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INTERTEMPORAL VOLATILITY SPILLOVER RELATIONSHIPS (PRE- AND POST-COVID-19) AMONG THE PHILIPPINE, US, AND JAPANESE STOCKS MARKETS:

A Multivariate DCC GARCH Approach

57211512 SESE, VIRGILIO GLENN C. SESE

HOT PAPERS IN FINANCE

C.E. PROF. ALEX COAD

D.E. PROF. ARIKAWA YASUHIRO D.E. PROF. MING YAN WILLIAM CHEUNG

Abstract

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This research investigates intertemporal relationships of volatility spillover effects among the Philippine, US, and Japanese stock markets, with particular emphasis on the pre- and post-COVID-19 periods. It aims to explore the extent to which these markets are interconnected and exhibit interdependencies, whereby changes in one market's volatility may be related to or associated with changes in the volatilities of the other markets. It is important to note that the study does not seek to establish a causal relationship between the markets but rather focuses on understanding the patterns of relatedness and potential influences that may exist among them. This study examines the transmission of volatility across different markets using the Multivariate Dynamic Conditional Correlation (DCC) Generalized Autoregressive Conditional Heteroskedasticity (GARCH) approach. The analytical framework also incorporates various tools and techniques, including time series visualization, descriptive statistics and distribution analysis, unit root analysis, autoregressive structure testing, and OLS regression analysis (with and without lag) to comprehensively analyze the research problem.

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57211512 Sese, Virgilio Glenn C. Sese
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c.e. Prof. alex coad
d.e. Prof. arikawa yasuhiro d.e. Prof. Ming yan william cheung

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CHAPTER 1. INTRODUCTION

Section 1. BACKGROUND OF THE STUDY

The increasing interconnectedness of global financial markets has facilitated the transmission of shocks and information across national boundaries. As a result, it is imperative for market participants and policymakers to thoroughly understand the mechanics of volatility spillover effects. Volatility spillover refers to the phenomenon where changes in volatility in one market are linked to the volatility of other markets. The understanding of volatility spillover effects and their interconnectedness is crucial to mitigate possible risks and promote financial stability.

The Philippine stock market has gained prominence in recent years as an emerging market with substantial potential for growth and investment opportunities. As an open economy, the Philippine stock market is vulnerable to external shocks from other markets, especially those of major economies such as the United States of America (USA) and Japan. Due to their size and extensive financial ties, both the USA and Japan are key players in the global financial landscape, affecting other economies.

In late 2019, the COVID-19 pandemic first surfaced, causing enormous disruptions in financial markets all around the world. The World Health Organization (WHO) declared COVID-19 as a Public Health Emergency of International Concern (PHEIC) on January 30, 2020, and then proclaimed COVID-19 to be a global pandemic on March 11, 2020. Around this time, governments all over the world responded by putting lockdowns, travel restrictions, and social distancing measures to stop the virus's spread, which led to business closures, disruptions in global supply networks, and a dramatic drop in consumer demand. Financial markets were heavily affected by these factors, which also had a major impact on investor sentiment, market liquidity, and asset prices.

During the pandemic's early phases, the volatility of the financial markets increased. Major indices dropped sharply and quickly, and stock markets experienced sharp falls. Investor confidence was significantly shaken, which resulted in large selloffs and more uncertainty in the market. Volatility indicators also increased as a result of the increased market anxiety.

The COVID-19 pandemic had a significant impact on numerous industries. More particularly, the travel, hospitality, and retail industries saw sharp drops in stock prices and market values. On the other hand, certain industries adjusted to the new economic environment, including technology and e-commerce, which experienced considerable stability or even growth.

In order to lessen the negative effects on financial markets and the overall economy, central banks and governments implemented a number of monetary and fiscal policies in response to the pandemic's disruptions. To stabilize markets and aid in the recovery of the economy, central banks implemented monetary policies, including interest rate cuts, liquidity injections, and asset purchase programs. To assist businesses, safeguard jobs, and promote economic growth, governments also adopted fiscal stimulus packages and relief measures.

Overall, the ensuing market volatility and uncertainty due to COVID-19 have highlighted how crucial it is to comprehend how volatility spreads and what effect it has on various markets. The primary objective of this study is to shed light on the connections and interdependencies among the stock markets of the Philippines, the USA, and Japan by examining the volatility spillovers, both before and after the COVID-19 epidemic.

In this study, a comprehensive set of statistical tools will be employed to examine the intertemporal relationships of volatility spillover effects among the Philippine, US, and Japanese stock markets. The analytical architecture that will be used in this study includes the usage of time series visualization, descriptive statistics and distribution analysis, unit root analysis, autoregressive structure testing, OLS regression analysis (with and without lag), and the Multivariate Dynamic Conditional Correlation (DCC) Multivariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model.

Section 2. RESEARCH QUESTION AND PURPOSE

The research question addressed in this study is: What are the intertemporal relationships of volatility spillover effects among the Philippine, US, and Japanese stock markets during the pre- and post-COVID-19 periods?

The significance of this study lies in its contribution to the current understanding of volatility spillover effects and the relationship between the Philippine stock market and the stock markets in the United States and Japan. More specifically, the study addresses the following 4 key points:

A. Filling the Knowledge Gap: By focusing on the volatility spillover effects among these three stock markets, the study seeks to close a substantial gap in the existing literature. Although studies on volatility spillovers in international financial markets have been conducted, little study has particularly addressed the effects of these spillovers involving the Philippine stock market. By presenting empirical evidence of the transmission of volatility among these markets, this study aims to close that knowledge gap. This is further explained in this literature's Chapter 2: Section 2.

B. Contribution to Methodology: On top of filling the knowledge gap, this study also contributes to the expansion of the existing methodological toolbox for examining volatility spillover effects by using the Multivariate DCC GARCH technique. Unlike traditional GARCH models, it captures time-varying correlations, providing a dynamic representation of interdependencies. This method is particularly suited for assessing the impact of significant events like COVID-19 on market volatility. This is further explained in this literature's Chapter 3: Section 2.

C. Policy Implications: Policymakers will be significantly impacted by the study's conclusions. The findings can be used by decision-makers to develop strategies that will strengthen the financial system's resilience and promote stability of the stock market. Comprehending transmission mechanisms related to volatility spillover is crucial to effectively manage risks and mitigate the potential negative impacts on financial stability.

D. Investment Decision-Making: Findings from this study can help investors and market players make wise investment decisions. For asset allocation, portfolio diversification, and risk management methods, knowledge of the volatility spillover effects can be very useful. In order to create effective investment strategies, investors and portfolio managers can get insights into the possible risks and opportunities resulting from volatility spillovers.

CHAPTER 2. REVIEW OF RELATED LITERATURES

Section 1. VOLATILITY SPILLOVER AND MARKET INTERCONNECTEDNESS

Volatility spillover effects, as previously discussed, refer to the close relationship among interconnected markets. These effects can be driven by various factors, including macroeconomic shocks, financial crises, and other global events. One of the most recent and significant global events that this study will be focusing on is the COVID-19 pandemic, which has had a profound impact on global financial markets, causing heightened volatility and significant disruptions.

According to empirical studies, information transmission and shocks play a significant role in affecting the volatility of the global financial markets (Bae and Karolyi, 1994; Gallo and Otranto, 2007; Bhargava et al., 2012; Jebran and Iqbal, 2016). This suggests that the amount of fluctuation and instability observed in financial markets around the world can be significantly affected when vital information is shared or unexpected occurrences happen. These empirical studies show how interdependent and interrelated many markets are, as well as how important information flow and unanticipated shocks are in determining market volatility.

The interconnectedness of markets and the flow of information have been facilitated by a number of factors, including global trade, investment policies, macroeconomic similarities, capital flows, technological advancements, and the dissemination of international news (Booth et al., 1997; Dornbusch et al., 2000; Gallo and Otranto, 2007). Global trade and investment policies have opened up channels for cross-border interchange of products, services, and capital, strengthening economic links. Furthermore, the existence of macroeconomic commonalities among nations, such as inflation, interest rates, and fluctuations in exchange values, adds to the markets' interconnection. Technology developments have also been crucial in enabling quicker and more effective communication, allowing market players to access and share information in real-time. Rapid worldwide news transmission through a variety of media outlets has also aided in the smooth flow of information, allowing market participants to stay current on happenings throughout the world and respond appropriately. Together, these elements strengthen market interdependence and advance effective information transfer, which eventually affects the dynamics of volatility in the global financial scene.

Previous crises have shown the significant impact of economic and financial shocks on international markets, including the Great Depression (1932), the Suez Crisis (1956), the International Debt Crisis (1982), the Mexican Peso Crisis (1994), the Asian Financial Crisis (1997), the US Subprime Crisis (2007-2008), the European Debt Crisis (2010), and Brexit (2016). Due to these events, there is now an increased relevance and focus on the understanding of the connections between international stock markets, especially in times of crisis. Notably, pandemics like SARS (2003) and COVID-19 (2019) also hold tremendous significance in this regard.

The most recent crisis, the COVID-19 pandemic, which originated in China and rapidly spread across the globe, resulted in unparalleled repercussions affecting multiple facets of society, economy, and global financial markets. Building upon this understanding of the broader implications of crises, previous research has focused on examining the effects of COVID-19 across various stock exchanges and industries in different parts of the world.

According to Liew and Puah's research (2020), investors' reactions to COVID-19 vary across nations and industries. While the energy sector saw the biggest impact globally, other industries such as communication, consumer goods, medical non-manufacturing, IT, and infrastructure performed rather well. These results align with earlier studies by Chen et al. (2009) and Wang et al. (2013) in differ rent market contexts (Taiwan) and during previous disease outbreaks (SARS). However, the findings contradict the observations of Aravind and Manojkrishnan (2020), who reported that during the COVID-19 pandemic, listed pharmaceutical businesses in India saw significantly negative returns. Furthermore, Al-Awadhi et al. (2020) showed that there was a significant negative influence on the stock value of all companies listed on the Hang-Seng stock exchange composite index and the Shanghai Stock Exchange, with the IT and pharmaceutical sectors performing relatively better. Greater negative effects on returns were observed for larger enterprises than for smaller firms, and foreign investors significantly outperformed Chinese locals in this regard.

Ru et al. (2020) presented an interesting observation when comparing the reactions of capital markets in sixty-five countries to both SARS and COVID-19. According to their study, while all markets experienced considerable impacts from both diseases, countries with prior experience in dealing with SARS were less affected compared to those without previous SARS experience. Akhtaruzzaman et al. (2020) examined how financial contagion occurred between China and G7 countries during the COVID-19 period, focusing on both financial and non-financial firms. Their analytical findings indicated a substantial increase in conditional correlations between the returns on securities for listed companies in these countries, aligning with earlier studies conducted by Baker et al. (2012) and Morales and Andreosso-O'Callaghan (2014). Moreover, Yan et al. (2020) examined the travel, technology, entertainment, and gold industry and found out that the pandemic had a considerable negative impact in the near term but will have a course correction in the long run. Baker et al. (2020) conducted a study showing that the COVID-19 pandemic had a more pronounced impact on the US stock market compared to previous infectious pandemics. In their industry-level examination of COVID-19's effect on US stock market volatility, Baek et al. (2020) found that certain macroeconomic indices and unfavorable press coverage of COVID-19 were significant influences, indicating a bias toward unfavorable news. Anggraini et al. (2022) created a systematic literature review to summarize literatures that relates to the effects of the COVID-19 pandemic on the stock market. Reviewing these literatures, spillover, market reactions, investor herding, policy, investor sentiment, and asset intensity are six topic clusters that have been found. Through these investigations, valuable insights were gained into various elements of stock markets, encompassing the market itself, industries, investors, government, and companies.

Overall, the volatility caused by COVID-19 had serious effects on the world's financial markets, leading policymakers and portfolio managers to acknowledge the imperative of studying financial asset volatility and information spillover effects across economies during this crisis (Zhang et al., 2020). The subsequent section of this chapter (Chapter 2: Section 2) will delve into existing literature that explores these aspects on volatility spillover among countries in greater detail.

Section 2. ANALYSIS OF PREVIOUS RESEARCH

Researchers have worked to understand the degree of financial information spillover and its transmission among foreign stock markets in the field of calculating returns and volatility. Several modeling strategies, including ARCH presented by Engle (1982), GARCH proposed by Bollerslev (1986), and EGARCH suggested by Nelson (1991), have been used to represent volatility clustering in financial data. Building upon these models, a number of ARCH model extensions have been developed over time to take volatility spillover effects into consideration.

Previous literatures have explored the economic integration of international stock markets by examining spillover effects within and between stock markets, forex markets, commodity markets, and swap markets of various nations. For instance, Bae and Karolyi (1994) investigated the international spillovers of stock return volatility between Japan and the US using an extended GARCH framework. Worthington and Higgs (2004) examined the transmission of equity returns and volatility in Asian developed and emerging markets using a multivariate GARCH analysis. Li, Hong (2007) studied the international linkages of the Chinese stock exchanges using multivariate GARCH. Using GARCH, EGARCH, and Cointegration techniques, Mishra et al. (2007) examined the long-term link and bidirectional volatility spillover between the stock and FX markets in India. Through GARCH, EGARCH, and TGARCH modeling, Bhargava et al. (2012) observed a unidirectional spillover of volatility from the US dollar interest rate swap market to the Indian swap market as well as asymmetric impacts for one-year swaps. Kumar's (2013) research examined the IBSA countries (India, Brazil, and South Africa) and revealed that there exist significant spillover effects of both returns and volatility between foreign exchange rates and stock prices. Dontis-Charitos et al. (2013) studied the return and volatility spillovers from major bank stocks to the national stock market in the UK using Gaussian estimation and continuous time models as well as discrete time multivariate GARCH.

In recent years, researchers have also demonstrated a significant interest in employing event-based methodologies in developed and emerging countries to estimate the implications of the COVID-19 on returns and volatility. Anh and Gan (2020) observed substantial changes in returns before and after the outbreak while using event research technique to analyze the effects of the COVID-19 pandemic and subsequent lockdowns on the returns of 723 listed enterprises in Vietnam. Gherghina et al. (2020) examined daily stock market returns in seven nations, including the USA, Germany, UK, Spain, Italy, France, and Romania, to determine the impact of COVID-19 on financial markets. The influence of the pandemic on the Romanian stock market was studied using an autoregressive distributed lag (ARDL) model, and it was discovered that the 10-year Romanian government bond was more sensitive to COVID-19 news than the stock index of the Bucharest Stock Exchange. Thakur (2020) used a VAR model to investigate the US stock market's movements during the COVID-19 outbreak and found a negative causal relationship between the Standard and Poor (S&P) index and the rise in global new COVID-19 cases. A study conducted by Akinlaso et al. (2021) investigated the transmission of volatility within financial markets during the COVID-19 pandemic, utilizing both symmetric models (GARCH and GARCH-M) and asymmetric models (Threshold GARCH and Exponential GARCH) to analyze the volatility dynamics.

