“Testing volatility spillovers using GARCH models in the Japanese stock market during COVID-19”

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TESTING VOLATILITY SPILLOVERS USING GARCH MODELS IN THE JAPANESE STOCK MARKET DURING COVID-19

Abstract

This paper investigates volatility spillovers in the stock market in Japan during the COVID-19 pandemic by using GARCH family models. The empirical analysis is focused on the dynamics of the NIKKEI 225 stock market index during the sample period from July 30, 1998, to January 24, 2022. In other words, the sample period covers both the period of the global financial crisis (GFC) and the COVID-19 pandemic. The econometrics includes GARCH (1,1), GJR (1,1), and EGARCH (1,1) models. By applying GARCH family models, this empirical study also examines the long-term behavior of the Japanese stock market.

The Japanese stock market is much more stable and efficient than emerging or frontier markets characterized by higher volatility and lower liquidity. The paper establishes that NIKKEI 225 index dynamics is different in intensity in the case of the two most recent extreme events analyzed, namely the global financial crisis (GFC)of 2007–2008 and the COVID-19 pandemic. The findings confirmed the presence of the leverage effect during the sample period. Moreover, the empirical results identified the presence of high volatility in the sample returns of the selected stock market. Nevertheless, the econometric framework showed that the negative implications of the GFC were much more severe and caused more significant contractions compared to the COVID-19 pandemic for the Japanese stock market. This study contributes to the existing literature by providing additional empirical evidence on the long-term behavior of the stock market in Japan, especially in the context of extreme events.

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INTRODUCTION

Considering the dynamics of the global economy, the stock market in Japan is very influential, stable, and with impressive international visibility. In this regard, NIKKEI 225 is the most important index of the Japanese stock market, which is the Tokyo Stock Exchange (TSE). This index is one of the most representative leading indexes traded on the Asian stock markets. FTSE Russell (2021) released the last official FTSE Equity Country Classification report. According to this FTSE Equity Country Classification, stock markets can be included in the following major categories: developed, advanced emerging, secondary emerging, and frontier. Given the advanced degree of economic development, Japan's stock market is included in the category of developed stock markets according to the selection criteria on which the FTSE Russell (2021) analysis is based. In addition, the following cluster of countries is also included in the same category of developed stock markets: USA, Australia, Denmark, Sweden, Finland, Switzerland, France,

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Germany, Hong Kong, Singapore, Italy, Netherlands, New Zealand, Austria, Norway, Ireland, Portugal, Luxembourg, Canada, Israel, South Korea, Spain, UK, Poland, and Belgium.

The formulation of research problems is focused on studying the long-term behavior of the Japanese stock market. In this sense, econometric models and statistical tests were applied to obtain accurate and rigorous empirical results. The NIKKEI 225 Stock Exchange Index is the most important stock market index on the Japanese market. It includes225 of the most liquid and representative blue-chip companies traded (listed) on the Tokyo Stock Exchange. Moreover, NIKKEI 225 index is highly influential and is also considered the barometer of the Japanese economy and essential for the stock market dynamics.

In 2020 and 2021, the economy in most countries has been affected by the Coronavirus pandemic (COVID-19). As a result, economic activity contracted sharply in the first half of 2020 due to containment measures and increased risk aversion, and the setback continued. However, unlike the COVID-19 pandemic, the root causes of one of the most intense extreme financial events of the last centuries, such as the GFC of 2007–2008 (global financial crisis), were more profound and more severe implications, both macroeconomic and microeconomic.

The recent COVID-19 pandemic has affected most economies around the world, including the behavior of stock markets. However, it is essential to mention that the COVID-19 pandemic represents extreme conditions that affect the movement of the prices of financial assets traded on the international stock markets. Meher et al. (2020a) highlighted that stock markets play a significant role and are considered a "barometer" that reveals the state of health of an economy. Palma-Ruiz et al. (2020) elaborated an empirical study on a developed stock market in Spain. They suggested that sustainable and responsible investing, also known as SRI, can play an essential strategic role considering the two pillars as financial returns and social goods. Moreover, Shen and Shafiq (2020) highlighted the significant importance of stock markets in economic research, while stock market price forecasting still represents an essential topic in financial and technical areas. Gillani et al. (2021) have also conducted a complex study on certain Asian countries and concluded that health represents an essential factor in achieving sustainable development.

