes				
Sr. No	**Country**	**Stock Exchange**	**Symbol**	**Index**
1	Australia	Australian Security Exchange	ASX	ASX 200
2	Japan	Japan Exchange Group	JPX	Nikkei 225
3	South Korea	Korea Exchange	KRX	KOSPI Composite Index
4	Taiwan	Taiwan Stock Exchange	TWSE	TAIEX
5	Singapore	Singapore Stock Exchange	SGX	Strait Time
6	Hong Kong	Hong Kong Stock Exchange	HKEX	Hang Seng Index (HSI)
7	China	Shanghai Stock Exchange	SSE	SSE Composite Index
8	China	Shenzhen Stock Exchange	SZSE	SSE Composite Index
9	India	National Stock Exchange	NSE	Nifty 50
10	India	Bombay Stock Exchange	BSE	S&P BSE SENSEX
11	Pakistan	Pakistan Stock Exchange	PSX	Karachi Stock Exchange 100 Index
12	Saudi Arabia	Saudi Exchange	-	Tadawul All Share Index (TASI)
13	United Arab Emirates	Abu Dhabi Securities Exchange	ADX	Abu Dhabi Securities Exchange General Index
14	United Arab Emirates	Dubai Financial Market	DFM	Dubai Financial Market General Index
15	European Union	Euronext	ENXB	Euro Stoxx 50
16	Germany	Deutsche Borse	DB1	DAX
17	France	Euronext Paris	-	CAC 40
18	UK	London Stock Exchange	LSE	FTSE 100
19	Switzerland	SIX Swiss Exchange	SIX	Swiss Market Index
20	Spain	BME Spanish Exchange	BME	IBEX 35
21	US	NASDAQ	COMP	NASDAQ Composite
22	US	NYSE	NYX	S&P 500
23	Brazil	Brasil, Bolsa, Balcão	B3	IBOVESPA
24	Canada	TMX Group	TSXV	TSX Composite Index

Table 3: Market Capitalization of Stock Exchanges as of December 2023 in Dollars and Rupees

Stock Exchanges & Indexes of the World				
Sr. No	**Stock Exchange**	**Country**	**Market Cap as of December 2023 (Trillions)**	
			In Dollars	**In Rupees**
1	NYSE	U.S.	$25.00	₹2,057.50
2	Nasdaq	U.S.	$21.70	₹1,785.91
3	Euronext	Netherlands	$7.20	₹592.56
4	Shanghai Stock Exchange	China	$6.70	₹551.41
5	Japan Exchange Group	Japan	$5.90	₹485.57
6	Shenzhen Stock Exchange	China	$4.50	₹370.35
7	Bombay Stock Exchange	India	$4.50	₹370.35
8	National Stock Exchange	India	$4.30	₹353.89
9	Hong Kong Exchanges	Hong Kong	$4.20	₹345.66
10	LSE Group	UK	$3.40	₹279.82
11	Saudi Exchange	Saudi Arabia	$3.10	₹255.13
12	TMX Group	Canada	$2.90	₹238.67
13	Deutsche Boerse AG	Germany	$2.10	₹172.83
14	SIX Swiss Exchange	Switzerland	$2.10	₹172.83
15	Nasdaq Nordic and Baltics	Scandinavia	$2.00	₹164.60
16	Korea Exchange	South Korea	$1.90	₹156.37
17	Tehran Stock Exchange	Iran	$1.70	₹139.91
18	ASX Australian Securities Exchange	Australia	$1.70	₹139.91
19	Taiwan Stock Exchange	Taiwan	$1.60	₹131.68
20	Johannesburg Stock Exchange	South Africa	$1.20	₹98.76
21	B3 - Brazil Stock Exchange	Brazil	$0.90	₹74.07
22	Abu Dhabi Securities Exchange	Abu Dhabi	$0.80	₹65.84
23	BME Spanish Exchanges	Spain	$0.80	₹65.84
24	Singapore Exchange	Singapore	$0.60	₹49.38
25	The Stock Exchange of Thailand	Thailand	$0.60	₹49.38
26	Bolsa Mexicana de Valores	Mexico	$0.50	₹41.15
27	Pakistan Stock Exchange	Pakistan	$0.02	₹6.30

1.1 Research Objectives

- To analyze the opening and closing prices of the selected stock indices to understand their movements and potential interdependencies.
- To investigate whether markets across time zones influence each other's movements, employing diverse econometric models.
- To analyze the overall adequacy and reliability of the time series models applied to all indices.
- To find appropriate indices for investment via ETFs.

1.2 Research Problem

The authors seek to investigate the individual behavior and dependence of indices. Analyzing these indicators can provide insight into how different markets and regions interact and influence each other. Determining the dependency of these indicators is important for investors and policymakers to manage risk, diversify resources, and make good decisions.

Additionally, understanding the behavior of individual indices can help uncover specific business, economic, and geographic conditions affecting a region or sector. This research helps us improve our understanding of the interaction between global financial markets and develop strategies for managing financial risk and global investment.

2. LITERATURE REVIEW

This literature review aims to provide an overview of the existing literature on stock market returns across time zones, focusing on the effects of global indices on each other and the co-movements of returns and volatilities among stocks in different regions.

Several studies have examined the correlation between stock markets across time zones. Olbryś (2013) in this decade-old study did a similar study to what the authors intend to do. The paper investigated the interdependence of price volatility across the U.S. stock market and two emerging markets namely Poland and Hungary. The paper addressed the problem of nonsynchronous trading effects using open-to-close logarithmic returns of major stock markets. Using a sample from 2004 to 2011, they noticed obvious evidence that the US prices spill over to other markets. Many papers have pointed out that the U.S market indices which include the DJIA, and NASDAQ influence all other markets to a certain extent.

One of the important things to first consider while studying the effects of the closing of one market over the opening of another is how the authors present and use the data. One such study by Sandoval (2014) in his paper titled “To lag or not to lag? How to compare indices of stock markets that operate at different times”, tries to get to the bottom of this very issue. The article concludes that using both lagged and original indices, the authors then obtain a better understanding of how indices that operate on different hours relate to each other. In 1990, Becker, Finnerty, and Gupta concluded that the correlation between the Japanese and US stock markets increases when one considers US data lagged by one day.