Recent studies have also looked on the integration of the stock market during the COVID-19 pandemic as well as the information flow between various economies. When Capelle-Blancard and Desroziers (2020) examined the integration of stock markets during the COVID-19 crisis in 74 countries, they discovered that before the crisis, stock prices were relatively less responsive to economic variables than they were during the crisis's immediate aftermath. Panel data analysis was used by Cao et al. (2020) to demonstrate how stock indexes changed in response to COVID-19 domestic and international spreads. In their investigation of the relationships between the spread of COVID-19, fluctuating oil prices, stock market volatility, geopolitical risk, and the ambiguity of the US economic policy, Sharif et al. (2020) found that the impact of COVID-19 on geopolitical risk was significantly greater than the ambiguity of the US economic policy, with different short-run and long-run observations.

In relation to the Philippine stock market, there have been limited studies conducted. One such study by Bartolome et al. (2022) focused on the effects of COVID-19 on the Philippine Stock Exchange index (PSEi). By employing Robust Least Squares Regression and Augmented Dickey-Fuller (ADF) tests, this research examined the impact of the COVID-19 pandemic on the PSEi. It investigated the correlation between the weekly increase in COVID-19 infections and the PSEi to evaluate the potential for extreme volatility. Furthermore, the study explored the short and long-term effects of COVID-19 infections on the fluctuations observed in the PSEi. Another study by Le and Tran (2021) examined the contagion effect from U.S. Stock Market to the Vietnamese and the Philippine Stock Markets using GARCH Model. The findings suggest that both the Vietnamese and Philippine stock markets are impacted by the contagion effect during the COVID-19 pandemic crisis. The study also reveals that the contagion effect in Vietnam is smaller during the pandemic compared to the global financial crisis, while the opposite is true for the Philippines. The findings indicate that the Philippines is more affected by the contagion effect from the COVID-19 pandemic than Vietnam at the time of the study. Unfortunately, other existing studies have only touched upon the topic in a limited manner without delving deep into its specific dynamics, such as the study by Yousaf et al. (2023) on spillovers and connectedness between Chinese and ASEAN stock markets, including the Philippines, while briefly discussing on the spillover during the Covid-19 pandemic.

Finally, in relation to this paper's methodology, the usage of multivariate DCC GARCH model has also been employed by previous research, covering stock markets, commodity markets, and even cryptocurrency markets. (Ampountolas, 2022; Ji et al., 2022; Yıldırım et al., 2022; Yadav et al., 2022; Mishra and Ghate, 2022; Derbali, 2021)

Section 3. GAPS IN LITERATURE

Despite the existing literature on volatility spillover effects, there remains a gap in understanding the specific spillover effects among the Philippine, US, and Japanese stock markets during the pre- and post-COVID-19 periods. As such, this thesis aims to fill this knowledge gap by applying a multivariate DCC GARCH approach to analyze and quantify these spillover effects. The findings of this research will contribute to the existing body of knowledge and provide insights for investors, policymakers, and market participants.

CHAPTER 3. DATA AND METHODOLOGY

Section 1. DATA COLLECTION

Table 1: Nature and Sources of Data

Data Source	Time Frame		Frequency
	Range	Reasoning	
Nikkei 225 index	**Pre-COVID-19:** October 20, 2016, to January 29, 2020 **Post-COVID-19:** January 30, 2020, to May 5, 2023	World Health Organization (WHO)'s PHEIC Declaration	Daily
Standard & Poor's 500 index (S&P 500)			
Philippine Stock Exchange index (PSEi)			

This research utilizes daily pricing data from Market Watch to analyze the Philippine Stock Exchange index (PSEi) and compare it with two of the most prominent benchmark indices, namely the Standard & Poor's 500 index (S&P 500) and the Nikkei 225 index.

The selected timeframe for this study spans from October 20, 2016, to May 5, 2023, covering both the pre-COVID and post-COVID periods.

The pre-COVID period, from October 20, 2016, to January 29, 2020, serves as a crucial baseline for understanding the volatility spillover effects among the stock markets before the pandemic. The starting point of October 20, 2016, was deliberately chosen to provide a balanced and equitable duration for analyzing the pre- and post-COVID periods, ensuring a fair and unbiased comparison and assessment of volatility spillover effects. By examining the pre-COVID period, the research establishes a benchmark and identifies any pre-existing patterns of volatility spillover effects.

The post-COVID period, on the other hand, begins on January 30, 2020, when the World Health Organization (WHO) declared a Public Health Emergency of International Concern (PHEIC), and extends until May 5, 2023. This timeframe captures the impact of the COVID-19 pandemic on the spillover effects and overall volatility dynamics of the three stock markets. Analyzing the post-COVID period is necessary to understand how the market has adapted and identify any lasting effects from the global crisis.

The choice of May 5, 2023, as the endpoint for the timeframe is based on the recommendation of the WHO Emergency Committee on COVID-19 to the Director-General, indicating that although the disease remained ongoing and well-established, it no longer met the criteria for a PHEIC. This recommendation acknowledges the evolved nature of the pandemic and its transition from an emergency phase to an established crisis. Thus, the chosen time frame for the post-COVID period aligns with this recommendation and allows for an analysis of the market's response.

To conduct the analysis, as previously mentioned, this study relies on three key stock market indices: the Philippine Stock Exchange index (PSEi) representing the Philippine stock market, the Standard & Poor's 500 index (S&P 500) representing the US stock market, and the Nikkei 225 index representing the Japanese stock market. These indices serve as reliable proxies for their respective economies and provide insights into the dynamics of the global financial system. The inclusion of these indices is driven by the fact that US and Japan possess well-established stock markets, making them compelling choices for comparison and analysis in this study.

By examining the interplay between these three indices, the research aims to shed light on the volatility spillover effects among the Philippine, US, and Japanese stock markets. Employing a multivariate DCC GARCH approach enables the modeling and quantification of these spillover effects accurately, considering the intricate relationships and dependencies among the variables.

Section 2. RESEARCH APPROACH AND METHODOLOGY

Table 2: Analytical Architecture

Analytical Workflow	Analytical Tools/Descriptions
a. Time Series Visualization	i. Time Plots of Stock Indices Prices ii. Time Plots of Stock Indices Returns (Conditional Heteroscedasticity)
b. Descriptive Statistics and Distribution Analysis	i. Mean, Median, Max, Min, Standard Deviation, Skewness, and Kurtosis ii. Histograms iii. Jarque-Bera (J-B) Test
c. Unit Root Analysis	i. Augmented Dickey-Fuller (ADF) unit-root test (with “trend”) ii. Augmented Dickey-Fuller (ADF) unit-root test (with “drift”)
d. Autoregressive Structure Testing	i. Ljung-Box Test
e. OLS Regression	Quantify the relationships between the stock price/returns of the indices
f. Multivariate DCC GARCH	Main Model of to check Volatility Spillover

This study utilizes a well-established research framework to investigate the volatility spillover effects among the Philippine, US, and Japanese stock markets, both before and after the COVID-19 pandemic.

For this study, both the price and returns are analyzed. The returns are calculated using the following formula: R[t] = log(P[t]) - log(P[t-1])

The breakdown of the variables used is as follows:

R[t] represents the log return at time t.

P[t] represents the closing price at time t.

P[t-1] represents the closing price at time t-1.

By subtracting the logarithm of the previous closing price from the logarithm of the current closing price, the log return is calculated. This operation calculates the change in the logarithm of the variable from one period to the next, providing information about the percentage change.

The first step of the framework involves visualizing the time series data. Time plots are created to examine the price movements of stock indices as well as their corresponding returns. These visual representations allow for the identification of patterns, trends, and potential outliers in the data, providing valuable insights into the dynamics of the market. Time plots for the returns are employed to investigate and identify patterns related to conditional heteroscedasticity.

Descriptive statistics and distribution analysis are then conducted to gain further insights into the data. Descriptive statistics, such as mean, median, maximum, minimum, standard deviation, skewness, and kurtosis, are computed to understand the central tendency, dispersion, and shape of the data. The mean is the average value of a set of data points. It is calculated by summing all the values ($x_1 + x_2 + x_3 + ... + x_n$) and dividing them by the total number of observations (n), as follows:

Mean = ($x_1 + x_2 + x_3 + ... + x_n$) / n

The median is the middle value in a sorted list of data points. The median is a measure of central tendency that is less affected by extreme values in the data. It represents the value that separates the higher and lower half of the observations. The formula is as follows:

Median = ((n + 1) / 2)th observation

“Max” or the maximum value in the data set represents the highest observed value. “Min” or the minimum value in the data set represents the lowest observed value.

The standard deviation measures the dispersion or variability of the data points around the mean. It quantifies the average amount by which each data point differs from the mean:

Standard Deviation = sqrt[((x_1 - mean)^2 + (x_2 - mean)^2 + ... + (x_n - mean)^2) / n]

The standard deviation helps assess the spread or volatility of the data set. A higher standard deviation indicates greater variability, while a lower standard deviation suggests less variability.

Skewness measures the asymmetry of the probability distribution of a variable. Positive skewness indicates a longer or fatter tail on the right side of the distribution, while negative skewness indicates a longer or fatter tail on the left side.

Skewness = (1/n) * Σ[(Xi - X̄) / s]^3

Where:

Xi represents each individual data point.

X̄ is the sample mean.

s is the sample standard deviation.

n is the sample size.

Kurtosis quantifies the degree of peakedness or flatness of the probability distribution of a variable. It assesses whether the distribution has heavy tails or is more concentrated around the mean.

Kurtosis = [(1/n) * Σ[(Xi - X̄) / s]^4] – 3

The same variables as in the skewness formula are used. Both skewness and kurtosis provide insights into the shape and characteristics of the distribution.

Additionally, histograms are then constructed to visualize the distribution characteristics of the data. A histogram is a graphical representation that displays the distribution of a dataset by dividing it into a set of contiguous intervals called bins. The x-axis represents the range of values observed in the dataset, while the y-axis represents the frequency or count of observations falling within each bin. The shape of the histogram provides insights into the symmetry or skewness of the distribution. A symmetric distribution will appear approximately bell-shaped, with the highest frequency occurring around the center and gradually decreasing towards the tails. On the other hand, a skewed distribution will show a longer or fatter tail on one side, indicating an imbalance in the distribution of values.

The Jarque-Bera (J-B) test is applied to assess the normality assumption of the data, which provides information about the underlying distribution. The Jarque-Bera test involves calculating the test statistic JB, which follows a chi-square distribution under the null hypothesis of normality.

The formula for the Jarque-Bera (J-B) test statistic is as follows:

$$J\text{-}B = (n/6) * (Skewness^2 + (1/4) * (Kurtosis - 3)^2)$$

Where:

n is the sample size.

Skewness is the skewness coefficient of the dataset.

Kurtosis is the kurtosis coefficient of the dataset.

The Jarque-Bera test helps determine if the distribution of the data significantly deviates from a normal distribution. The Jarque-Bera (J-B) test is applied to test the hypothesis regarding the normality assumption of the data. The null hypothesis (H0) assumes that the dataset follows a normal distribution, while the alternative hypothesis (H1) suggests that the data significantly deviates from normality. A significant result suggests non-normality in the data.

Unit root analysis is performed to determine the stationarity of the time series data. The Augmented Dickey-Fuller (ADF) test, considering both "trend" and "drift" specifications, is employed to detect the presence of unit roots. The ADF unit-root test (with "trend") is used to determine if a time series has a unit root, indicating non-stationarity. The test is performed with a trend component included in the regression equation. This ADF test involves estimating an autoregressive model and testing the coefficient on the lagged dependent variable. The test statistic follows a specific distribution under the null hypothesis of a unit root. The ADF test with a "trend" specification is given by the following equation:

$$\Delta yt = \alpha + \beta t + \gamma yt\text{-}1 + \Sigma\delta i\Delta yt\text{-}i + \varepsilon t$$

Where:

Δ yt represents the differenced time series.

α is the intercept term.

βt is the coefficient on a time trend, allowing for a linear trend in the data.

$\gamma yt-1$ captures the coefficient on the lagged level of the time series.

$\Sigma\delta i\Delta yt-i$ represents the coefficients on the lagged differences of the time series.

εt is the error term, assumed to be white noise.

The null hypothesis of the ADF test with the "trend" specification is that the time series has a unit root, indicating non-stationarity. The alternative hypothesis is that the time series is stationary.

The ADF unit-root test (with "drift"), similar to the ADF test with trend, includes an additional constant term in the regression equation. The ADF test with a "drift" specification includes an additional term capturing a constant drift:

$$\Delta yt = \alpha + \gamma yt-1 + \Sigma\delta i\Delta yt-i + \varepsilon t$$

Where:

Δyt, α, γ, $\Sigma\delta i$, and εt have the same interpretation as in the "trend" specification. Note that α is an intercept constant called a drift.

The null hypothesis of the ADF test with the "drift" specification is also that the time series has a unit root, indicating non-stationarity. The alternative hypothesis is that the time series is stationary.

The next step focuses on examining the autoregressive structure in the data. The Ljung-Box test is used to assess the absence of autocorrelation in the residuals, indicating the independence of the observed data points. The formula for the Ljung-Box test is as follows:

$$Q(m) = n(n+2) * \Sigma((r(h))^2 / (n-h))$$

Where：

Q(m) is the test statistic for a specified lag length m.

n is the sample size.

r(h) is the autocorrelation coefficient at lag h.

The formula involves summing the squared autocorrelation coefficients for lags 1 to m and adjusting it by dividing by n-h for each lag h. The null hypothesis (H0) for the Ljung-Box test assumes that there is no serial correlation in the time series, while the alternative hypothesis (H1) suggests the presence of serial correlation. A significant result suggests the presence of autocorrelation in the time series.

The Ordinary Least Squares (OLS) regression is then employed to quantify the relationships between the variables in this study. It estimates the coefficients of a linear regression model that minimizes the sum of squared residuals. In this study, two OLS regression models are employed to examine the relationships between the Philippine Stock Exchange Index (PSEi) and the stock indices of the United States (S&P) and Japan (Nikkei).