Duttilo et al. (2021), Kumar et al. (2020) and Hawaldar (2016) consider that volatility represents one of the most relevant measures of risk, while volatility modeling has a significant utility for investors because it contributes to identifying potential losses and a potentially attractive investment opportunity. However, Baek et al. (2020) suggested that COVID-19 pandemic news affected the volatility patterns. Hamzaoui and Regaieg (2016) have conducted an empirical study using Generalized Autoregressive Conditional Heteroscedastic, also known as GARCH-M (1,1) model, Glosten-Jagannathan-Runkle also known as GJR – GARCH (1,1), but also GJR – GARCH (1,1) – M model. It is essential to mention that the Glosten-Jagannathan-Runkle (GJR) –GARCH model proposed by Glosten et al. (1993) highlights the asymmetry based on specific categories of shocks a positive return6 which was not anticipated and, on the other hand, an unanticipated negative stock return. Poon and Granger (2003) have provided a complex study highlighting previous studies on volatility forecasting models. Watanabe (2020) developed research-based specific models, such as an asymmetric HAR – CJ model and an asymmetric HARQ model, which are different from symmetrical models due to an additional return term added in the case of the econometric approach regarding the explanatory variables with a dummy variable. In this sense, it is mentioned that the acronym HAR states for the heterogeneous autoregressive model, which represents an often-used linear regression model applied for realized volatility (RV) forecasting.

It is worth mentioning that this empirical study extends other previous research published by the co-authors of this study (either together with certain co-authors or separately).

1. LITERATURE REVIEW

Baek et al. (2020) and Meher et al. (2020a) investigated the linkage between the COVID-19 pandemic and stock market volatility, suggesting that all news related to the COVID-19 pandemic is significantly negative-positive news. However, the negative information exhibits much stronger implications. Spulbar et al. (2020) investigated volatility spillovers in the case of selected stock markets, both developing (emerging) and developed. In contrast, the findings reveal the existence of high positive volatility in the post-GFC period (global financial crisis), which erupted in mid-2007 in the US in the following stock markets, such as Hungary, the USA, Germany, India, and Canada. Hawaldar (2014) and Hawaldar et al. (2007) found that earnings announcements, changes in Board of Directors, government policy, bonus, and rights issues affect stock returns.

Engle (1982) argued the necessity of specific stochastic processes known as autoregressive conditional heteroscedastic (ARCH). Bollerslev (1986) designed a new model based on a generalized ARCH model using lagged values related to conditional distributions variability such as conditional variance. On the other hand, Meher et al. (2021) highlighted the option of confident investors regarding fundamental analysis and technical analysis for stock market asset prices forecasting while conducting an empirical study using Auto-Regressive Integrated Moving Average (ARIMA) models. In addition, a variety of recent empirical studies, such as Hawaldar (2014, 2015), Ejaz et al. (2020), Hawaldar et al. (2007), Zulfiqar et al. (2020), Sajeev et al. (2021), Spulbar et al. (2021), and Rabbani et al. (2022) examined relevant issues regarding the dynamics of stock market behavior. For example, topics of international portfolio diversification, correlation, cointegration, market efficiency, volatility spillovers, GARCH models, stock market feedback (response) regarding both positive news and negative news, but also financial integration, extreme events, abnormal returns, and quantitative finance framework are of immense importance.

Furthermore, Spulbar et al. (2019) investigated the presence of volatility spillovers and patterns, financial contagion, but also causal relationships between a particular cluster of developed (advanced) stock markets like France, UK (from Europe)and the USA, Canada (from North America)considering the selected period from January 2000 to June 2018. The econometric framework included: GARCH (1,1) model, Granger causality test and Vector Auto Regression (VAR), descriptive statistics, but also various statistical tests like Unit Root Test, BDS test, and Augmented Dickey-Fuller stationary (ADF) test. The empirical results (findings) have confirmed the presence of persistent volatility patterns and high uncertainty using the GARCH model. Hawaldar (2015) found that risk and volatility directly affect the stock prices and investors' sentiments.

Trivedi et al. (2021b) conducted a comparative study on two unrelated and geographically distant stock markets such as Belgium with its Brussels Stock Exchange and Indonesia with its Jakarta Stock Exchange for the selected period starting in January 2018 up to September 2021. The primary aim of this study was to focus on understanding the behavior of the selected stock markets in the pre-COVID-19 pandemic and the post-COVID-19 pandemic timeframe based on the GARCH family models. Moreover, Birau et al. (2021) examined the behavior of the selected stock markets from Spain and Hong Kong during the sample period from January 2015 to September 2021 while considering the negative and severe impact of the COVID-19 pandemic. The econometric analysis included various statistical tests and GARCH models to investigate the volatility patterns.