Baumöhl and Výrost (2010) performed Granger causality analysis on stock market indices from several Asian, European, and U.S. markets using daily data to point out the problems caused by nonsynchronous trading effects and proposed a data-matching process to address these issues1. The paper also suggested modifications to the regressions used in the Granger causality testing to account for nonsynchronous trading effects. The results showed that the proposed modifications led to substantially different conclusions, emphasizing the importance

of choosing the right methodology when dealing with nonsynchronous trading effects.

A study (2021) published by Indian authors focused on the causality and cointegration of the developed markets with Sensex. It analyzed the interdependence of Sensex with 22 global indices and studied by taking the daily closing prices of stock indices from 2005 to 2018. This paper studies the *normality, stationarity, and causality* of such time series using various statistical tools. It also looks into the degree of association of these indices. It concludes that there is significant interdependence among stock markets as well as bi-directional and unidirectional causality among the indices. It finds that interdependence leads to short and long-term gains due to international portfolio diversification**. A deeper study of volatility spillover between India, Asian, and US, UK markets is studied by Mishra et al. (2022).** This study uses the multivariate GARCH-BEKK model across pre and post-2008 crisis periods. The findings of the study show the tendency of Indian markets to move along with the US and Hong Kong market indices. It also points out that during the recession there's a decrease in the cointegration coefficient due to reduced investor confidence in developing countries. Volatility transmission from India to Asian markets is higher compared to the US and UK.

A study by Kahya (1997) which was two decades old studied the effects of non-overlapping trading hours on the correlations and cross-serial correlations of returns in non-contemporaneous stock markets. It uses the returns data of the US, UK, and Japan. The results of the study indicate that the daily correlations of returns are biased downward while daily cross-serial correlations are biased upward.

In another recent study concerning spillovers, He and Hamori (2021) seek to examine how returns and volatility spillover throughout the financial markets can explain certain hedging strategies, portfolio diversification, and risk management to investors. It is known that returns measure the market level and volatilities measure the risk, whereas skewness and kurtosis can have a decent amount of impact on risk management, asset pricing, and allocation of portfolios. The paper studies the high moment spillover effects throughout global markets using empirical methods where the change in the Log of daily prices is taken as daily returns along with descriptive statistics of returns of the stocks. It is found that developed markets except Japan have relatively high skewness and volatility spillovers to global financial markets as compared to emerging markets, especially the US. Previously published papers talk about the volatility spillovers caused by the US whereas this paper also shows the significant effect of skewness spillovers. Japan remains a minor producer as well as the receiver of spillover effects. Understanding the spillover mechanism across global markets could also help investors grasp the transmission of risk throughout markets. (Shigeyuki Hamori and Xie He 2021, #)

Nasser & Hajilee's (2016) study took the monthly data from 2001 to 2014 to determine the short-run and long-run relationship between emerging markets (Brazil, China, Mexico, Russia, and Turkey) and developed markets (US, UK, and Germany). The testing approach of cointegration and error-correction modeling is used. The results show evidence of the existence of short-run integration among stock markets in emerging countries and developed markets. However, the long-run coefficients for stock market returns in all emerging countries show a significant relationship only with Germany's stock market return. The empirical findings in this study have important implications for academicians, international investors, and policymakers in emerging markets. Geert Bekaert and Arnaud Mehl (2019) took a different approach to analyzing market integration. They tried to identify a temporal pattern of integration while trying to differentiate between regional and global patterns of integration for 17 countries. The authors test whether the pattern of integration formed over a long term is shaped in a U structure, is flat, a J shape, or rather a swoosh shape. Beta exposure of market returns is used

as the measure of actual global equity and regional integration, which in turn depends on formal market integration and global uncertainty. From 1885 to 2014 the authors can find a swoosh pattern in the actual global market integration and thus the presence of other patterns is rejected whereas there is no significant pattern found for regional integration. Findings reveal that segmented markets are not impacted significantly by changes in global interest rates whereas local interest rates in the integrated markets suffer due to changes in global interest rates. Thus in conclusion the trilemma concept holds which means countries cannot have fixed exchange rates, full market integration, and isolated local interest rates. (Geert Bekaert and Arnaud Mehl 2019, #)

Maslov (2001) analyzes the cross-correlation matrix of daily returns of stock market indices in a diverse set of 37 countries worldwide. The observed correlation structure is robust with respect to changes in the time horizon of returns ranging from 1 to 10 trading days and to replacing individual returns with just their signs. This last observation confirms that it is correlations between signs and not absolute values of fluctuations, which are mostly responsible for the observed effect. Negative changes in the index are somewhat more correlated than positive ones. In the data set, the reaction of Asian stock indices to changes in European and American ones persists for about 3 days.

Linton, Tang, and Wu (2023) proposed a framework for modeling daily stock returns correlated across sectors and periods to reduce bias in empirical research. MSCI indices of 42 developed and emerging markets covering the period between May 5, 2014, and June 23, 2023, are used in the study. The market is divided into Asia Pacific, Europe, and America in terms of closed time. The findings show that the economy increased during the Asian sub-period, with the VIX index rising due to the rise in international stocks. The United States has the highest level of global integration but the lowest level of regional integration. This study challenges the ineffectiveness of the global economy and shows that it takes more than 1/3 of a day for global news to disappear completely. This article presents a best practice model that includes international and national factors to measure market performance and the level of international and regional integration, concluding that the United States is the most integrated market and has a higher volatility index of international integration. level. This study shows the impact of the timing of international news on returns and illustrates the complexity of the market over different periods. (Linton†, Tang‡, and Wu§ 2023, #)

Moreover, Barigozzi (2018) provides a 2-stage dynamic factor model to examine any co-movements of returns and volatilities among stocks in the US, Europe, and Japan. The paper tries to investigate whether the global financial crisis and the European sovereign debt crisis were characterized by either a financial contagion or interdependence. One of the findings reveals the renowned home bias phenomenon which shows that domestic assets are largely over-weighted in portfolios. Other findings reveal how the volatilities are interconnected and are driven by a global shock explaining a certain amount of variances in volatilities in all the markets. It confirms the global belief that co-movements are increased during a period of crisis but no larger effect of international shocks on a given market which shows limited evidence of financial contagion. This is one of the first papers to shine some light on aspects like the origin of volatility shocks, interdependence, and contagion. In the financial events of the past decade, there is no evidence in the sense of financial contagion, during this turmoil period there has been an efficient spread of information throughout the markets rather than an irrational response. (Matteo Barigozzi 1, 2018)

This literature review provides an overview of the existing literature on stock market returns across time zones, focusing on the effects of global indices on each other and the co-movements

of returns and volatilities among stocks in different regions. The studies discussed in this review demonstrate the importance of understanding the interdependence between stock markets across time zones and the impact of global indices on stock market returns.