The first model, OLS Regression (no lags), investigates the contemporaneous relationship between the PSEi and the S&P and Nikkei indices. The regression equation is expressed as:

$PSEi(t) = \beta0 + \beta1 * S\&P(t) + \beta2 * Nikkei(t) + \varepsilon$

Where:

PSEi(t) represents the PSEi at time t.

$\beta0$ is the intercept term.

$\beta1$ and $\beta2$ are the coefficients measuring the association of the S&P and Nikkei indices.

ε represents the error term.

This model quantifies the direct influence of the current values of the S&P and Nikkei on the PSEi, helping us understand how changes in the US and Japanese markets affect the Philippine market at the same point in time.

The second model, OLS Regression (with lag = 1), explores the lagged relationship between the PSEi and the S&P and Nikkei indices. The regression equation is formulated as:

$PSEi(t) = \beta0 + \beta1 * S\&P(t-1) + \beta2 * Nikkei(t-1) + \varepsilon$.

Here, the inclusion of lagged variables (t-1) allows us to examine any delayed effects or dependencies between the indices. By considering the previous period's values of the S&P and Nikkei, this model captures potential spillover effects and provides insights into the influence of past market conditions on the current value of the PSEi. The coefficients ($\beta0$, $\beta1$, $\beta2$) estimated from these regression models represent the strength and direction of the relationships, indicating the magnitude of the association of the US and Japanese indices on the Philippine market. By utilizing these OLS regression models, this research aims to gain a deeper understanding of the interdependencies and dynamics among these stock markets and uncover potential spillover effects.

After checking important assumptions, to analyze the volatility spillover effects, a multivariate DCC GARCH model is then constructed. It estimates time-varying conditional variances and conditional correlations, capturing the evolving volatility dynamics and interconnectedness among the markets. The multivariate DCC GARCH model incorporates the following key concepts to analyze the volatility dynamics and correlations among the indices:

A. Standardized Returns:

The vector of standardized returns for the 3 indices (PSEi, S&P, and Nikkei) at time t, denoted as R(t), is calculated using the formula:

$R(t) = H(t)^{0.5} * Z(t)$

R(t): Vector of standardized returns for the 3 indices at time t.

H(t): Conditional covariance matrix capturing volatility dynamics and correlations.

Z(t): Vector of standardized residuals.

B. Conditional Covariance Matrix:

The conditional covariance matrix H(t) is composed of the diagonal matrix D(t) and the correlation matrix R(t) in the following way:

$H(t) = D(t) * P(t) * D(t)$

H(t): Conditional covariance matrix capturing volatility dynamics and correlations.

D(t): Diagonal matrix of time-varying standard deviations of each series at time t.

P(t): Time-varying correlation matrix at time t.

C. Dynamic Conditional Correlation:

The Dynamic Conditional Correlation (DCC) mechanism updates the correlation matrix over time using a two-step procedure.

In the first step, the standardized residuals from each series are calculated:

$e(t) = D(t)^{-0.5} * Z(t)$

In the second step, these residuals are used to update the correlation matrix:

$$P(t) = (Q(t)^{-0.5}) * Q(bar) * (Q(t)^{-0.5})$$

$Q(t)$: Symmetric, positive definite matrix calculated as:

$$Q(t) = (1 - a - b) * Q(bar) + a * e(t-1) * e(t-1)' + b * Q(t-1)$$

$Q(bar)$: Unconditional correlation matrix of $e(t)$.

a, b: Parameters estimated from the data.

D. Diagonal Matrix:

The diagonal matrix, $D(t)$, is defined as:

$$D(t) = diag(sqrt(h_{1t}), sqrt(h_{2t}), sqrt(h_{3t}))$$

$D(t)$: Diagonal matrix consisting of diagonal elements representing the square root of the conditional variances for each index at time t.

$sqrt(h_{1t})$, $sqrt(h_{2t})$, $sqrt(h_{3t})$: Square root of the conditional variances for indices 1, 2, and 3, respectively.

E. GARCH(1,1) Model for Conditional Variances:

To estimate the conditional variances for each index, the multivariate DCC GARCH model utilizes the univariate GARCH(1,1) model.

The conditional variance for index i at time t, denoted as h_{it}, is given by the formula:

$$h_{it} = \omega_{i} + \alpha_{i} * e_{i,t-1}^2 + \beta_{i} * h_{i,t-1}$$

h_{it}: Conditional variance for index i at time t.

ω_{i}, α_{i}, β_{i}: Parameters of the GARCH(1,1) model for index i.

$e_{i,t-1}$: Standardized residual of index i at the previous time period.

By applying the DCC(1,1) specification to different time frames for both returns and prices, valuable insights into the changing volatility dynamics and spillover effects among these stock markets under varying market conditions can be examined. The estimated parameters, including the mean, autoregressive terms, omega (constant term), and the coefficients representing volatility persistence, as well as the DCC parameters (dcca1 and dccb1), provide important information about the interrelationships and volatility transmission mechanisms among the markets.

The contribution of the Multivariate DCC GARCH Model on top of existing models is as follows:

The frameworks of Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) are powerful tools for modeling and forecasting time-series data. Each possesses unique strengths, and their combination constitutes an effective method for studying financial market dynamics.

ARIMA models are equipped to tackle data autocorrelation and non-stationarity through differencing and are capable of forecasting future values based on past data points and error terms. Nonetheless, they are premised on the assumption of constant variance over time, an assumption that often falls short, particularly in financial data known for periods of volatility clustering.

GARCH models complement the ARIMA framework by modeling time-varying volatility, allowing the variance to be a function of past errors and variances. They consider "volatility clustering" and "leverage effects", signifying that a system's shocks could result in future increased volatility.

Incorporating GARCH analysis in this study serves to underscore the dynamic nature of volatility in the stock markets and capture the risk dynamics of the stock prices and returns. The ability of GARCH models to measure, forecast, and simulate the volatility in the markets is an added benefit not inherent to ARIMA models.

Further refinement of the analysis is achieved through the application of the Multivariate Dynamic Conditional Correlation GARCH (DCC-GARCH) model. In comparison to the Constant Conditional Correlation GARCH (CCC-GARCH) model, the DCC-GARCH model, with its provision for conditional correlations to change over time, presents a more robust model. The CCC-GARCH model postulates that the correlations between different series remain constant over time. On the other hand, the DCC-GARCH model permits these correlations to be dynamic, thereby capturing the changing market conditions. This assumption is more congruent with reality where markets are interconnected and in constant response to various factors.

Overall, the multivariate DCC-GARCH model facilitates a comprehensive examination of the volatility spillover effects among the Philippine, US, and Japanese stock markets. By considering the dynamic interdependencies and relationships between these three stock indices, it estimates time-varying conditional variances and conditional correlations, effectively capturing the evolving volatility dynamics and interconnectedness among these markets.

This study can thus analyze the spillover of volatility and correlation among these markets over time, particularly highlighting the changes in these dynamics pre and post the COVID-19 periods. Through the use of the multivariate DCC-GARCH model, this research attains an enhanced depth and nuanced understanding, surpassing the scope of traditional frameworks or standalone ARIMA or GARCH models.

Section 3. SCOPE AND LIMITATIONS

The research scope and limitations for this study acknowledge that alternative methodologies may provide more accurate results and further insights beyond the multivariate DCC GARCH approach employed. The chosen approach may have limitations in fully encompassing the intricacies of the current dataset, such as challenges associated with deviations from stationarity, normality, skewness, and the presence of fat-tailed distributions. Additionally, it should be noted that certain trading days may be absent in other stocks, and to address this, a forward fill strategy was employed to replace missing values with the last observed value, assuming constant stock prices until the next observed value. Furthermore, the limitations of the study include the potential concern that the chosen time frame for each period may be excessively long. In relation to the time frame limitation, the declaration by the World Health Organization of COVID-19 as a PHEIC on January 30, 2020, serves as the breakpoint for distinguishing the pre- and post-COVID periods. However, while using the declaration of COVID-19 as PHEIC as a breakpoint can be convenient, it may not capture the actual breakpoints in the data. The impact of COVID-19 on markets can vary based on factors like location, interventions, and market-specific conditions. Hence, local factors, news, sentiment, and investor behavior can contribute to variations in breakpoints.

CHAPTER 4. ANALYSIS

Section 1. TIME SERIES VISUALIZATION

Figure 1: Time Plots of Stock Indices Prices for Pre- and Post-COVID periods

Figure 1a: Time Plot for Nikkei225:

Figure 1b: Time Plot for S&P500:

Figure 1c: Time Plot for PSEi:

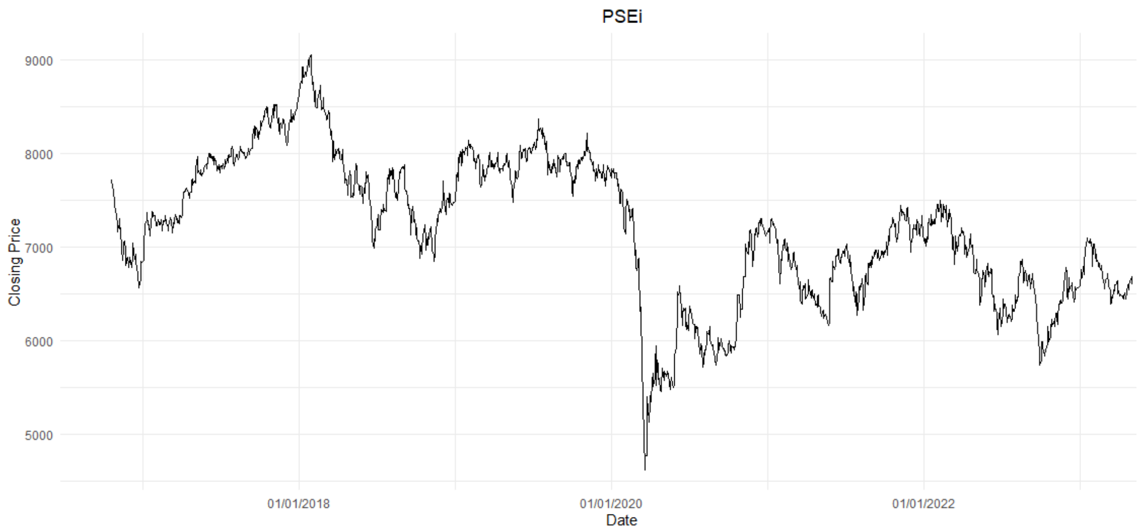


Figure 1 depicts the Time Plots of Stock Indices Prices for both the pre- and post-COVID periods, presenting the observed trends in the Nikkei 225 (Figure 1a), S&P500 (Figure 1b), and PSEi (Figure 1c). Notably, these indices exhibited a significant decline that occurred around the same time, particularly in the month of March. The downward movement started around the beginning of the year, in January 2020, and persisted until reaching its lowest points in March 2020. This pattern aligns with expectations, considering the timing of the World Health Organization's declaration of a Public Health Emergency of International Concern (PHEIC) for COVID-19 on January 30, 2020, followed by the declaration of COVID-19 as a pandemic on March 11, 2020.

Taking a broader perspective encompassing the entire study period, it is worth noting that the Nikkei and S&P500 indices demonstrated a recovery, attaining higher highs in stock prices. However, the PSEi, although it has exhibited some recovery since the WHO announcement, has not yet regained its previous levels and remains relatively stagnant.

Figure 2: Time Plots of Stock Indices Returns for Pre- and Post-COVID periods.

(log difference transformation)

Figure 2a: Time Plot for Nikkei225:

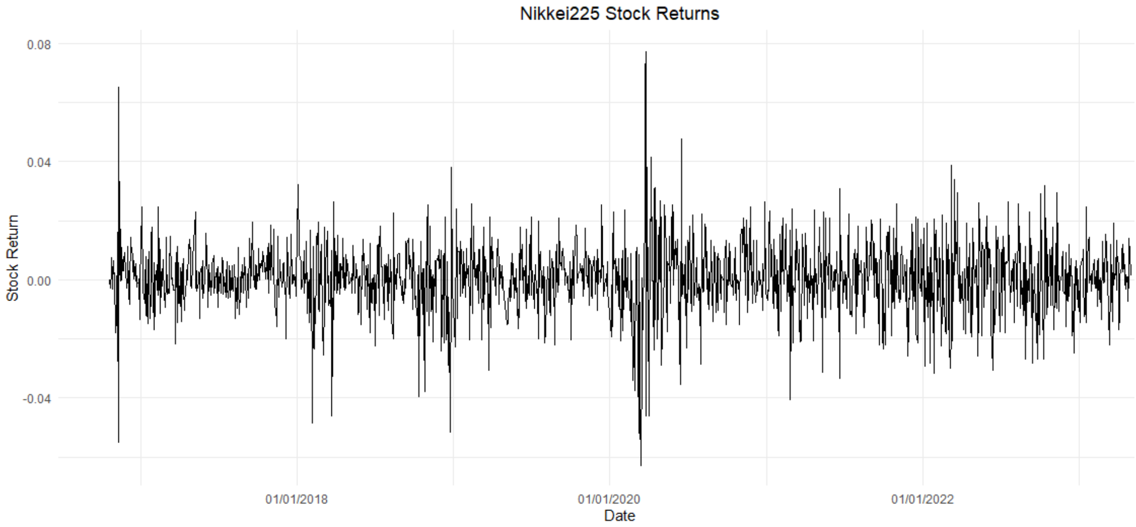


Figure 2b: Time Plot for S&P500:

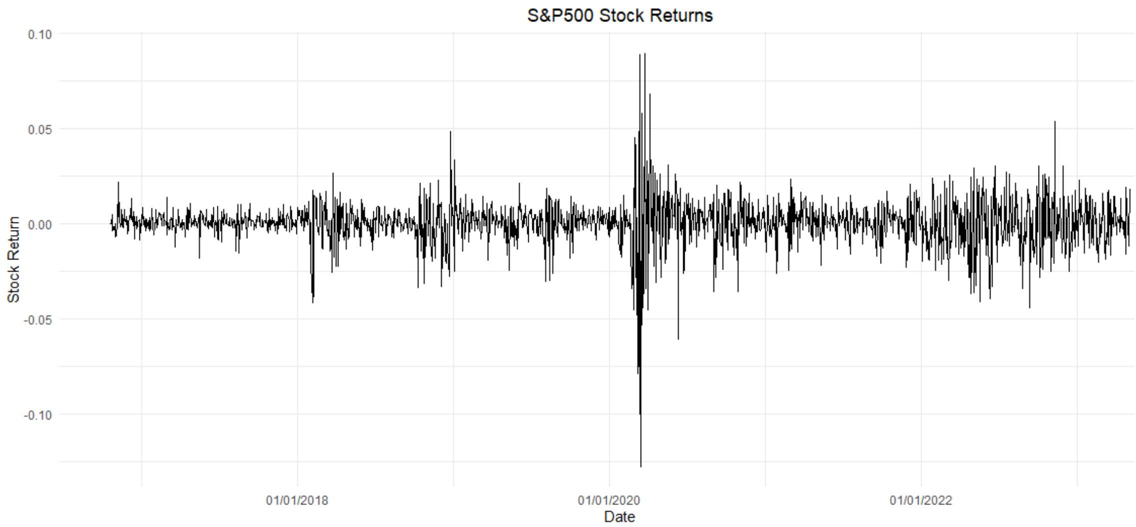
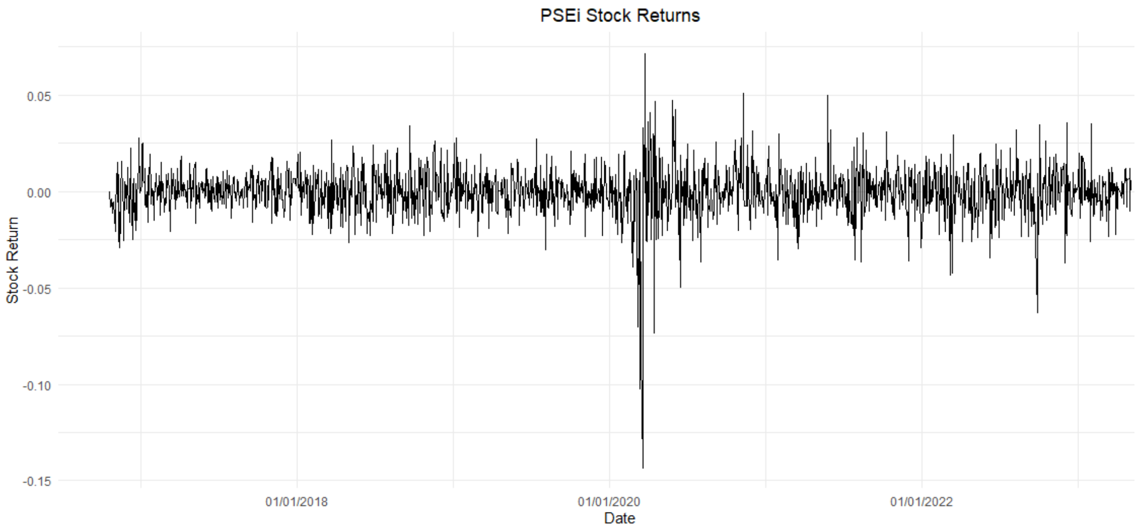


Figure 2c: Time Plot for PSEi:



For the purpose of analysis, the daily closing numbers presented in Figure 1 have been transformed into log returns to facilitate analysis. Figure 2 provides a visual representation of the time plots of stock indices returns for the pre- and post-COVID periods. Upon examination of the entire time frame, it becomes evident that the data for the three indices generally exhibit stationarity, revealing the absence of noticeable trends in both mean and variance, except around March 2020 where volatility seems to increase.

Based on the observed time plot, there is evidence of conditional heteroscedasticity, suggesting varying levels of volatility over time. Notably, the plot indicates a sudden increase in volatility and clustering of volatile periods around March in the dataset. This finding highlights the presence of changing patterns in market volatility and potential spillover effects during that particular period. The presence of a clustered peak signify a pattern where a period of high volatility are closely grouped together, indicating a non-random behavior in the data. This observation suggests that there is an underlying factor or event that contributed to the occurrence of this concentrated period of elevated volatility. This surge in volatility is likely influenced by the declaration of WHO.

Section 2. DESCRIPTIVE STATISTICS AND DISTRIBUTION ANALYSIS

Table 3: Mean, Median, Max, Min, Standard Deviation, Skewness, and Kurtosis

Table 3a: Stock Prices for Pre- and Post-COVID periods

Descriptive Statistic	Nikkei225	S&P500	PSEi
Mean	23855.89	3289.527	7193.917
Median	22873.92	3036.51	7226.305
Max	30670.1	4796.56	9058.62
Min	16251.54	2085.18	4623.42
Standard Deviation	3489.487	733.0191	756.0787
Skewness	0.1808992	0.3483462	-0.1994056
Kurtosis	1.761639	1.78064	2.572117

Table 3b: Stock Returns for Pre- and Post-COVID periods

Descriptive Statistic	Nikkei225	S&P500	PSEi
Mean	-0.0003296278	-0.0004002175	9.009689e-05
Median	-0.000723715	-0.0007087905	-0.0002497822
Max	0.06273569	0.1276521	0.1432235
Min	-0.0773137	-0.08968316	-0.07171695
Standard Deviation	0.01182671	0.01245651	0.01303951
Skewness	0.08699267	0.8484793	1.324274
Kurtosis	7.366942	18.59285	17.51814

Table 3c: Stock Prices for Pre-COVID period

Descriptive Statistic	Nikkei225	S&P500	PSEi
Mean	21254.84	2685.618	7777.183
Median	21466.99	2713.06	7835.85
Max	24270.62	3329.62	9058.62
Min	16251.54	2085.18	6563.67
Standard Deviation	1582.422	266.0414	451.0507
Skewness	-0.3617835	-0.02400512	-0.0005242413
Kurtosis	2.52833	2.452317	3.05453

Table 3d: Stock Returns for Pre-COVID periods

Descriptive Statistic	Nikkei225	S&P500	PSEi
Mean	-0.0003820603	-0.0005162985	4.171966e-05
Median	-0.0006716548	-0.0006903271	-0.0001093228
Max	0.05505637	0.04184256	0.02995364
Min	-0.06508317	-0.04840324	-0.03420565
Standard Deviation	0.01006083	0.007916263	0.009802278
Skewness	0.4224905	0.6788286	-0.02583251
Kurtosis	8.608105	8.512479	3.315051

Table 3e: Stock Prices for Post-COVID periods

Descriptive Statistic	Nikkei225	S&P500	PSEi
Mean	26463.46	3893.436	6610.65
Median	27445.56	3965.34	6644.76
Max	30670.1	4796.56	7507.2
Min	16552.83	2237.4	4623.42
Standard Deviation	2879.176	523.651	509.2406
Skewness	-1.195463	-0.6524367	-0.5652649
Kurtosis	3.749236	2.925737	3.044703

Table 3f: Stock Returns for Post-COVID periods

Descriptive Statistic	Nikkei225	S&P500	PSEi
Mean	-0.0002992478	-0.0002808162	0.0001267659
Median	-0.0007674668	-0.0008353946	-0.0006801944
Max	0.06273569	0.1276521	0.1432235
Min	-0.0773137	-0.08968316	-0.07171695
Standard Deviation	0.01336319	0.01574812	0.01562977
Skewness	-0.06283751	0.7376887	1.543067
Kurtosis	6.294527	14.01897	16.47729

Table 3a, 3c, and 3e show key statistical measures including the Mean, Median, Max, Min, Standard Deviation, Skewness, and Kurtosis for the closing prices. According to Tables 3a and 3e, the PSEi exhibits its lowest closing price on March 19, 2020, at 4623.42 since 2016. It is also worth mentioning that this occurred merely four days after the announcement of the first lockdown in the Philippines on March 15. This starkly contrasts with the maximum closing price of 9058.62 recorded on January 29, 2018, almost two years prior. Unfortunately, this peak has yet to be surpassed to date. The mean price of the PSEi throughout the study duration stands at 7193.917, signifying a difference of 2570 compared to its lowest point during the pandemic.

Looking at S&P500, the lowest closing price within our study period is observed on November 4, 2016, at 2085.18, as illustrated in Tables 3a and 3c. Notably, this is relatively close to the lowest price during the COVID-19 pandemic, as illustrated in Table 3e, which occurred on March 23, 2020, at 2237.40. In contrast, the S&P500 demonstrates a significant recovery, reaching its highest closing price of 4796.56 on January 3, 2022. The overall average closing price of the S&P500 within the full timeframe is 3289.527, representing an increase of 1052 compared to its lowest point during the pandemic.

Nikkei225, according to Tables 3a and 3c, exhibits its lowest closing price on November 9, 2016, at 16251.54, which is close to the lowest dip during the COVID-19 pandemic observed on March 19, 2020, at 16552.83. Notably, this date coincides with the exact day when the PSEi also experienced its lowest closing price. The highest closing price for the Nikkei225 is recorded on September 14, 2021, at 30670.1, which can be seen in Table 3e, indicating significant recovery since the pandemic. The overall average closing price of the Nikkei225 is 23855.89, representing a difference of 7303 compared to its lowest point during the pandemic.

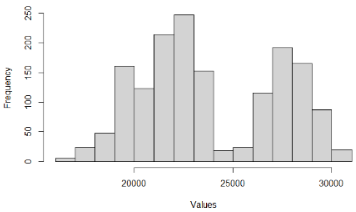
Tables 3b, 3d, and 3f present more or less the same key statistical insights but with a focus on daily returns (using log differences) rather than stock prices. Comparing Tables 3b and 3f, the lowest daily returns for the three indices are the same, indicating that for the whole duration of the study, the lowest daily returns happened in the post-COVID period.

Figure 3: Histograms

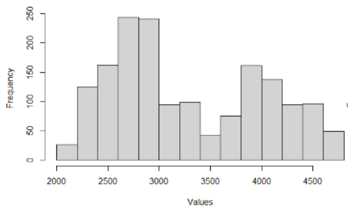
Figure 3a: Data for both Pre- and Post-COVID periods

Stock Prices

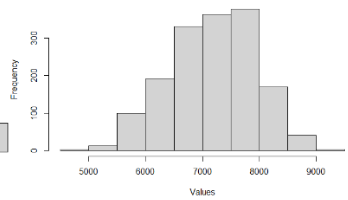
Nikkei225:



S&P500:

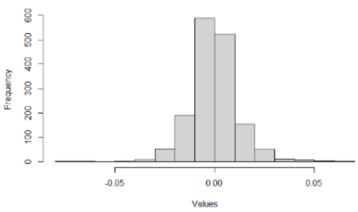


PSEi:

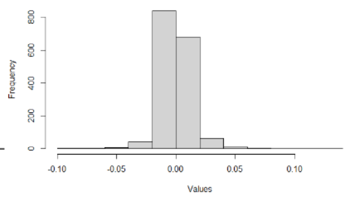


Stock Returns

Nikkei225:



S&P500:



PSEi:

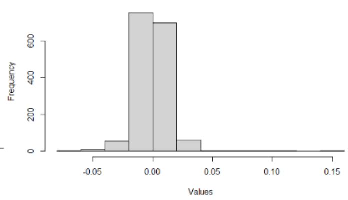
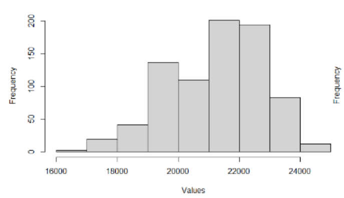


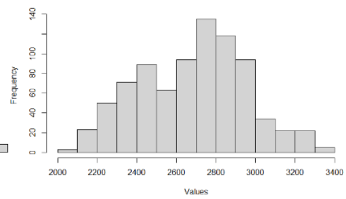
Figure 3b: Data for Pre-COVID Period

Stock Prices

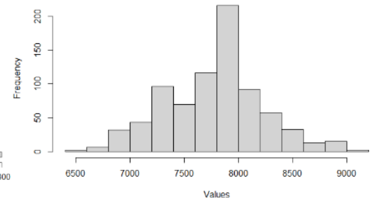
Nikkei225:



S&P500:

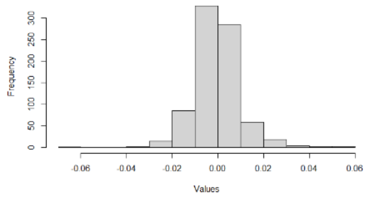


PSEi:

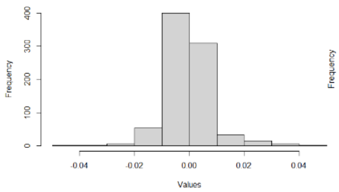


Stock Returns

Nikkei225:



S&P500:



PSEi:

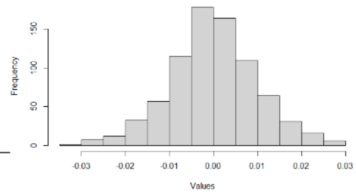
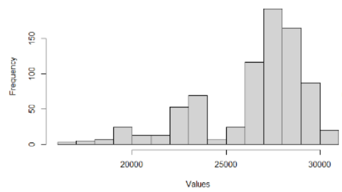


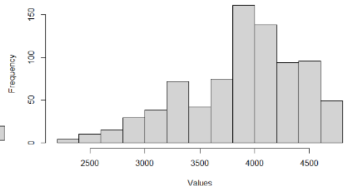
Figure 3c: Data for Post-COVID Period

Stock Prices

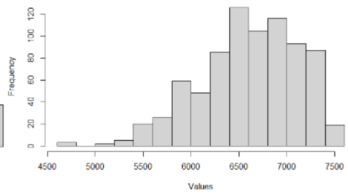
Nikkei225:



S&P500:

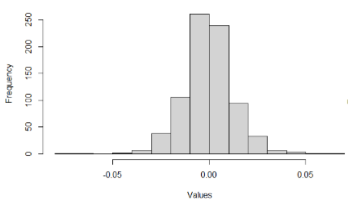


PSEi:

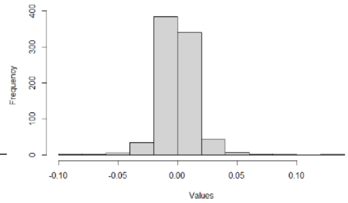


Stock Returns

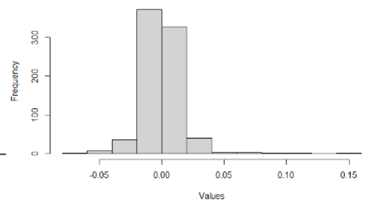
Nikkei225:



S&P500:



PSEi:



The distribution of the data for each stock market index can be analyzed through the analysis of the descriptive statistics table (skewness and kurtosis) and histograms. When considering the entire dataset, which includes both pre- and post-COVID periods, the histograms provide insights into the distribution of both stock prices and stock returns for each index. The skewness values indicate the degree of asymmetry in the distributions. For stock prices, the skewness values for Nikkei225, S&P500, and PSEi are 0.1808992, 0.3483462, and -0.1994056, respectively. These values suggest that the distributions of these indices are approximately symmetric, with S&P500 exhibiting a slightly more pronounced right skew. For stock returns, the skewness values for the same indices are 0.08699267, 0.8484793, and 1.324274, respectively. These values indicate that the distributions of stock returns are positively skewed, with PSEi showing the highest degree of skewness. The kurtosis values for both stock prices and stock returns indicate the tails and peaks of the distributions. The kurtosis values for stock prices for Nikkei225, S&P500, and PSEi are 1.761639, 1.78064, and 2.572117, respectively, while the kurtosis values for stock returns are 7.366942, 18.59285, and 17.51814, respectively. These values suggest that the distributions of both stock prices and stock returns have more peaked shapes and heavier tails compared to a normal distribution, particularly for S&P500 in the case of stock returns.