Takaishi (2022) analyzed various critical issues regarding Japanese stock market behavior dynamics by considering specific stock market indices considering the efficient market hypothesis (also known as the EMH) framework. The empirical findings indicate the presence of multifractality in the Japanese stock markets, which leads to the possibility of identifying attractive opportunities to obtain significant profits (returns).

Sakamoto and Sengoku (2021) elaborated a two-way study addressing the period of calm and normalcy and the COVID-19 pandemic to explore dynamics and fluctuations recorded by the price of traded financial assets. Moreover, stock price predictability is an essential aspect considering the negative effects of the COVID-19 pandemic, which has determined

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high volatility. Nevertheless, Mazur et al. (2021) argued that companies' reaction differs depending on the COVID-19 pandemic revenue shock.

Sultonov (2020) conducted an empirical case study on Japan, considering the implications of political and economic events manifested internationally. It was concluded that this developed economy is susceptible to changes in this context, especially in the case of foreign exchange and stock markets. Finally, Spulbar and Birau (2019) elaborated a series of empirical studies on the behavior of stock markets, both emerging and developed, including Japan. They highlighted the importance of the correlation between specific stock markets in the international diversification of portfolios, which has a massive effect on investment risk diversification.

Du (2021) analyzed the linkage between reactions to news and stock market efficiency and their impact on the behavior of the Japanese stock market. The empirical evidence was based on the NIKKEI 225 index for the sample period from January 5, 1998, to December 29, 2017, using an ARCH model. On the other hand, Ohmura (2022) investigated the causal relationship between stock market prices and political assistance based on an empirical case study for the stock market in Japan by using a Linear non-Gaussian Acyclic Model (also known by the acronym LiNGAM).

Kahraman and Keser (2022) examined the linkage between the stock market in Japan and specific main Western stock markets using representative stock indices (including the NIKKEI 2225 index) for the sample period from January 2002 to September 2020. The empirical evidence revealed a strong connectedness between selected stock market indices, which also caused financial fragility and volatility spillovers. Finally, Nguyen and Le (2021) investigated the impact of return spillovers from the stock markets of the United States of America (USA) and Japan on the Vietnamese stock market based on the leading stock indices, i.e., S&P 500 index, NIKKEI 225 index, and Vietnam Stock Index (VN-Index) for the sample period from January 2012 to December 2015.

Higashide et al. (2021) investigated the impact of volatility patterns on the behavior of the Tokyo Stock Exchange, considering that it is perceived more as an unobservable variable, in contrast to stock market returns. Moreover, volatility forecasting is essential for financial risk management even though volatility is considered a daily varying random variable representing the uncertainty of stock returns on financial assets. Trivedi et al. (2021) also conducted a comparative and relevant research study for selected stock markets in the European Union using GARCH models for an exceptionally period from 2000 to 2018.

This empirical study aims to examine the presence of volatility clusters in the Japanese stock market during the selected period from July 30, 1998, to January 24, 2022. Based on daily observations, this incredibly long timeframe also covers two extreme events, namely the GFC of 2007–2008 (also known as a global financial crisis)and the most recent economic crisis caused by the COVID-19 pandemic.

2. RESEARCH METHODOLOGY

The present study focuses on modeling the behavior of the Japanese stock market to capture changes, volatility clusters, the fitness of econometric models, and changes in volatility patterns during the COVID-19 pandemic. The study used a sample number of 5900 daily observations (daily closing prices) from July 30, 1998, to January 24, 2022, for the NIKKEI 225 index, representing the Japanese stock market, such as the Tokyo Stock Exchange.

For the conversion of series returns to log returns, the paper explores a formula:

$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right) = \ln(p_t) - \ln(p_{t-1}). \quad (1)$$

where ln, indicates the natural logarithm function, total return of R at time *t*. = *r1+r2+r3+2…+rt – 1 +rt* which equivalent to R = *Ln (P1 / P0) + … Ln (Pt-1 / Pt-2) + Ln (Pt / Pt-1).*

Augmented Dickey-Fuller (ADF) regression process is managed by:

$$\Delta y_t = c + \beta \cdot t + \delta \cdot y_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta y_{t-i} + \varepsilon_t. \quad (2)$$

where, *y(t – 1)*, indicates the first lag of the returns and $\Delta y(t-1)$ represents first difference of series at time (*t*–1).