3. RESEARCH METHODOLOGY

Data Collection & Data Sampling: For the study, the authors have collected quantitative secondary data of the following 15 major indices:

- KS11: KOSPI Index - South Korea, Korea Exchange
- N225: Nikkei 225 - Japan, Tokyo Stock Exchange
- TAIEX: Taiwan Weighted Index - Taiwan, Taiwan Stock Exchange
- HANGSENG: Hang Seng Index - Hong Kong, Hong Kong Stock Exchange
- SSE: Shanghai Composite - China, Shanghai Stock Exchange
- NIFTY50: Nifty 50 - India, National Stock Exchange of India
- SNP500: S&P 500 - United States, New York Stock Exchange
- NASDAQ: United States
- TSX: S&P/TSX Composite Index - Canada, Toronto Stock Exchange
- IBOVESPA: Ibovespa - Brazil, B3 (B3 S.A. - Brasil, Bolsa, Balcão)
- NASDAQ: NASDAQ Composite - United States, NASDAQ
- IBEX35: IBEX 35 - Spain, Bolsa de Madrid
- SWISS: Swiss Market Index - Switzerland, SIX Swiss Exchange
- CAC40: CAC 40 - France, Euronext Paris
- DAX: DAX - Germany, Frankfurt Stock Exchange
- EURO STOXX 50: EURO STOXX 50 - Eurozone, Euronext

Source: Yahoo Finance

The study has six-year daily opening and closing price data from 2nd January 2018 to 31st December 2023. There are a total of 1564 data points for each index. Post data collection the following steps were performed to clean the data and make it ready for further analysis.

1. As every country has different holidays to match opening and closing dates. For each country, the missing values have been assumed using averages. To make the data uniform across all the stock indexes, the average of the previous day and the following day whenever there is a gap of one day. In case there is a gap of two days, then it has been taken as a weighted average of the previous two days and the next two days, the extremes are given weights of 0.33, and the previous & following days are given the weight of 0.67, giving them higher weights as they are the closer dates. For gaps for more than two days, the authors have taken the simple moving average for the same number of days, if there is a gap of three days, hence moving average of three days will be taken, and so on.

2. After the data was arranged in a manner where all dates were filled for each index, the log daily returns were calculated to convert the non-stationary data to stationary data in three different ways.
3. To analyze the time zone effect, calculate the Close-Close (CC), Close-Open (CO) and Open-Close (OC) log returns for each index. All our models have been run on all three data sets separately.

3.1 Methodology and Data Analysis Tools:

Ljung box test helps in identifying significant auto-correlation which in turn helps to determine the adequacy of the models to be used for analyzing data. The null hypothesis is that there is no auto-correlation in the residuals and the p-value determines significance.

This study uses a GARCH model to measure the volatility of daily closing prices of the indices using logarithmic percentage change. Model parameters include regression mean, standard deviation, variance, and ARCH/GARCH coefficient for each parameter. This study aims to reveal patterns of change in different sectors and shed light on the diversity of risk management strategies and business practices.

$$v_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta v_{t-1}^2$$

$$\varepsilon_t^2 = v_t^2 + u_t$$

$$L(\mu, \omega, \alpha, \beta) = \frac{1}{v_t\sqrt{2\pi}} e^{-\frac{\varepsilon_t^2}{2v_t^2}}$$

An Augmented Dickey-Fuller test or the unit root test is first run to check the stationarity of the data sets. As the non-stationary time series data sets have been converted to daily log returns the data has now become stationary which is proved using the ADF test, the interpretation of which will be explained ahead.

The Engle-Granger test was used to compare log-returns of the Nifty 50 to major worldwide stock market indices. Significant cointegration findings demonstrate long-term linkages between the Nifty 50 and specific global markets, implying possible prospects for portfolio diversification and risk management techniques.

Post cointegration, the autoregressive model choice includes Vector Autoregression (VAR), suitable for capturing interdependencies among time series data, and Vector Error Correction (VEC), requiring non-stationary but cointegrated or long-term relationship data.

The primary data analysis entails employing Granger Causality to examine the interdependence among indices. Granger Causality assesses whether one time series variable predicts another. Used across disciplines like economics and neuroscience, it reveals temporal relationships and directional influences.

4. DATA ANALYSIS

4.1. Ljung Box Test

The Ljung-Box test will help evaluate whether there is a significant effect on the return of these indicators at different times. If the p-value associated with the LJung box test is less than the alpha (0.05) it means there is no proof of auto-correlation. Euro Indices such as CAC 50, SWISS, DAX and EURO STOXX 50 have extremely high p-values and thus depict no

autocorrelation which indicates that their price movements follow a different pattern than those which depict autocorrelation. Trading hour difference and the amount of liquidity levels impact autocorrelation, the Euro Indices may have similar trading hours and potential to other indices in regions with different economic structures, resulting in more flexible price movements and lower autocorrelation. This shows how different factors such as market trends, market sentiments, and other underlying economic factors influence the returns of the indices. This information is useful for understanding the time series properties of the data and can guide the selection of appropriate models, such as autoregressive models or ARCH/GARCH models, to include autocorrelation in the examination.