For the pre-COVID period, the stock price distributions exhibit slight left-skewness, as indicated by negative skewness values (-0.3617835 for Nikkei225, -0.02400512 for S&P500, and -0.0005242413 for PSEi). This implies that the distributions have longer tails on the left side. The kurtosis values (2.52833 for Nikkei225, 2.452317 for S&P500, and 3.05453 for PSEi) suggest that the distributions are more peaked and have heavier tails compared to a normal distribution.

Analyzing the stock returns during the pre-COVID period, positive skewness values (0.4224905 for Nikkei225, 0.6788286 for S&P500, and -0.02583251 for PSEi) indicate slightly right-skewed distributions, except for PSEi, which exhibits a left-skewed distribution. The kurtosis values (8.608105 for Nikkei225, 8.512479 for S&P500, and 3.315051 for PSEi) are significantly high, indicating distributions with heavy tails and higher peakedness.

Examining the post-COVID period, the stock price distributions show negative skewness (-1.195463 for Nikkei225, -0.6524367 for S&P500, and -0.5652649 for PSEi), indicating left-skewed distributions with longer tails on the left side. The kurtosis values (3.749236 for Nikkei225, 2.925737 for S&P500, and 3.044703 for PSEi) remain high, suggesting heavier tails and higher peakedness compared to a normal distribution.

Regarding stock returns in the post-COVID period, the Nikkei225 exhibits slightly negative skewness (-0.06283751), while the S&P500 and PSEi demonstrate positive skewness (0.7376887 and 1.543067, respectively). These skewness values suggest slightly left-skewed distributions for Nikkei225 and right-skewed distributions for S&P500 and PSEi. The kurtosis values (6.294527 for Nikkei225, 14.01897 for S&P500, and 16.47729 for PSEi) indicate significantly higher peakedness and heavier tails compared to a normal distribution.

Table 4: Normality Test (Jarque-Bera (J-B))

Period	Index	Classification	X-Squared	DF	P-Value	Normally Distributed
Pre- and Post-COVID	Nikkei225	Stock Prices	110.68	2	<2.2e-16	No
		Stock Returns	87.055	2	<2.2e-16	No
	S&P500	Stock Prices	135.26	2	<2.2e-16	No
		Stock Returns	115.05	2	<2.2e-16	No
	PSEi	Stock Prices	22.638	2	1.214e-05	No
		Stock Returns	56.471	2	5.462e-13	No
Pre-COVID	Nikkei225	Stock Prices	24.836	2	4.045e-06	No
		Stock Returns	38.591	2	4.168e-09	No
	S&P500	Stock Prices	10.365	2	0.005614	No
		Stock Returns	18.261	2	0.0001083	No
	PSEi	Stock Prices	0.098424	2	0.952	Yes
		Stock Returns	4.1237	2	0.1272	Yes
Post-COVID	Nikkei225	Stock Prices	208.48	2	< 2.2e-16	No
		Stock Returns	370.07	2	<2.2e-16	No
	S&P500	Stock Prices	58.577	2	1.906e-13	No
		Stock Returns	156.28	2	<2.2e-16	No
	PSEi	Stock Prices	42.35	2	6.366e-10	No
		Stock Returns	98.326	2	<2.2e-16	No

Table 4 illustrates the results of the normality test, specifically employing the Jarque-Bera (J-B) test, which assesses the goodness-of-fit of the data to a normal distribution. The table includes the test statistics (X-squared), degrees of freedom (DF), and p-values for each index and classification (stock prices and stock returns) during different periods.

For the combined pre- and post-COVID period, all indices, namely Nikkei225, S&P500, and PSEi, show extremely low p-values, indicating strong evidence against the null hypothesis of the data being normally distributed. This suggests that the distributions of both stock prices and stock returns for these indices deviate significantly from a normal distribution.

When examining the pre-COVID period separately, Nikkei225, S&P500, and PSEi still exhibit very low p-values, except for PSEi price and return ($p = 0.952$ and 0.1272, respectively), which suggests that the distribution of PSEi stock prices during this period can be reasonably approximated by a normal distribution.

In the post-COVID period, all indices and classifications display extremely low p-values, indicating strong evidence against normality. This implies that the distributions of both stock prices and stock returns for all indices experienced significant deviations from a normal distribution during the post-COVID period.

Overall, the results of the Jarque-Bera test suggest that the assumption of normality does not hold for most of the distributions of stock prices and stock returns for the examined indices during both the pre- and post-COVID periods. As such, this study will make use of statistical approaches considering non-normality when analyzing the data.

Section 3. UNIT ROOT ANALYSIS

The reliability of the analysis conducted in this research hinges upon examining the presence of a unit root in the underlying time series data. This assessment serves to determine whether the variables exhibit a stable behavior over time or if they are influenced by random shocks. It is crucial to ascertain the constancy of the statistical properties of the data for most statistical tests and techniques employed in modeling and predicting variable relationships.

By establishing the stability of the variables, this study strengthens the credibility of its analysis and improves the precision of modeling and predicting volatility spillover patterns. This assessment is particularly relevant as non-stationary series may demonstrate time-varying volatility, which is crucial to consider in financial and stock market analysis. Consequently, by conducting a thorough examination of the unit root presence, this research ensures a robust and reliable analysis of volatility dynamics, thereby contributing to a comprehensive understanding of the interdependencies between the studied stock markets.

Table 5: Augmented Dickey-Fuller (ADF) unit-root test (with trend vs. with drift).

Periods	Classification	Index	ADF with “trend”		ADF with “drift”	
			p-value	Stationary	p-value	Stationary
Data for both Pre- and Post-COVID periods	Stock Prices	Nikkei225	0.03384	Yes	0.3496	No
		S&P500	3.947e-06	Yes	1.847e-05	Yes
		PSEi	0.04059	Yes	0.06602	No
	Stock Returns	Nikkei225	<2.2e-16	Yes	<2.2e-16	Yes
		S&P500	<2.2e-16	Yes	<2.2e-16	Yes
		PSEi	<2.2e-16	Yes	<2.2e-16	Yes
Data for Pre-COVID Period	Stock Prices	Nikkei225	0.1422	No	0.3492	No
		S&P500	0.01753	Yes	0.2953	No
		PSEi	0.07668	No	0.04409	Yes
	Stock Returns	Nikkei225	<2.2e-16	Yes	<2.2e-16	Yes
		S&P500	<2.2e-16	Yes	<2.2e-16	Yes
		PSEi	<2.2e-16	Yes	<2.2e-16	Yes
Data for Post-COVID Period	Stock Prices	Nikkei225	0.2435	No	0.3073	No
		S&P500	0.0008622	Yes	0.0007642	Yes
		PSEi	0.1049	No	0.04664	Yes
	Stock Returns	Nikkei225	<2.2e-16	Yes	<2.2e-16	Yes
		S&P500	<2.2e-16	Yes	<2.2e-16	Yes
		PSEi	<2.2e-16	Yes	<2.2e-16	Yes

Table 5 presents the results of the Augmented Dickey-Fuller (ADF) unit-root test, which is commonly used to examine the stationarity of time series data. In this case, the ADF test is applied to investigate the presence of unit roots in the stock prices and stock log returns of three stock market indices during different time frames.

The ADF test produces a p-value, which measures the statistical significance of the test results. If the p-value is below a predetermined significance level (0.05 in this study), it suggests that the time series is stationary and does not contain a unit root. Conversely, if the p-value exceeds the significance level, it indicates that the time series is non-stationary and likely contains a unit root.

The results of the ADF test with trend suggest that, in general, stock prices and log returns exhibit stationary behavior, aside from four instances of non-stationary results. More specifically, a closer examination of the pre-COVID period reveals that the p-values for Nikkei225 and PSEi stock prices are above 0.05, indicating that we cannot reject the null hypothesis of non-stationarity for these indices. Similarly, during the post-COVID period, the p-values for Nikkei225 and PSEi stock prices are greater than 0.05, suggesting the presence of non-stationarity. Everything else is stationary.

The results of the ADF test with drift also suggests that in general, stock prices and log returns exhibit stationary behavior. However, there are five instances where the ADF test with drift indicates non-stationarity. The Nikkei225 stock prices exhibit non-stationarity in all three periods. Similarly, the stock prices of the S&P500 during the Pre-COVID period are also non-stationary. Additionally, the PSEi stock prices in the combined data for Pre- and Post-COVID periods show non-stationarity.

Overall all stock returns are stationary. On the other hand, the stock prices exhibit both stationarity and non-stationarity. The non-stationarity suggests that these stock prices are influenced by persistent trends, cycles, or other factors that lead to changes in their statistical properties over time. In this study, the implications of non-stationarity when using these data for analysis will be considered.

Section 4. AUTOREGRESSIVE STRUCTURE TESTING

Table 6: Ljung-Box Test (Lag = 20)

Periods	Classification	Index	Ljung-Box Test (Lag = 20)		
			Test Statistic	P-value	Autocorrelation
Data for both Pre- and Post-COVID periods	Stock Prices	Nikkei225	29033.48695	0	Yes
		S&P500	31492.75334	0	Yes
		PSEi	27773.64878	0	Yes
	Stock Returns	Nikkei225	30.7477516	0.058609842	No
		S&P500	331.238237	0	Yes
		PSEi	32.35781201	0.039631703	Yes
Data for Pre-COVID Period	Stock Prices	Nikkei225	11956.24039	0	Yes
		S&P500	13856.18972	0	Yes
		PSEi	12468.24956	0	Yes
	Stock Returns	Nikkei225	20.04324204	0.455227649	No
		S&P500	36.5486791	0.013247627	Yes
		PSEi	20.97744312	0.39846136	No
Data for Post-COVID Period	Stock Prices	Nikkei225	13712.96968	0	Yes
		S&P500	14942.17621	0	Yes
		PSEi	10165.49876	0	Yes
	Stock Returns	Nikkei225	34.54411563	0.02267112	Yes
		S&P500	246.1470872	0	Yes
		PSEi	29.96242291	0.070464836	No

Table 7: Ljung-Box Test (Lag = 40)

Periods	Classification	Index	Ljung-Box Test (Lag = 40)		
			Test Statistic	P-value	Autocorrelation
Data for both Pre- and Post-COVID periods	Stock Prices	Nikkei225	29033.48695	0	Yes
		S&P500	31492.75334	0	Yes
		PSEi	27773.64878	0	Yes
	Stock Returns	Nikkei225	30.7477516	0.058609842	No
		S&P500	331.238237	0	Yes
		PSEi	32.35781201	0.039631703	Yes
Data for Pre-COVID Period	Stock Prices	Nikkei225	11956.24039	0	Yes
		S&P500	13856.18972	0	Yes
		PSEi	12468.24956	0	Yes
	Stock Returns	Nikkei225	20.04324204	0.455227649	No
		S&P500	36.5486791	0.013247627	Yes
		PSEi	20.97744312	0.39846136	No
Data for Post-COVID Period	Stock Prices	Nikkei225	13712.96968	0	Yes
		S&P500	14942.17621	0	Yes
		PSEi	10165.49876	0	Yes
	Stock Returns	Nikkei225	34.54411563	0.02267112	Yes
		S&P500	246.1470872	0	Yes
		PSEi	29.96242291	0.070464836	No

Table 8: Ljung-Box Test (Lag = 60)

Periods	Classification	Index	Ljung-Box Test (Lag = 60)		
			Test Statistic	P-value	Autocorrelation
Data for both Pre- and Post-COVID periods	Stock Prices	Nikkei225	75735.16196	0	Yes
		S&P500	87958.60498	0	Yes
		PSEi	63839.6883	0	Yes
	Stock Returns	Nikkei225	70.65349437	0.163460645	No
		S&P500	397.9346609	0	Yes
		PSEi	85.36608361	0.017395114	Yes
Data for Pre-COVID Period	Stock Prices	Nikkei225	22500.21263	0	Yes
		S&P500	31252.29382	0	Yes
		PSEi	22569.71584	0	Yes
	Stock Returns	Nikkei225	67.78452413	0.228951528	No
		S&P500	76.02591715	0.079340673	No
		PSEi	82.13194304	0.030473015	Yes
Data for Post-COVID Period	Stock Prices	Nikkei225	30756.18172	0	Yes
		S&P500	36446.74418	0	Yes
		PSEi	14230.44432	0	Yes
	Stock Returns	Nikkei225	68.38183389	0.214063526	No

		S&P500	294.6401944	0	Yes
		PSEi	68.55779275	0.20980346	No

Table 9: Ljung-Box Test (Lag = 80)

Periods	Classification	Index	Ljung-Box Test (Lag = 80)		
			Test Statistic	P-value	Autocorrelation
Data for both Pre- and Post-COVID periods	Stock Prices	Nikkei225	94964.78298	0	Yes
		S&P500	113676.0895	0	Yes
		PSEi	75847.39204	0	Yes
	Stock Returns	Nikkei225	91.84631813	0.17206273	No
		S&P500	434.3342374	0	Yes
		PSEi	95.3302186	0.116212762	No
Data for Pre-COVID Period	Stock Prices	Nikkei225	24640.77328	0	Yes
		S&P500	36526.07844	0	Yes
		PSEi	24090.81147	0	Yes
	Stock Returns	Nikkei225	90.08525084	0.206599918	No
		S&P500	94.96110471	0.121376184	No
		PSEi	99.31452314	0.070691399	No
Data for Post-COVID Period	Stock Prices	Nikkei225	35232.81265	0	Yes
		S&P500	43897.23315	0	Yes
		PSEi	14712.97693	0	Yes
	Stock Returns	Nikkei225	84.86782229	0.333681518	No
		S&P500	321.2776022	0	Yes
		PSEi	78.56826581	0.524342736	No

Table 10: Ljung-Box Test (Lag = 100)

Periods	Classification	Index	Ljung-Box Test (Lag = 100)		
			Test Statistic	P-value	Autocorrelation
Data for both Pre- and Post-COVID periods	Stock Prices	Nikkei225	112357.4002	0	Yes
		S&P500	137828.503	0	Yes
		PSEi	85268.79234	0	Yes
	Stock Returns	Nikkei225	109.8061587	0.236150931	No
		S&P500	457.1251221	0	Yes
		PSEi	106.4024516	0.311952932	No
Data for Pre-COVID Period	Stock Prices	Nikkei225	26358.25762	0	Yes
		S&P500	40793.05371	0	Yes
		PSEi	24460.50433	0	Yes
	Stock Returns	Nikkei225	112.4319011	0.186259092	No
		S&P500	106.7040498	0.30476103	No
		PSEi	115.8363256	0.133030372	No

Data for Post-COVID Period	Stock Prices	Nikkei225	38025.43524	0	Yes
		S&P500	49379.62425	0	Yes
		PSEi	15075.09485	0	Yes
	Stock Returns	Nikkei225	94.93425876	0.624405183	No
		S&P500	334.8802032	0	Yes
		PSEi	86.57389933	0.828388846	No

The Ljung-Box test was conducted with different lags to investigate the presence of autocorrelation in the data. Autocorrelation refers to the correlation between a time series and its lagged values, indicating the relationship between values at different time points. The results of this study revealed that the data exhibits statistically significant autocorrelation in general.

Interestingly, as the number of lags increased, there were less autocorrelated data. This indicates that the immediate dependencies between adjacent time points became weaker when considering more distant lags. This describes a common pattern observed in time series analysis. It is generally expected that as the number of lags increases, the autocorrelation between adjacent time points decreases. This behavior is a common feature in many time series data (the decay of autocorrelation). It suggests that the influence of past observations on the current observation diminishes as the time lag increases. In other words, the immediate dependencies between adjacent time points become weaker when considering more distant lags. However, despite this weakening trend, the overall analysis still demonstrated the presence of autocorrelation.

To accurately capture the volatility dynamics and correlations among the indices, it is crucial to account for the autocorrelation present in the data. The multivariate DCC GARCH model takes into consideration the past conditional correlation matrix and incorporates the square root of the conditional variances to estimate the conditional covariance matrix. By acknowledging and addressing the autocorrelation in the data, the multivariate DCC GARCH model can effectively capture the evolving relationships and spillover effects between the markets. This ensures that the estimated parameters, including the dynamic conditional correlations, provide valuable insights into the interrelationships and volatility transmission mechanisms among the indices under varying market conditions.

Section 5. ORDINARY LEAST SQUARES (OLS) REGRESSION

Dependent Variable: Philippine Stock Exchange Index (PSEi)

Independent Variables: Nikkei225 and S&P500

Method: Least Squares

Null Hypothesis: No Significant Relationship between the two foreign stock indices and PSEi

Table 11: OLS Regression (no lags): PSEi(t) = β0 + β1 * S&P(t) + β2 * Nikkei(t) + ε

Periods	Classification	Variable (t)	OLS Regression				
			Estimate	**Std. Error**	**Pr(>|t|)**	**Adj R-sq**	**p-value**
Data for both Pre- and Post-COVID periods	Stock Prices	Intercept	8001.695	133.15414	< 2e-16*	0.2513	<2.2e-16
		Nikkei225	0.09355	0.01184	5.06e-15*		
		S&P500	-0.91391	0.05734	< 2e-16*		
	Stock Returns	Intercept	0.0001107	0.0003185	0.728	-0.001121	0.9233
		Nikkei225	-0.0058174	0.0271039	0.830		
		S&P500	0.0087073	0.0255593	0.733		
Data for Pre-COVID Period	Stock Prices	Intercept	5.690e+03	2.066e+02	< 2e-16*	0.1159	< 2.2e-16
		Nikkei225	7.301e-02	1.531e-02	2.22e-06*		
		S&P500	1.972e-01	9.510e-02	0.0384 *		
	Stock Returns	Intercept	0.0001246	0.0003414	0.715	0.01847	0.0001779
		Nikkei225	0.1383480	0.0339176	4.97e-05*		
		S&P500	-0.0295447	0.0430928	0.493		
Data for Post-COVID Period	Stock Prices	Intercept	3.803e+03	1.335e+02	< 2e-16*	0.3637	< 2.2e-16
		Nikkei225	8.436e-02	8.893e-03	< 2e-16*		
		S&P500	1.465e-01	4.981e-02	0.00336 *		
	Stock Returns	Intercept	8.241e-05	5.387e-04	0.878	-0.002288	0.939
		Nikkei225	4.864e-04	4.077e-02	0.990		
		S&P500	1.213e-02	3.421e-02	0.723		

*Significant (Significance Level: 5%, Confidence Level: 95%)

This research employs a "no lag" Ordinary Least Squares (OLS) regression model to examine the relationship between the PSEi index and two other indices, namely the S&P 500 and Nikkei 225 for different periods (both Pre- and Post-COVID, Pre-COVID, and Post-COVID) using stock prices and stock returns. This approach facilitates the establishment of immediate associations between the variables, shedding light on their concurrent influence on one another. By examining the variables' contemporaneous relationships, this research gains insights into the direct connections and concurrent effects among the variables under investigation.

1. Both Pre- and Post-COVID Periods:

A. Stock Prices:

The regression analysis reveals that the Philippine Stock Exchange index (PSEi) closing price is significantly influenced by the Nikkei 225 index and the S&P 500 index. The intercept term is estimated to be 8001.695, indicating a baseline level of stock prices. The Nikkei 225 index demonstrates a positive relationship with the PSEi index, with an estimate of 0.09355, implying that a one-unit increase in the Nikkei 225 index corresponds to a 0.09355 increase in the PSEi index. This relationship is statistically significant (p-value: 5.06e-15*). On the other hand, the S&P 500 index exhibits a negative relationship with the PSEi index, with an estimate of -0.91391. This indicates that a one-unit increase in the S&P 500 index is associated with a -0.91391 decrease in the PSEi index. The negative relationship is statistically significant as well (p-value: $<$ 2e-16*). The model's overall performance, as indicated by the adjusted R-squared value of 0.2513, suggests that the predictors explain approximately 25.13% of the variability in the PSEi index's closing price.

B. Stock Returns:

The regression results show that the returns of the Nikkei 225 index and the S&P 500 index do not have a significant association with the returns of the PSEi index.

2. Pre-COVID Period:

A. Stock Prices:

During the Pre-COVID period, the PSEi index's closing price is significantly influenced by the values of the Nikkei 225 index and the S&P 500 index. The intercept term is estimated to be 5.690e+03, representing the baseline level of stock prices. Both the Nikkei 225 index and the S&P 500 index demonstrate positive relationships with the PSEi index. The estimate for the Nikkei225 variable is 7.301e-02, indicating that a one-unit increase in the Nikkei 225 index corresponds to a 0.07301 increase in the PSEi index during the Pre-COVID period. This relationship is statistically significant (p-value: 2.22e-06*). Likewise, the estimate for the S&P500 variable is 1.972e-01, implying that a one-unit increase in the lagged S&P 500 index is associated with a 0.1972 increase in the PSEi index. This relationship is also statistically significant (p-value: 0.0384*). The model's overall performance, as indicated by the adjusted R-squared value of 0.1159, suggests that the predictors explain approximately 11.59% of the variability in the PSEi index's closing price.

B. Stock Returns:

For stock returns in the Pre-COVID period, the regression results indicate that the values of the Nikkei 225 index have a significant positive association. The estimate for the Nikkei225 variable is 0.1383480, meaning that a one-unit increase in the Nikkei 225 index corresponds to a 0.1383480 increase in the PSEi log returns. This relationship is statistically significant (p-value: 4.97e-05*), suggesting a positive association between the Nikkei 225 index and the PSEi returns.

3. Post-COVID Period:

A. Stock Prices:

In the Post-COVID period, the regression analysis shows that the PSEi index's closing price is significantly influenced by the values of the Nikkei 225 index and the S&P 500 index. The intercept term is estimated to be 3.803e+03, indicating a baseline level of stock prices. Similar to the Pre-COVID period, both the Nikkei 225 index and the S&P 500 index exhibit positive relationships with the PSEi index. The estimate for the Nikkei225 variable is 8.436e-02, indicating that a one-unit increase in the Nikkei 225 index corresponds to an 0.08436 increase in the PSEi index during the Post-COVID period. This relationship is statistically significant (p-value: < 2e-16*). Similarly, the estimate for the S&P500 variable is 1.465e-01, implying that a one-unit increase in the S&P 500 index is associated with a 0.1465 increase in the PSEi index. This relationship is statistically significant as well (p-value: 0.00336*). The adjusted R-squared value of 0.3637 indicates that the predictors explain approximately 36.37% of the variability in the PSEi index's closing price during this period.

B. Stock Returns:

The regression results for stock returns in the Post-COVID period suggest that the returns of the Nikkei 225 index and the S&P 500 index do not have a significant association.

Overall, in the combined Pre- and Post-COVID periods, the PSEi's prices are significantly influenced by these indices. The Nikkei 225 index shows a positive relationship, while the S&P 500 index demonstrates a negative relationship with the PSEi index. During the Pre-COVID period, both Nikkei 225 and S&P500 prices positively affect the PSEi's prices, and only the Nikkei 225 index has a significant positive association with the stock returns. In the Post-COVID period, similar patterns are observed, with both indices positively related to PSEi stock prices, but no significant association is found on stock returns.

However, it is important to note that this model exhibit relatively weak explanatory capability when it comes to stock prices and, especially, stock returns. This suggests that there are likely other influential factors contributing significantly to the fluctuations observed in the PSEi index price and returns, which have not been accounted for in the analysis. These unaccounted factors encompass a range of factors, including local market dynamics, specific events or news, regulatory changes, investor sentiment, macroeconomic variables, or other external factors. These factors hold the potential to exert a significant impact on stock prices and returns, and their consideration is essential for a more comprehensive understanding of the fluctuations in the PSEi index.

Following the primary analysis conducted without accounting for time lags, this study delves deeper into the interrelations among the variables by integrating a lag of one period into the equation. This step enriches the analysis, shedding light on the temporal shifts and inherent lags that characterize the interactions among these stock market indices. The subsequent findings are presented below in Table 12:

Table 12: OLS Regression (with lag = 1): PSEi(t) = β0 + β1 * S&P(t-1) + β2 * Nikkei(t-1) + ε

<table>
<tr><th rowspan="2">Periods</th><th rowspan="2">Classification</th><th rowspan="2">Lagged Variable (t-1)</th><th colspan="5">OLS Regression</th></tr>
<tr><th>Estimate</th><th>Std. Error</th><th>Pr(>|t|)</th><th>Adj R-sq</th><th>p-value</th></tr>
<tr><td rowspan="6">Data for both Pre- and Post-COVID periods</td><td rowspan="3">Stock Prices</td><td>Intercept</td><td>8022.31638</td><td>133.30330</td><td>< 2e-16*</td><td rowspan="3">0.2518</td><td rowspan="3">< 2.2e-16</td></tr>
<tr><td>Nikkei225</td><td>0.09197</td><td>0.01184</td><td>1.44e-14*</td></tr>
<tr><td>S&P500</td><td>-0.90861</td><td>0.05734</td><td>< 2e-16*</td></tr>
<tr><td rowspan="3">Stock Returns</td><td>Intercept</td><td>0.0001098</td><td>0.0003187</td><td>0.731</td><td rowspan="3">-0.001216</td><td rowspan="3">0.9974</td></tr>
<tr><td>Nikkei225</td><td>-0.0010610</td><td>0.0271135</td><td>0.969</td></tr>
<tr><td>S&P500</td><td>0.0015585</td><td>0.0255683</td><td>0.951</td></tr>
<tr><td rowspan="6">Data for Pre-COVID Period</td><td rowspan="3">Stock Prices</td><td>Intercept</td><td>5.663e+03</td><td>2.073e+02</td><td>< 2e-16*</td><td rowspan="3">0.1183</td><td rowspan="3">< 2.2e-16</td></tr>
<tr><td>Nikkei225</td><td>7.347e-02</td><td>1.532e-02</td><td>1.94e-06*</td></tr>
<tr><td>S&P500</td><td>2.036e-01</td><td>9.500e-02</td><td>0.0324*</td></tr>
<tr><td rowspan="3">Stock Returns</td><td>Intercept</td><td>7.742e-05</td><td>3.449e-04</td><td>0.822</td><td rowspan="3">0.0005998</td><td rowspan="3">0.2882</td></tr>
<tr><td>Nikkei225</td><td>3.498e-02</td><td>3.425e-02</td><td>0.307</td></tr>
<tr><td>S&P500</td><td>-4.995e-02</td><td>4.351e-02</td><td>0.251</td></tr>
<tr><td rowspan="6">Data for Post-COVID Period</td><td rowspan="3">Stock Prices</td><td>Intercept</td><td>3.840e+03</td><td>1.347e+02</td><td>< 2e-16*</td><td rowspan="3">0.3547</td><td rowspan="3">< 2.2e-16</td></tr>
<tr><td>Nikkei225</td><td>7.984e-02</td><td>8.984e-03</td><td>< 2e-16*</td></tr>
<tr><td>S&P500</td><td>1.673e-01</td><td>5.053e-02</td><td>0.000975*</td></tr>
<tr><td rowspan="3">Stock Returns</td><td>Intercept</td><td>7.435e-05</td><td>5.393e-04</td><td>0.890</td><td rowspan="3">-0.001972</td><td rowspan="3">0.8244</td></tr>
<tr><td>Nikkei225</td><td>-2.209e-02</td><td>4.079e-02</td><td>0.588</td></tr>
<tr><td>S&P500</td><td>1.041e-02</td><td>3.425e-02</td><td>0.761</td></tr>
</table>

*Significant (Significance Level: 5%, Confidence Level: 95%)

As previously mentioned, this research proceeds to further investigate the relationships between the variables by incorporating "lagged" variables (lag = 1). This enables a more detailed examination of the temporal dynamics existing between the stock market indices. In other words, by considering the influence of past values on the present, a deeper understanding of how these stock indices interact and evolve over different time periods is obtained. This transition to the analysis with lagged variables allows for a more comprehensive exploration of the temporal aspects. The study examines the key findings for each period, as follows:

1. Both Pre- and Post-COVID Periods:

   A. Stock Prices:

   The regression results indicate that the PSEi index's closing price is significantly influenced by the lagged values of the Nikkei 225 index and the S&P 500 index. The intercept term is estimated to be 8022.31638, which is statistically significant. Furthermore, there is a positive relationship between the PSEi index and the lagged Nikkei 225 index ($\beta 1 = 0.09197$), suggesting that an increase in the Nikkei 225 index is associated with an increase in the PSEi index. Conversely, the lagged S&P 500 index exhibits a negative relationship with the PSEi index ($\beta 2 = -0.90861$), indicating that an increase in the S&P 500 index is associated with a decrease in the PSEi index. The model's overall performance, as indicated by the adjusted R-squared value of 0.2518, suggests that the predictors explain approximately 25.18% of the variability in the PSEi index's closing price.