4.2. GARCH model

Understanding market volatility is crucial for making investment decisions, risk management, and business prospects. Modern financial models are often assumed to be unregulated and fail to reflect the dynamic nature of the economy. The GARCH model, proposed by Robert F. Engle in the 1980s, addresses this limitation by modeling volatility as a function of past and future changes. After prioritizing the data, including taking the natural logarithm of the percentage change in a constant rate, by fitting a GARCH model to each data. The GARCH model provides insight into the underlying volatility dynamics of each market, allowing us to estimate parameters such as average volatility, volatility persistence, and long-term volatility. The results display long-run volatility around an average of 1% for all countries with the lowest in the SWISS index and the highest in the S&P 500 index. This indicates that the S&P 500 might be a leading indicator for market movement or a lagging indicator that reacts strongly to past events. This conveys significant fluctuations in the index value over a large period. High log-likelihood values indicate how well the GARCH model fits the data, the values for the dataset range about and around 5000 which suggests that the GARCH model adequately captures the current volatility dynamics in each country's index data set. The ARCH and GARCH coefficients range between 0.75 and 0.90 which shows that the volatility is persistent and the shocks that affect the markets affect volatility levels for a significant period. The findings show that discrepancies in the daily percentage changes in each country's closing price index introduce risk and appear to be linked to an average length of around 1%.

4.3 Cointegration Test

The Engle-Granger test was used to compare log-returns of the Nifty 50 to major worldwide stock market indices. Overall, these results suggest a strong and statistically significant cointegration relationship between Nifty 50 and other Indices log CC returns, with the model capturing the long-term equilibrium and directional movement patterns between these stock market indices.

4.4 Vector Error Correction

The data gathered is a time series. To study all the indices together, an autoregressive model must be run.

Before running an autoregressive model, it is crucial to run an ADF/ unit root test to test stationarity in the gathered data. Initial test results on close prices confirm that the data is nonstationary. Therefore, by using a log of returns of prices of Close-Close, Close-Open, and Open-Close. All variables are now stationary.

The choice of autoregressive model is between Vector Autoregression (VAR), which is a straightforward model to capture interdependencies among time series data, and Vector Error Correction (VEC), which requires the data to be non-stationary but cointegrated or share a

long-term relationship. After running a cointegration test, it is confirmed that all indices are cointegrated, taking NIFTY50 as a common base index for the test. For the endogenous variables, 10 lags have been used, representative of 2 weeks of trading days, to find patterns in 5 years of daily price data. For exogenous variables, none as such have been selected. The model has been run for CC, CO, and OC separately.

4.4.1 VEC on CC:

Table 4: Vector Error Correction on Close-Close Data (Refer table 1 in appendix)

Determinant resid covariance (dof adj)	3.56 × 10^(−66)
Determinant resid covariance	6.60 × 10^(−62)
Log likelihood	85274.24
Akaike information criterion	-106.3609
Schwarz criterion	-97.1148
Number of coefficients	2685

Indices- The R2 ranges from 0.59-0.71, which is high considering that the model was run on time series data. Despite taking 10 lags, (which is high), not see a huge drop in degrees of freedom, and standard error is low. This is reflected by adjusted R2, which penalizes overfitting, ranging from 0.54-0.67. The F statistic of the model measures the reliability of the model, and is an indicator of the quality of the model, ranging from 13-20, suggesting each variable explains a significant portion in an autoregressive manner. AIC and SC are also quality indicators, which evaluate the quality of the model fit, if the goal is to have a better forecast and if the goal is to have a better goodness of fit, respectively. Lower values indicate a better model for both AIC and SC. The values for both variables are negative, indicating good forecasting ability and a good goodness of fit. The log-likelihood for the variables is very high, indicating a better fit.

Model

- Log-likelihood – 85274, which is very high, and favorable for the model
- AIC, SC – Extremely low and negative values, making the model a great fitting model (-106, -97)

4.4.2 VEC ON CO:

Table 5: Vector Error Correction on Close-Open Data (Refer table 2 in appendix)

Determinant resid covariance (dof adj)	5436.74
Determinant resid covariance	1.01 × 10^(−72)
Log likelihood	99185.64
Akaike information criterion	-124.3565
Schwarz criterion	-115.1055
Number of coefficients	2685

Indices- The R2 ranges from 0.44-0.72, which is high considering that the model was run on time series data. Despite taking 10 lags, (which is high), it has not seen a huge drop in degrees of freedom, and standard error is low. This is reflected by adjusted R2, which penalizes overfitting, ranging from 0.37-0.68. The F statistic of the model measures the reliability of the model, and is an indicator of the quality of the model, ranging from 6-22, suggesting each variable explains a significant portion in an autoregressive manner. AIC and SC are also quality indicators, which evaluate the quality of the model fit, if the goal is to have a better forecast and if the goal is to have a better goodness of fit, respectively. Lower values indicate a better model for both AIC and SC. The values for both variables are negative, indicating good

forecasting ability and a good goodness of fit. The log-likelihood for the variables is very high, indicating a better fit.

Model –

- Log-likelihood – 99185, which is very high, and favorable for the model
- AIC, SC – Extremely low and negative values, making the model a great fitting model (-124, -115)

4.4.3 VEC on OC:

Table 6: Vector Error Correction on Open-Close Data (Refer table 3 in appendix)

Determinant resid covariance (dof adj)	2.08 × 10^(−66)
Determinant resid covariance	3.86 × 10^(−67)
Log likelihood	85689.18
Akaike information criterion	-106 8953
Schwarz criterion	-97.64915
Number of coefficients	2685

Indices- The R2 ranges from 0.55-0.65, which is high considering that the model was run on time series data. Despite taking 10 lags, (which is high), it has not seen a huge drop in degrees of freedom, and standard error is low. This is reflected by adjusted R2, which penalizes overfitting, ranging from 0.5-0.61. The F statistic of the model measures the reliability of the model, and is an indicator of the quality of the model, ranging from 10-16, suggesting each variable explains a significant portion in an autoregressive manner. AIC and SC are also quality indicators, which evaluate the quality of the model fit, if the goal is to have a better forecast and if the goal is to have a better goodness of fit, respectively. Lower values indicate a better model for both AIC and SC. The values for both variables are negative, indicating good forecasting ability and a good goodness of fit. The log-likelihood for the variables is very high, indicating a better fit.

Model –

- Log-likelihood – 85689, which is very high, and favorable for the model
- AIC, SC – Extremely low and negative values, making the model a great fitting model (-106, -97)

4.5 Granger Causality

Examines if values of one variable can be used to predict other variables in the autoregressive model. The null hypothesis is that X does not Granger cause Y, and the alternative hypothesis is that X Granger causes Y. Significance level is at 5%.