B. Stock Returns:

The regression results for stock returns indicate that the lagged values of the Nikkei 225 index and the S&P 500 index do not have a significant relationship with the PSEi index's returns.

2. Pre-COVID Period:

A. Stock Prices:

In the Pre-COVID period, the regression results show that the PSEi index's closing price is significantly influenced by the lagged Nikkei 225 index and the lagged S&P 500 index. The intercept term ($\beta 0$) is estimated to be 5.663e+03, which is statistically significant. Moreover, the lagged Nikkei 225 index ($\beta 1 = 7.347e-02$) and the lagged S&P 500 index ($\beta 2 = 2.036e-01$) both exhibit positive relationships with the PSEi index. These findings suggest that an increase in either of these indices is associated with an increase in the PSEi index during the Pre-COVID period. The adjusted R-squared value of 0.1183 indicates that the predictors explain approximately 11.83% of the variability in the PSEi index's closing price during this period.

B. Stock Returns:

For stock returns in the Pre-COVID period, the regression results show that neither the lagged Nikkei 225 index nor the lagged S&P 500 index has a significant association.

3. Post-COVID Period:

A. Stock Prices:

During the Post-COVID period, the regression results indicate that the PSEi index's closing price is significantly influenced by the lagged Nikkei 225 index and the lagged S&P 500 index. The intercept term (β0) is estimated to be 3.840e+03, which is statistically significant. The lagged Nikkei 225 index (β1 = 7.984e-02) and the lagged S&P 500 index (β2 = 1.673e-01) both exhibit positive relationships with the PSEi index, suggesting that an increase in either index corresponds to an increase in the PSEi index during the Post-COVID period. The adjusted R-squared value of 0.3547 indicates that the predictors explain approximately 35.47% of the variability in the PSEi index's closing price during this period.

B. Stock Returns:

For stock returns in the Post-COVID period, the regression results show that neither the lagged Nikkei 225 index nor the lagged S&P 500 index has a significant association.

In summary, the analysis reveals that the PSEi index's closing prices are significantly influenced by the lagged values of the Nikkei 225 prices and the S&P 500 prices. Specifically, in the combined data periods, an increase in the lagged Nikkei 225 index prices is associated with an increase in the PSEi index prices, while an increase in the lagged S&P 500 index prices is associated with a decrease in the PSEi index. However, in the separate analysis of the pre-COVID period, there is a positive relationship between the PSEi index prices and both the lagged Nikkei 225 index prices and the lagged S&P 500 index prices. Similarly, in the separate analysis of the post-COVID period, there is also a positive relationship between the PSEi index prices and both lagged indices. This discrepancy suggests that the relationships between the variables may vary depending on the time period being examined. However, when considering stock returns, the lagged values of these indices do not appear to have a significant association with the PSEi index's returns in all periods. It is also important to note that the models' explanatory power for stock prices and, especially, stock returns, is also quite low. This implies that there are likely other factors or variables at play that are not captured by the model.

For both the OLS models (with and without lags), when examining the relationship between the two indices (Nikkei 225 and S&P 500) and the PSEi index, it is essential to distinguish between association and causality. Focusing on the association rather than causality acknowledges that while there may be significant statistical associations between the two indices and the PSEi index, establishing a direct cause-and-effect relationship requires a more comprehensive analysis and consideration of unaccounted factors. It highlights the importance of further investigation and consideration of other influential factors that may be driving the PSEi index.

Section 6. MULTIVARIATE DCC GARCH MODELLING

Table 13: Assumptions Verification List

Assumption	**Test Used**	**Assumption Verified on Data/ General Description**
Normality	Jarque-Bera Test	Normally Distributed for the Stock Prices and Log Returns but only for PSEi Pre-Covid
Stationarity	Augmented Dickey-Fuller (ADF) Test	Stationary for Stock Log Returns (All periods and indices)
Autoregressive structure	Ljung-Box Test	Data autoregressive structure highly dependent on the lag, but data generally shows an autoregressive structure
Conditional heteroscedasticity	Time Plots	Sudden increase in volatility and presence of clustered peak around March for all data

In general the multivariate DCC GARCH model relies on several important assumptions, each of which is evaluated through specific tests to ensure their validity. One such assumption is normality, which assumes that the standardized residuals of the model follow a normal distribution. This assumption is important because departures from normality can impact parameter estimation and inference in the multivariate DCC GARCH model. To assess this assumption, the Jarque-Bera test is used, which examines whether the standardized residuals conform to a normal distribution. The test results indicate that the stock prices and log returns were normally distributed, but only for the PSEi pre-Covid period.

Another crucial assumption in the multivariate DCC GARCH model is stationarity. Stationarity implies that the statistical properties of the time series, such as mean and variance, remain constant over time. To assess this assumption, the Augmented Dickey-Fuller (ADF) test is employed. The ADF test helps determine whether the underlying time series is stationary or requires preprocessing, such as differencing, before fitting the multivariate DCC GARCH model. In this case, the test results show that the stock log returns exhibit stationarity across all periods and indices.

The multivariate DCC GARCH model also assumes an autoregressive structure, which means that the current variance depends on past variances and squared error terms. The Ljung-Box test is used to examine the absence of autocorrelation in the model's residuals, which is aligned with the autoregressive structure assumption. The test results suggest that the data's autoregressive structure is highly dependent on the lag, but generally, the data exhibits an autoregressive structure.

Lastly, the multivariate DCC GARCH model assumes conditional heteroscedasticity, which means that the variability of the series is not constant over time and is dependent on past values or shocks. To evaluate this assumption, time plots are used. These plots provide a visual representation of the time-varying volatility and can reveal patterns such as sudden increases or decreases in volatility or clustered peaks. In this case, the time plots indicate a sudden increase in volatility and the presence of a clustered peak around March for all the data, confirming the assumption of conditional heteroscedasticity.

Despite the non-fulfillment of some assumptions, it is important to acknowledge that the study continues with the application of the multivariate DCC GARCH model, considering the limitations and potential implications of the model's assumptions.

Table 14: **Multivariate DCC GARCH model**

Table 14a: Multivariate DCC GARCH model: Parameters explanations

Multivariate DCC GARCH Parameters	Explanations
mu	This is the "mean" of the stock index returns or the stock index prices. If significant, this parameter can provide insights into the average price or return level for each market over the different periods.
ar1	This represents the coefficient for the first lag of the autoregressive model in the mean equation. It shows how much the previous period's prices (or returns) influences the current period's prices (or returns). It provides a measure of the inertia or momentum in the stock market returns or prices.
omega	This parameter represents the long-term or baseline level of volatility in the stock market returns or prices. A significant and high Omega would suggest a high level of inherent market risk or uncertainty.
alpha1	This represents the short-term persistence of shocks, showing how much a new piece of information or 'shock' affects the current period's volatility. If this is high, it suggests that new information causes big changes in volatility, contributing to uncertainty.
beta1	This represents the long-term persistence of shocks, showing how much past volatilities influence current volatility. If this is high, it suggests that shocks to the market have a lasting impact on future volatility.
[Joint]dcca1	This parameter measures the short-run dynamics of the correlation between the markets. A significant and high dcca1 would suggest that the correlations between the markets respond quickly to changes, thus a change in one market's volatility quickly influences the others.
[Joint]dccb1	This parameter measures the long-run dynamics of the correlation. A significant and high dccb1 suggests that changes in the correlation between markets are persistent over time, indicating a lasting interrelationship in terms of volatility.

These parameters help analyze the individual behavior of each market (through the mu, ar1, omega, alpha1, and beta1 parameters) and the interrelationships between them (through the [joint]dcca1 and [joint]dccb1 parameters) over the different periods.

Table 14b: Multivariate DCC GARCH model: Optimal Parameters

Periods	Classification	Variable	Multivariate DCC GARCH model				
			mu	ar1	omega	alpha1	beta1
Data for both Pre- and Post-COVID periods	Stock Prices	PSEi	6.6931e+03*	9.9567e-01*	5.9964e+02*	1.2359e-01*	7.9538e-01*
		Nikkei225	2.9157e+04*	1.0000e+00*	1.1870e+04	1.9964e-01*	6.5932e-01*
		S&P500	4.1363e+03*	1.0000e+00*	9.3958e+00*	1.6346e-01*	8.3554e-01*
	Stock Log Returns	PSEi	-0.000092	-0.061385*	0.000011*	0.150517*	0.780567*
		Nikkei225	-0.000850*	-0.014055	0.000013*	0.156507*	0.747601*
		S&P500	-0.000856*	-0.059151*	0.000002	0.208507*	0.790493*
Data for Pre-COVID Period	Stock Prices	PSEi	7.4836e+03*	9.8955e-01*	4.9698e+01	3.1845e-02*	9.5989e-01*
		Nikkei225	2.3381e+04*	1.0000e+00*	2.5161e+03	9.6223e-02	8.5059e-01*
		S&P500	3.2734e+03*	1.0000e+00*	1.4522e+01*	2.1001e-01*	7.7011e-01*
	Stock Log Returns	PSEi	-0.000134	-0.050542	0.000001	0.035681*	0.957154*
		Nikkei225	-0.000689*	0.003185	0.000021*	0.221587*	0.586809*
		S&P500	-0.000784*	-0.072275	0.000003	0.249019*	0.721975*
Data for Post-COVID Period	Stock Prices	PSEi	6.6871e+03*	9.8553e-01*	1.0160e+03*	1.8084e-01*	7.1083e-01*
		Nikkei225	2.9158e+04*	1.0000e+00*	8.2843e+03	8.6375e-02	8.3938e-01*
		S&P500	4.1363e+03*	1.0000e+00*	3.5382e+01	1.1649e-01*	8.8009e-01*
	Stock Log Returns	PSEi	-0.000134	-0.050542	0.000001	0.035681*	0.957154*
		Nikkei225	-0.000689*	0.003185	0.000021*	0.221587*	0.586809*
		S&P500	-0.000784*	-0.072275	0.000003	0.249019*	0.721975*

*Significant (Significance Level: 5%, Confidence Level: 95%)

1. Both Pre- and Post-COVID Periods:

A. Stock Prices:

For all three markets, mu is significant. The ar1 term signifies that past prices significantly influence present prices in all markets. Omega, showing long-term volatility, is significant only for the PSEi and S&P500, not for Nikkei225. The volatility persistence parameters alpha1 and beta1 are significant for all three markets, suggesting both short-term shocks and volatility clustering.

B. Stock Returns:

The mean term (mu) is only significant for Nikkei225 and S&P500. Alpha1 and Beta1 are significant for all markets, meaning that all markets exhibit short-term volatility persistence and long-term volatility clustering. Omega is only significant for PSEi and

Nikkei225, suggesting that long-term volatility is a significant factor for these markets, but not for the S&P500. The ar1 term indicates past returns significantly influence current returns only in the PSEi and S&P500.

2. Pre-COVID Period:

A. Stock Prices:

Mu is significant for all markets. The ar1 term indicates that past prices significantly affect current prices in all three markets. Omega is significant only for the S&P500. Both alpha1 and beta1 are significant for the PSEi and S&P500, demonstrating that these markets have significant short-term shocks and long-term volatility clustering, respectively. For the Nikkei225, only beta1 is significant (alpha1 is not significant).

B. Stock Returns:

Mu is only significant for Nikkei225 and S&P500. Alpha1 and beta1 are significant for all markets, highlighting both markets exhibit short-term volatility persistence and long-term volatility clustering. Omega is only significant for Nikkei225, suggesting long-term volatility significantly affects Nikkei225, but not the other markets. The ar1 term is not significant for all markets.

3. Post-COVID Period:

A. Stock Prices:

Mu is significant for all markets. The ar1 term denotes that past prices significantly impact present prices in all three markets. Omega is significant only for PSEi and S&P500. Both alpha1 and beta1 are significant for the PSEi and S&P500, showing both short-term shocks and long-term volatility clustering are significant for these markets. For Nikkei225, only beta1 is significant.

B. Stock Returns:

Mu is only significant for Nikkei225 and S&P500. Alpha1 and beta1 are significant for all markets, signifying both markets exhibit short-term volatility persistence and long-term volatility clustering. Omega is significant only for Nikkei225, denoting that long-term volatility significantly affects Nikkei225 but not the other markets. The ar1 term is not significant for all markets.

Table 14c: Multivariate DCC GARCH model: DCC Parameters

Periods	Classification	DCC Parameters	Estimate	Standard Error	Test Statistic	Pr(>|t|)	Significant*
Data for both Pre- and Post-COVID periods	Stock Prices	[Joint]dcca1	8.7670e-03	2.3804e-02	0.36831	0.712639	No
		[Joint]dccb1	5.0949e-01	3.5695e+00	0.14273	0.886502	No
	Stock Log Returns	[Joint]dcca1	0.008289	0.011559	0.71707	0.473333	No
		[Joint]dccb1	0.614587	0.498439	1.23302	0.217567	No
Data for Pre-COVID Period	Stock Prices	[Joint]dcca1	7.0980e-03	9.6760e-03	0.73350	0.463252	No
		[Joint]dccb1	8.7381e-01	5.7367e-02	15.23187	0.000000	Yes
	Stock Log Returns	[Joint]dcca1	0.017388	0.011426	1.52181	0.128057	No
		[Joint]dccb1	0.854041	0.061069	13.98478	0.000000	Yes
Data for Post-COVID Period	Stock Prices	[Joint]dcca1	0.0000e+00	5.5800e-04	0.000008	0.999993	No
		[Joint]dccb1	9.3001e-01	6.2927e-01	1.477912	0.139431	No
	Stock Log Returns	[Joint]dcca1	0.000000	0.000170	0.000127	0.999899	No
		[Joint]dccb1	0.918905	0.277166	3.315359	0.000915	Yes

*Significant (Significance Level: 5%, Confidence Level: 95%)

1. Both Pre- and Post-COVID Periods:

   A. Stock Prices:

   Both [Joint]dcca1 and [Joint]dccb1 are not significant, implying that neither short-term nor long-term correlations significantly influence the current period's correlation.

   B. Stock Returns:

   Again, both [Joint]dcca1 and [Joint]dccb1 are not significant, suggesting that neither past shocks nor long-term correlations significantly affect current correlations.

2. Pre-COVID Period:

   A. Stock Prices:

   [Joint]dcca1 is not significant, indicating that short-term shocks don't influence current correlations. However, [Joint]dccb1 is significant, indicating that long-term correlations significantly impact current correlations.

B. Stock Returns:

[Joint]dcca1 is not significant, but [Joint]dccb1 is significant, suggesting that long-term correlations play a significant role in current correlation dynamics.

3. Post-COVID Period:

A. Stock Prices:

Neither [Joint]dcca1 nor [Joint]dccb1 are significant, suggesting that neither short-term nor long-term correlations significantly influence the current period's correlation.

B. Stock Returns:

While [Joint]dcca1 is not significant, [Joint]dccb1 is significant, suggesting that long-term correlations significantly influence the current correlations.

CHAPTER 5. CONCLUSION

Section 1. KEY FINDINGS AND RESULTS

The time plots revealed distinct trends and patterns in the stock indices of the Nikkei 225, S&P 500, and PSEi. A significant decline in all these indices was noted around the onset of the COVID-19 pandemic. Interestingly, while the Nikkei and S&P 500 showed a recovery, the PSEi has been relatively stagnant. The plots also hinted at the existence of conditional heteroscedasticity, pointing towards volatility clustering, particularly around March 2020, the time when COVID-19 was declared a pandemic. This observation signifies non-random behavior in the data, caused by COVID-19.

These trends hint at possible periods of increased volatility spillover among these markets, particularly during significant global events like the COVID-19 pandemic. The observation of volatility clustering indicates that shocks in one market could potentially be associated with a surge in volatility in another market, hence influencing each other.

A. OLS Regressions Findings:

The no lag OLS regression found that both the Nikkei 225 and S&P 500 indices significantly influence the PSEi index's prices. The direction of the relationship varied; the Nikkei 225 had a positive relationship with the PSEi index, whereas the S&P 500 had a negative relationship during the combined period. During the pre-COVID period, both indices had a positive relationship with the PSEi prices, but only the Nikkei 225 had a significant positive association with PSEi stock returns. A similar pattern was observed in the post-COVID period.

The finding that the Nikkei 225 has a positive relationship with the PSEi index across all periods suggests that an increase in the Japanese stock market corresponds with a surge in the Philippine stock market. This could be attributed to several factors such as similar regional economic dynamics, close trade and investment relationships, or similar responses to global economic events among Asian markets.

In contrast, the negative relationship between the S&P 500 and the PSEi index in the combined period implies that when the U.S. stock market prospers, the Philippine stock market tends to decline, and vice versa. This counterintuitive relationship might reflect the reality of international capital flows, where positive prospects in a larger and more developed market like the U.S. could attract global capital, leading to outflows from emerging markets like the Philippines. However, the positive relationship of the S&P 500 with the PSEi index during the separate pre and post-COVID periods indicates that the relationship between these markets can vary over time and may be affected by global events such as the COVID-19 pandemic.

The analysis with lagged variables revealed similar patterns. The PSEi index's closing prices were significantly influenced by the lagged prices of both the Nikkei 225 and the S&P 500. An increase in the lagged Nikkei 225 prices was associated with an increase in PSEi index prices, while an increase in the lagged S&P 500 prices led to a decrease in the PSEi index during the combined period. In contrast, both lagged indices showed a positive relationship with the PSEi index during the separate pre and post-COVID analyses. The significant relationships of lagged variables suggest that past stock market performance is a crucial determinant of the PSEi index's future prices, highlighting the importance of considering temporal dynamics in financial market analyses.

In the combined period, the influence of the lagged Nikkei 225 prices on the PSEi index remains positive, strengthening the argument for a persistent and positive association of the Japanese market on the Philippine market. Conversely, the lagged S&P 500 prices show a negative influence, further emphasizing the complex dynamics between US and Philippines.

In the separate pre and post-COVID periods, however, both lagged indices display a positive relationship with the PSEi index, suggesting that the influence of these indices on the Philippine market can change in response to significant global events. This flexibility underlines the importance of understanding temporal dynamics and incorporating them into financial market analyses, as it can provide a more nuanced understanding of market relationships.

Moreover, in both separate analyses of the pre-COVID period and post-COVID period, a unit change in the Nikkei 225 has a larger association with the PSEi index than a unit change in the S&P 500. This might indicate that the Philippine stock market is more sensitive to changes in the Japanese market compared to the US market. The differential relationships of the Nikkei 225 and S&P 500 with the PSEi index indicate that regional versus international market dynamics could have varying effects on a country-specific index like the PSEi. These could be attributed to a variety of factors. For example, the proximity and similar time zones of Japan and the Philippines could be one of those reasons. Being in the same or similar time zones means that trading hours overlap more significantly than with markets on the other side of the globe, which might lead to a stronger association in market behavior. Additionally, being geographically close might lead to closer economic ties. Japan and the Philippines are both part of the ASEAN+3 regional cooperation (which includes 10 Southeast Asian countries, plus China, Japan, and South Korea), which fosters economic integration in the region. These countries often have significant trade and investment relationships. As such, the economic health and stock market performance of one can directly be related to the other.

These OLS regression findings lay a critical foundation for understanding the intertemporal volatility spillover relationships among the Philippine, US, and Japanese stock markets in five ways:

i. Intertemporal Relationships: The OLS analysis, especially with the lagged variables, provides evidence of intertemporal dynamics. The fact that previous prices of the Nikkei 225 and S&P 500 significantly affect the PSEi index's future prices underlines the existence of time-lagged effects or 'spillovers'.

ii. Direction of Spillovers: The significant influence of both the Nikkei 225 and the S&P 500 on the PSEi suggests spillovers from these larger markets to the Philippines. The direction of these relationships (positive or negative) further illustrates how these spillover effects operate.

iii. Influence of Global Events: The findings indicate that these relationships aren't static but can change over time, especially in response to significant global events like COVID-19. This supports the exploration of pre- and post-COVID periods and can be linked to potential changes in volatility spillovers during different market conditions.

iv. Magnitude of Spillovers: The finding that a unit change in the Nikkei 225 has a larger association with the PSEi than a unit change in the S&P 500 suggests that the magnitude of spillover effects may differ depending on the specific market.

v. Regional vs International Dynamics: The differential relationships of the Nikkei 225 and S&P 500 with the PSEi might imply that regional (Asia) and international (U.S.) market dynamics have varying effects on a country-specific index like the PSEi. This nuanced understanding extends to volatility spillovers, exploring whether regional or international spillovers have a more significant association.

B. Multivariate DCC GARCH Model Findings:

From the multivariate DCC GARCH model results, valuable insights into the mean and volatility dynamics, as well as the influence of past prices and returns, among the stock markets of the Philippines, the US, and Japan, both before and after the COVID-19 pandemic can be made. These can be summarized into five key points, as follows:

i. Mean Price and Mean Returns are not zero, except for PSEi Returns: The significant mu parameter across all three markets in all periods for stock prices indicates that the average level is statistically different from zero. However, the mu parameter for PSEi stock returns in all periods is not significant, indicating that the mean return of the Philippine stock market could be approximately zero. This suggests that despite fluctuations, the average change in PSEi's stock prices over time may not exhibit any discernible increase or decrease.

ii. Influence of Past Prices: Similarly, the significant ar1 term in all the stock prices for all periods highlights the past's powerful influence on present prices across all markets, suggesting a level of predictability in these markets that investors could potentially exploit.

iii. Volatility Clustering: The significant alpha1 and beta1 parameters across all markets in all periods (with the exception of alpha1 in the Nikkei225 stock price model during the pre- and Post- COVID period) imply the existence of volatility clustering. This phenomenon, where large price changes tend to be followed by large price changes (of either sign) and small price changes tend to be followed by small changes, is an ubiquitous feature of financial time series data. Its presence here suggests that the volatility of these markets can change over time.

iv. Long-Term Volatility of Stock Prices: The Omega parameter (indicative of long-term volatility) for stock prices is significant for PSEi in both combined and pre-COVID periods and for S&P500 in both combined and pre-COVID periods. However, for Nikkei225, Omega is not significant in any period. This suggests that in terms of stock prices, long-term volatility is a more persistent characteristic of the Philippine and US markets, but less so for the Japanese market.

v. Influence of Past Returns: The ar1 term for stock returns, which reflects the influence of past returns on current returns, appears significant only in the combined data set for the PSEi and S&P500 but is not significant for any markets in the separated pre- and post-COVID periods. This could suggest that the overall influence of past returns on the current ones may be obscured when data is separated into pre- and post-COVID periods. This phenomenon could be due to the impact of other influential factors that might have changed or become more pronounced during these separate periods, or due to a reduced sample size leading to less statistical power to detect the effect.

vi. Impact of COVID-19: The changes in model parameters between the pre- and post-COVID periods suggest that the pandemic has significantly impacted these stock markets' volatility dynamics. Notably, the Omega parameter became significant for the PSEi price in the post-COVID period, implying increased long-term volatility possibly due to the economic and financial fallout of the pandemic. This highlights the profound influence of major global events on financial markets and the need for dynamic volatility models that can adapt to such changes.

vii. Findings from [Joint]dcca1 and [Joint]dccb1: Key insights also emerge when examining the significance of the [Joint]dccb1 parameter, which provides an understanding of long-term interdependencies among the three markets. In the pre-COVID era, the [Joint]dccb1 parameter exhibited significance for both stock prices and returns, emphasizing the markets' long-term interconnectedness. These dependencies insinuate that over an extended period, the volatility in one market could reverberate through to the others, potentially engendering simultaneous volatility shifts across these markets.

During the post-COVID period, however, the parameter [Joint]dccb1 becomes significant exclusively for stock returns, suggesting an intensification in long-term linkages at the returns level. This could be the result of the global nature of the COVID-19 shock, which might have synchronized the markets more closely in terms of returns. In terms of volatility spillover, it means that a shock to returns in one market is more likely to induce similar volatility patterns in the returns of the other markets.

Conversely, the [Joint]dcca1 parameter – a measure of short-term volatility response to sudden market shocks – remains insignificant across all periods and for both stock prices and returns. In other words, a sudden increase or decrease in one market doesn't immediately or significantly affect the correlation with other markets. This could imply that the markets are somewhat insulated from each other in the short term. This short-term insulation could be attributed to several factors. For example, differing domestic economic conditions among these countries could buffer the immediate transmission of shocks. For instance, an economic shock in the US might not instantaneously affect Japan or the Philippines due to the unique economic circumstances in each of these countries. Similarly, different policy settings across these countries might help shield their markets from immediate foreign shocks. Central banks and governments might implement measures that prevent foreign shocks from destabilizing their domestic markets, at least in the short run. The behaviors of investors in each market could also play a role. Investors might react differently to foreign shocks based on their perceptions, risk tolerance, and investment horizons, among other factors. As a result, the reaction in one market might not immediately spillover to the others.

For both the models used in this study, namely the OLS model and the multivariate DCC GARCH model, it's crucial to differentiate between association and causality when examining the relationships among the Nikkei 225, the S&P 500, and the PSEi index. This research primarily focuses on uncovering associations, not causality. This study recognizes that even though significant statistical associations exist between the two indices and the PSEi index, establishing a direct causal link necessitates a more in-depth analysis and the inclusion of potentially unobserved factors. It underscores the importance of subsequent research, taking into consideration other influential factors.

Section 2. IMPLICATIONS AND FUTURE DIRECTIONS

Understanding the intertemporal volatility spillovers among the Nikkei 225, the S&P 500, and the PSEi index is crucial for a range of market stakeholders. Policymakers can use this data to monitor economic indicators, assess financial stability, and implement relevant macro-prudential policies. Investors can make informed decisions based on the demonstrated influence of past stock market performance in these indices on future prices, recognizing the significant volatility spillover effects, especially during global events like COVID-19. For portfolio managers, these findings can help diversify investments and structure portfolios more effectively, based on regional and international market dynamics and the predictability from past prices.

However, this study has some limitations that should be acknowledged. The analysis heavily relies on Ordinary Least Squares (OLS) models and Multivariate DCC GARCH model. This approach may not fully capture the complexities of the current dataset, including issues related to stationarity, normality, skewness, and fat-tailed distributions. Future research could consider alternative models, such as OLS with multiple lags, to better capture the lagged effects and volatility spillover dynamics. (e.g., PSEi(t) = S&P (t)+ Nikkei (t) + S&P (t-1) +Nikkei (t-1)+ S&P (t-2) +Nikkei (t-2)+ S&P (t-3) +Nikkei (t-3)+ S&P (t-4) +Nikkei (t-4)).

Alternative robust GARCH models can also be explored. For instance, the Asymmetric GARCH (AGARCH) model introduces asymmetry in the volatility dynamics, allowing for different reactions to positive and negative shocks. The Exponential GARCH (EGARCH) model accounts for both asymmetry and non-normality by modeling the logarithm of the conditional variance. The Generalized Hyperbolic GARCH (GHGARCH) model, based on the flexible Generalized Hyperbolic distribution, can capture a wide range of skewness and kurtosis patterns. Additionally, the Skewed Student's t GARCH (STGARCH) model extends the Student's t distribution to incorporate skewness in the conditional distribution of error terms.

Considering these alternative models would provide a more comprehensive analysis of the volatility spillover effects. Future research should consider exploring these robust models to capture the complexities of the data.

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