If p-value <0.05, then X Granger causes Y.

If p-value>0.05, then X does not Granger cause Y.

4.5.1 Superiority of some indices

a) ON CC RETURNS

1) IBOVESPA ON CC RETURNS – Out of the 15 indices, SNP500, NIFTY 50, NASDAQ, and SWISS MARKET INDEX, are significant(<0.05), influencing other markets and their major indices.

Dependent variable: D(IBOVESPA)

Excluded	Chi-sq	df	Prob.
D(CAC40)	24.75457	10	0.0058
D(DAX)	19.69252	10	0.0323
D(EURO_STOXX_50)	20.84673	10	0.0222
D(HANGSENG)	16.86222	10	0.0775
D(IBEX35)	22.21352	10	0.0141
D(KS11)	9.552329	10	0.4806
D(N225)	17.68554	10	0.0605
D(NASDAQ)	24.75555	10	0.0058
D(NIFTY50)	18.89876	10	0.0416
D(SNP500)	41.89997	10	0.0000
D(SSE)	7.808144	10	0.6476
D(TSX)	17.32107	10	0.0676
D(TAIEX)	10.18308	10	0.4246
D(SWISS)	24.02504	10	0.0075
All	344.4543	140	0.0000

2) NIKKEI 225 ON CC DATA – Establishes NASDAQ, SNP500, SWISS MARKET INDEX. Significant as p-value (<0.05).

Dependent variable: D(N225)

Excluded	Chi-sq	df	Prob.
D(CAC40)	11.86893	10	0.2939
D(DAX)	8.442127	10	0.5857
D(EURO_STOXX_50)	9.379588	10	0.4965
D(HANGSENG)	22.87295	10	0.0112
D(IBOVESPA)	13.27127	10	0.2089
D(IBEX35)	24.91859	10	0.0055
D(KS11)	8.482510	10	0.5818
D(NASDAQ)	41.24956	10	0.0000
D(NIFTY50)	16.21206	10	0.0937
D(SNP500)	44.00997	10	0.0000
D(SSE)	6.979500	10	0.7274
D(TSX)	13.28128	10	0.2084
D(TAIEX)	6.967853	10	0.7285
D(SWISS)	23.52067	10	0.0090
All	401.3401	140	0.0000

S&P 500: Encompasses 500 companies across various industries. It is the best single gauge of large-cap U.S. equities. A change in the S&P 500 is often considered indicative of the health of the U.S. economy and also directs global stock price movement.

NASDAQ: It is another U.S. index heavily weighted towards technology and biotech. The performance of the NASDAQ is often seen as a proxy for the performance of the tech and growth sectors.

Swiss Market Index (SMI): This index is a blue-chip stock market index, diversified across various sectors, with a strong presence in financials, pharmaceuticals, and consumer goods.

Global Investors use these indices as a benchmark for their investment decisions and portfolio returns. Market movements in these indices affect the sentiment of the home market and the global market. Movements in these indices influence other major indices of the world, therefore Granger causes other indices in the world

b) ON CO RETURNS – NIFTY50, SNP500, NASDAQ heavily influence CAC40, DAX, EURO STOXX 50, IBEX35, KS11. This means the U.S. and Indian indices have a heavy influence on European markets and the Korean index. Apart from reasons such as the U.S. market being a superpower that directs global market movement, and market sentiment, the reason for NIFTY50's influence on other indices is that India is showing a favorable macroeconomic environment. Higher GDP, higher Capital expenditure, PLI schemes to promote the manufacturing sector, robust services sector, increasing FDI, and favorable young demographic are some of the various reasons for NIFTY50's increasing influence over the global market.

Dependent variable: D(CAC40)

Excluded	Chi-sq	df	Prob.
D(DAX)	8.178346	10	0.6114
D(EURO_STOXX_50)	22.88593	10	0.0112
D(IBEX35)	37.09178	10	0.0001
D(HANGSENG)	12.40356	10	0.2590
D(IBOVESPA)	35.97820	10	0.0001
D(KS11)	15.04387	10	0.1305
D(N225)	9.545777	10	0.4812
D(NASDAQ)	57.35397	10	0.0000
D(NIFTY50)	21.49850	10	0.0179
D(SNP500)	38.71199	10	0.0000
D(SSE)	3.134949	10	0.9781
D(SWISS)	11.51887	10	0.3185
D(TAIEX)	5.314575	10	0.8692
D(TSX)	30.46161	10	0.0007

Dependent variable: D(EURO_STOXX_50)

Excluded	Chi-sq	df	Prob.
D(CAC40)	12.53389	10	0.2509
D(DAX)	13.00395	10	0.2235
D(IBEX35)	29.45073	10	0.0011
D(HANGSENG)	11.84043	10	0.2959
D(IBOVESPA)	16.69629	10	0.0814
D(KS11)	13.03826	10	0.2215
D(N225)	5.828793	10	0.8294
D(NASDAQ)	32.45967	10	0.0003
D(NIFTY50)	19.37189	10	0.0358
D(SNP500)	20.43002	10	0.0254
D(SSE)	2.652033	10	0.9885
D(SWISS)	16.92569	10	0.0760
D(TAIEX)	3.749495	10	0.9579
D(TSX)	16.27951	10	0.0919
All	281.3451	140	0.0000

Dependent variable: D(DAX)

Excluded	Chi-sq	df	Prob.
D(CAC40)	21.34097	10	0.0188
D(EURO_STOXX_50)	20.22583	10	0.0272
D(IBEX35)	38.91795	10	0.0000
D(HANGSENG)	16.76433	10	0.0797
D(IBOVESPA)	43.43475	10	0.0000
D(KS11)	17.72011	10	0.0599
D(N225)	8.678384	10	0.5629
D(NASDAQ)	46.79524	10	0.0000
D(NIFTY50)	21.40434	10	0.0184
D(SNP500)	28.87356	10	0.0013
D(SSE)	1.827922	10	0.9975
D(SWISS)	16.70831	10	0.0811
D(TAIEX)	5.701362	10	0.8397
D(TSX)	26.74694	10	0.0029
All	354.1399	140	0.0000

Dependent variable: D(IBEX35)

Excluded	Chi-sq	df	Prob.
D(CAC40)	24.45578	10	0.0065
D(DAX)	6.760642	10	0.7478
D(EURO_STOXX_50)	20.87309	10	0.0220
D(HANGSENG)	19.10618	10	0.0389
D(IBOVESPA)	43.67238	10	0.0000
D(KS11)	16.65984	10	0.0822
D(N225)	8.645418	10	0.5661
D(NASDAQ)	52.53878	10	0.0000
D(NIFTY50)	20.11662	10	0.0282
D(SNP500)	35.75437	10	0.0001
D(SSE)	2.697860	10	0.9877
D(SWISS)	11.95605	10	0.2880
D(TAIEX)	8.315100	10	0.5981
D(TSX)	32.47731	10	0.0003
All	384.4445	140	0.0000

Dependent variable: D(KS11)

Excluded	Chi-sq	df	Prob.
D(CAC40)	9.889842	10	0.4502
D(DAX)	18.99610	10	0.0403
D(EURO_STOXX_50)	6.439875	10	0.7771
D(IBEX35)	5.773060	10	0.8340
D(HANGSENG)	21.80762	10	0.0161
D(IBOVESPA)	18.25101	10	0.0509
D(N225)	10.37440	10	0.4083
D(NASDAQ)	36.42198	10	0.0001
D(NIFTY50)	20.13066	10	0.0280
D(SNP500)	37.13465	10	0.0001
D(SSE)	8.688962	10	0.5619
D(SWISS)	13.65192	10	0.1895
D(TAIEX)	10.16973	10	0.4257
D(TSX)	24.44672	10	0.0065
All	324.2682	140	0.0000

4.5.2 Time Zone Differences – Through the course of a trading day in the global market, countries in the East start and end their trading days first compared to countries in the West. There can be overlaps in the trading hours among the various countries.

a) ON CC RETURNS

1) NIFTY50- NIFTY50 is influenced by countries in the east such as Japan (NIKKEI225) since their trading hours began before the market opening in India. This has an impact on the 24-hour close-close return. On the other hand, the countries in the West influence Indian markets as well. Even though NIFTY50 is not a leading indicator for TSX, IBOVESPA, SNP500, and NASDAQ (p value>0.05) over the week, from Monday to Friday; IBOVESPA, SNP500, NASDAQ, and TSX become leading indicators for NIFTY50 over the weekend. This means that the close of SNP500, NASDAQ, AND TSX influenced the close-close return of NIFTY50 on Monday.

Dependent variable: D(NIFTY50)

Excluded	Chi-sq	df	Prob.
D(CAC40)	21.73786	10	0.0165
D(DAX)	10.68297	10	0.3827
D(EURO_STOXX_50)	17.75265	10	0.0593
D(HANGSENG)	25.54515	10	0.0044
D(IBOVESPA)	31.59563	10	0.0005
D(IBEX35)	27.03594	10	0.0026
D(KS11)	6.770144	10	0.7470
D(N225)	23.18290	10	0.0101
D(NASDAQ)	16.54090	10	0.0852
D(SNP500)	25.01804	10	0.0053
D(SSE)	12.72599	10	0.2394
D(TSX)	40.36844	10	0.0000
D(TAIEX)	9.557102	10	0.4802
D(SWISS)	26.22029	10	0.0035
All	511.4828	140	0.0000

Dependent variable: D(NASDAQ)

Excluded	Chi-sq	df	Prob.
D(CAC40)	12.28728	10	0.2663
D(DAX)	14.44570	10	0.1536
D(EURO_STOXX_50)	16.69240	10	0.0815
D(HANGSENG)	18.67341	10	0.0446
D(IBOVESPA)	14.28496	10	0.1604
D(IBEX35)	16.21313	10	0.0937
D(KS11)	8.203760	10	0.6089
D(N225)	6.732799	10	0.7504
D(NIFTY50)	13.16489	10	0.2146
D(SNP500)	33.72984	10	0.0002
D(SSE)	5.648766	10	0.8439
D(TSX)	15.81486	10	0.1051
D(TAIEX)	4.039291	10	0.9456
D(SWISS)	19.63606	10	0.0329
All	307.2278	140	0.0000

Dependent variable: D(SNP500)

Excluded	Chi-sq	df	Prob.
D(CAC40)	11.24359	10	0.3389
D(DAX)	16.09562	10	0.0969
D(EURO_STOXX_50)	16.65832	10	0.0823
D(HANGSENG)	17.77277	10	0.0589
D(IBOVESPA)	14.33911	10	0.1581
D(IBEX35)	17.59864	10	0.0621
D(KS11)	9.637268	10	0.4729
D(N225)	9.685822	10	0.4685
D(NASDAQ)	22.87182	10	0.0112
D(NIFTY50)	11.43471	10	0.3247
D(SSE)	4.701964	10	0.9102
D(TSX)	21.63194	10	0.0171
D(TAIEX)	5.374362	10	0.8648
D(SWISS)	26.14415	10	0.0036
All	311.6909	140	0.0000

4.5.3 Volatility (in comparison with the GARCH model)

a) CC – 24 Hour returns – 24hour volatility.

1) SNP500 – By the GARCH model, SNP500 has the highest volatility of 2.58%, among all indices. By Granger causality, it is significant for 8 indices out of 15. This indicates that the SNP500 is the world's most influential index, as changes in SNP500 direct market movements across the globe, making it a leading indicator.
2) IBOVESPA – By Garch model, IBOVESPA has a volatility of 1.41%. This is due to more than 5 indices being significant for this index. A higher number of variables causes an index to increase volatility.
3) SWISS MARKET INDEX – Has the lowest volatility of 0.93%. This is because SWISS MARKET INDEX is a small index of 20 large instruments and it is very stable. This is confirmed by Granger causality, as only 2 other indices of Granger cause the SWISS MARKET INDEX.

b) CO – OVERNIGHT RETURN – OVERNIGHT VOLATILITY

1) SWISS MARKET INDEX – Has a very low volatility of 0.47%. Only one index granger causes the SWISS MARKET INDEX, showing the stability of the SWISS MARKET INDEX.
2) NIFTY50 – Has a median volatility of 0.76%. This occurs due to the Indian market being influenced by indices in the East and the West. Granger causality confirms this as 6 indices Granger cause NIFTY50.

c) OC – INTRADAY RETURN – INTRADAY VOLATILITY

1) SWISS MARKET INDEX – Has a very low volatility of 0.72%. Only one index granger causes the SWISS MARKET INDEX, showing the stability of the SWISS MARKET INDEX.
2) NIFTY50 – Has a median volatility of 0.94%. This occurs due to the Indian market being influenced by indices in the East and the West. Granger causality confirms this as 8 indices Granger cause NIFTY50.

4.5.4 Monday and Friday Anomalies

Using the T-test, we have tried to find if Mondays & Fridays have some effect on the stock indices. Looking at the P values for CC, OC, and CO returns for the indexes, we have not found any significant impact in any of the indices, other than CC returns for Monday of KS 11, Nikkie 225, NIFTY 50, IBOVESPA, IBEX 35, DAX and Euro Stoxx 50.

5. CONCLUSION

A comprehensive analysis of various market indices using advanced econometric methods provides valuable information about the dynamics of financial markets. This study first ensures the stability of the data by developing the Dickey-Fuller test and the Engel-Granger test to establish a basis for further analysis. The integrated relationship between the Nifty 50 Index and other major global indices reflects the interaction between the market and provides opportunities for diversification of products and strategies, and risk management. The Vector Error Correction (VEC) model is used to analyze relationships between indices, show meaningful relationships, and show the impact of some indices on others. High R-squared values, F-statistics, and log-likelihood show the robustness of the model in how it captures the

autoregressive dynamics of the data. In addition, Granger causality analysis gives an idea about the direction of the effect of indices, as some indices become indicators of market movements. Furthermore, this study investigates the impact of time zone differences on business dynamics and highlights the role of trading hours and overlapping periods in influencing reward. This shows the importance of considering the period when analyzing the global market. Examining volatility using the GARCH model shows that the indices have different volatility and this has implications for risk management and decision making. sorry investment. Essentially, the S&P 500 has become a major driver of global economic volatility, disrupting its status as a gauge of market movements. Additionally, the fact that no significant results were obtained in searches made on Mondays and Fridays shows that these measurement days do not have a significant effect on stock returns. Overall, the research contributes to a deeper understanding of the interrelationships and dynamics in the financial world. These findings provide useful information to help investors, policymakers, and researchers make informed decisions and improve risk management in the worldwide financial transition.

6. LIMITATIONS

Our study comprises time series data only, and they come with several limitations, which affect the analysis in terms of accuracy and reliability. Some of the limitations are -

1. Data Quality & Preprocessing: Since the data is based on stock indexes of different countries, data has been assumed, using averages, in places where the indexes were closed on the weekdays only. Time series data has to be preprocessed to make it usable. So the missing values had to be assumed, which can distort the analysis and lead to incorrect conclusions, but since the number of days assumed is much less than the actual data, it should not have a major impact on the overall data.
2. Stationarity Assumption: Times series data often exhibits nonstationarity, and hence to make it stationary, different approaches have been used such as taking the logarithmic returns.
3. Seasonality and Trends: Time series data often contain seasonal patterns and long-term trends, these make analysis complicated, and doing a vast international study, it is difficult to incorporate such trends for all of them. It can lead to inaccurate forecasting.
4. Data Volume: Using daily returns for the analysis, has added a lot of variables, with the broad number of countries, which has led to the accumulation of a lot of data points.
5. External Factors & Regime Shifts: Times series data is impacted by multiple external factors, both micro and macro-economic, which have not explicitly accounted for in the analysis, and could create an impact. Market dynamics can change over time due to shifts in economic conditions, policy changes, or other external factors, one major such condition is the pandemic. In such a large international study, considering all such points is not feasible.
6. Market Noise: Stock Index data is impacted by several market-related factors such as market sentiment, certain events, investor behavior, and news. This impacts the overall trend and pattern comparison.
7. Volatility Clustering: Usually trends tend to follow or cluster, hence high volatility periods are followed by more such periods, and vice versa.
8. Index Composition: The composition of the index may have changed, and some might be impacted by survivorship bias.

7. RECOMMENDATIONS

- Invest in ETFs of SWISS MARKET INDEX due to their strong influence and stability
- Invest in ETFs of NIFTY 50 due to its strong influence and favorable macroeconomic environment in Indian markets

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Abbreviations	Full Form
VEC	Vector Error Correction
ADF	Augmented Dickey-Fuller Test
GARCH	Generalized autoregressive conditional heteroskedasticity
CC	Close - Close
OC	Open - Close
CO	Close - Open
All Stock Indexes	Have been mentioned in the paper

APPENDIX

Table 1

VEC CC –

Error Correction:	D(CAC40)	D(DAX)	D(EURO_S...	D(HANGS...	D(IBEX35)	D(IBOVESPA)	
R-squared	0.613603	0.619440	0.618434	0.621835	0.613162	0.666753	0.676677
Adj. R-squared	0.567948	0.574474	0.573350	0.577153	0.567455	0.627377	0.638474
Sum sq. resids	0.181676	0.190797	0.184401	0.222473	0.186896	0.293159	0.124772
S.E. equation	0.011441	0.011724	0.011526	0.012660	0.011604	0.014533	0.009481
F-statistic	13.43999	13.77593	13.71734	13.91681	13.41504	16.93337	17.71289
Log likelihood	4826.410	4788.375	4814.850	4669.109	4804.413	4454.863	5118.168
Akaike AIC	-6.003104	-5.954121	-5.988217	-5.800526	-5.974776	-5.524615	-6.378838
Schwarz SC	-5.434906	-5.385923	-5.420019	-5.232329	-5.406578	-4.956417	-5.810641
Mean dependent	3.00E-06	4.97E-06	2.68E-06	-1.44E-06	3.82E-06	-1.09E-05	1.61E-06
S.D. dependent	0.017405	0.017973	0.017646	0.019469	0.017644	0.023808	0.015769

D(N225)	D(NASDAQ)	D(NIFTY50)	D(SNP500)	D(SSE)	D(TSX)	D(TAIEX)	D(SWISS)
0.710443	0.652552	0.685749	0.676959	0.592446	0.695482	0.677480	0.628361
0.676230	0.611499	0.648619	0.638790	0.544292	0.659501	0.639373	0.584450
0.118780	0.280193	0.119014	0.189537	0.153098	0.121704	0.099454	0.105088
0.009251	0.014208	0.009260	0.011686	0.010502	0.009364	0.008465	0.008701
20.76539	15.89539	18.46861	17.73577	12.30297	19.32940	17.77811	14.30983
5156.387	4489.991	5154.858	4793.518	4959.306	5137.505	5294.274	5251.489
-6.428058	-5.569853	-6.426089	-5.960744	-6.174251	-6.403741	-6.605633	-6.550533
-5.859861	-5.001655	-5.857891	-5.392546	-5.606053	-5.835544	-6.037435	-5.982335
7.98E-07	-1.02E-05	-6.68E-06	-7.86E-06	2.88E-06	-2.06E-07	-3.60E-07	6.29E-06
0.016258	0.022795	0.015621	0.019443	0.015558	0.016047	0.014096	0.013498

Table 2

VEC CO –

Error Correction:	D(CAC40)	D(SWISS)	D(TAIEX)	D(TSX)	D(DAX)	D(EURO_S...	D(HANGS...	D(IBEX35)
R-squared	0.679351	0.563297	0.639296	0.721827	0.673775	0.624484	0.591784	0.687327
Adj. R-squared	0.641437	0.511661	0.596646	0.688936	0.635202	0.580083	0.543516	0.650357
Sum sq. resids	0.067323	0.028605	0.026225	0.036622	0.075865	0.010814	0.107881	0.059693
S.E. equation	0.006967	0.004541	0.004348	0.005138	0.007396	0.002792	0.008819	0.006560
F-statistic	17.91829	10.90896	14.98936	21.94578	17.46747	14.06453	12.26043	18.59116
Log likelihood	5593.160	6257.364	6324.766	6065.630	5500.460	7012.202	5227.254	5686.495
Akaike AIC	-6.995052	-7.850984	-7.937843	-7.603905	-6.875592	-8.823714	-6.523524	-7.115329
Schwarz SC	-6.426557	-7.282489	-7.369347	-7.035409	-6.307097	-8.255219	-5.955028	-6.546834
Mean dependent	3.11E-06	4.92E-06	-1.68E-08	-1.11E-06	3.28E-06	2.12E-06	2.47E-06	3.05E-06
S.D. dependent	0.011635	0.006499	0.006847	0.009213	0.012245	0.004309	0.013053	0.011095

D(IBOVESPA)	D(KS11)	D(N225)	D(NIFTY50)	D(NASDAQ)	D(SNP500)	D(SSE)
0.444249	0.674983	0.619216	0.689764	0.656868	0.689073	0.572617
0.378537	0.636553	0.574191	0.653082	0.616296	0.652308	0.522082
0.011733	0.051923	0.061324	0.049751	0.099145	0.039662	0.052145
0.002908	0.006118	0.006649	0.005989	0.008455	0.005347	0.006132
6.760509	17.56385	13.75293	18.80362	16.19012	18.74299	11.33128
6948.916	5794.710	5665.576	5827.872	5292.783	6003.740	5791.399
-8.742160	-7.254781	-7.088371	-7.297515	-6.607968	-7.524149	-7.250514
-8.173665	-6.686286	-6.519876	-6.729020	-6.039473	-6.955654	-6.682019
4.32E-08	-8.37E-06	2.99E-06	-1.34E-06	-2.86E-06	-2.05E-06	-1.22E-06
0.003689	0.010149	0.010190	0.010168	0.013649	0.009069	0.008869

Table 3

VEC - OC

Error Correction:	D(TAIEX)	D(SWISS)	D(TSX)	D(CAC40)	D(DAX)	D(EURO_S...	D(HANGS...
R-squared	0.622645	0.600432	0.643518	0.557239	0.577493	0.593115	0.580754
Adj. R-squared	0.578059	0.553221	0.601397	0.504924	0.527571	0.545040	0.531217
Sum sq. resids	0.070236	0.083467	0.063776	0.105331	0.110649	0.149091	0.146264
S.E. equation	0.007114	0.007755	0.006779	0.008711	0.008929	0.010364	0.010265
F-statistic	13.96486	12.71799	15.27805	10.65165	11.56799	12.33712	11.72380
Log likelihood	5564.365	5430.350	5639.288	5249.697	5211.446	4979.902	4994.766
Akaike AIC	-6.953465	-6.780876	-7.049952	-6.548226	-6.498964	-6.200775	-6.219918
Schwarz SC	-6.385267	-6.212678	-6.481755	-5.980028	-5.930767	-5.632578	-5.651720
Mean dependent	-1.43E-06	6.94E-06	3.89E-06	-3.85E-07	-1.60E-09	-1.08E-06	4.17E-06
S.D. dependent	0.010951	0.011602	0.010737	0.012381	0.012990	0.015365	0.014993

D(IBEX35)	D(IBOVESPA)	D(KS11)	D(N225)	D(NASDAQ)	D(NIFTY50)	D(SNP500)	D(SSE)
0.561244	0.658818	0.622492	0.594784	0.615637	0.637032	0.637163	0.555834
0.509403	0.618505	0.577887	0.546905	0.570222	0.594145	0.594292	0.503353
0.120075	0.301969	0.100010	0.078708	0.177158	0.093689	0.117188	0.119692
0.009301	0.014750	0.008488	0.007530	0.011298	0.008216	0.009189	0.009286
10.82617	16.34275	13.95574	12.42277	13.55592	14.85384	14.86225	10.59121
5147.970	4431.871	5289.948	5475.933	4845.967	5340.644	5166.865	5150.449
-6.417218	-5.495005	-6.600062	-6.839579	-6.028289	-6.665350	-6.441552	-6.420411
-5.849020	-4.926807	-6.031865	-6.271382	-5.460092	-6.097152	-5.873355	-5.852213
-1.82E-06	-6.97E-07	5.03E-06	-5.04E-06	3.64E-06	3.48E-06	3.45E-06	-1.00E-06
0.013279	0.023880	0.013065	0.011187	0.017233	0.012896	0.014426	0.013177