Moreover, the ADF process is applied as:

$$(1-L)y_t = \beta_0 + (\alpha - 1)y_t - 1 + \varepsilon_i. \qquad (3)$$

Further, the symmetric GARCH (1, 1) model is applied as:

$$h_t = \omega + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1}, \qquad (4)$$

where the distribution of mean property is the following equation:

$$ht = \mu + \varepsilon t. \qquad (5)$$

The variance equation is calculated by:

$$\sigma_t^2 = \omega + \alpha r_{t-1}^2 \qquad (6)$$

In the GARCH concept, the first subscript indicates order of y^2 terms at the right side whereas the second subscript refers to the order of σ^2, terms. In the process, with the certain constraints that imposed on the coefficients the $\mathrm{y_t}$ series = $\mathrm{y_t^2}$ and statistically will become (AR) term. The model considers values of past squared observations and past variances that models variance at time (t), this provides property of mean equation and variance equation represented in formula (5) and formula (6).

Process of mean equation $(\varepsilon \mathrm{t})$ represents the white noise which independently and identically distributed with expectations between (0) and (1). Further as process to conditional variance, which represented by (σ_t^2) which also can be predicted by using ($(\mathrm{r_{t-1}^2})$.

Therefore, $(\mathrm{h_t})$ represents the degree of constant which is denoted by (ω),, the ARCH term $(\alpha_1 \mathrm{u_{t-1}^2})$ and the GARCH term $(\beta_1 \mathrm{h_{t-1}})$.

Generalized Autoregressive Conditional Heteroscedastic represents a generalized version of the ARCH model designed by Engle. Sultonov (2020) pointed out that ARCH models are used to estimate future volatility. In this case, they play the role of a function of prior volatility. As an additional explanation, GARCH (1, 1) processes one ARCH effect and one GARCH effect.

The exponential GARCH model, also known as the EGARCH model, was developed by Nelson (1991). Moreover, the GJR (where the acronym comes from Glosten, Jagannathan, and Runkle) model was developed by Glosten et al. (1993).In addition, Hamori (2003) stated that under the exponential GARCH or EGARCH model, under the conditions in which the log value of volatility serves as an explained variable, it does not benefit from using non-negative constraints on model parameters.

The EGARCH model is applied based on the following:

$$\ln(\sigma 2t) = \omega + \alpha\left(|zt-1| - \mathrm{G}\left[|zt-1|\right]\right) + \qquad (7)$$
$$+\gamma zt - 1 + \beta \ln(\sigma 2t - 1)$$

where $(\varepsilon t = \sigma tzt)$ and zt, represents standard gaussian process. Whereas $\mu, \omega, \alpha, \gamma, \beta$, considers process of log likelihood. The coefficient of second term $\mathrm{G}\left[|zt-1|\right]$, performs 1(y-1) which is linear in (zt) with slope coefficient ɵ+1, is positive while $\mathrm{G}\left[|zt-1|\right]$ is linear in (zt), with slope coefficient of ɵ - 1, if zt is negative. This indicates the position of large innovations increase in the conditional variance which derive $zt-1>0$, and decrease the conditional variance if $zt-1<0$.

Let assume that $zt-1<0$ indicates that their innovations produce negative effect which results (0) to increase, stating volatility is more likely to be high at the time (t) in case volatility is also high at time (t-1). In other notion, it indicates that volatility of previous time impacts to the volatility of following time. Here, the asymmetric factor ϕi. denotes the presence of asymmetric effect to different shocks in the asset returns.

In the process of asymmetric GARCH models such as Exponential GARCH or GJR, the effect of previous return on conditional variance reflects on (*y*). This indicates that (*rt*) from results of log likelihood, which let the data unrestricted, otherwise happens under regular conditions. And the model allows exponential function for the time-varying variance process indicated in formula (7).

As an additional explanation, the paper highlights the fact that the Glosten-Jagannathan-Runkle Generalized Autoregressive Conditional Heteroscedastic model, also known as the GJR GARCH model, is used:

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$$h_t = \delta + \alpha_1 e_{i-1}^2 + \gamma d_{i-1} e_{t-1}^2 + \beta_i h_{i-1}. \quad (8)$$

On the other hand, the econometric framework includes discussing mean and variance equations.

The mean equation is based on:

$$rt = \mu + \varepsilon t. \quad (9)$$

The mean equation provides the sum of average return based on (μ), which represents the stock returns of financial assets in time (t), while the residual return is determined by (εt) which indicates white-noise process. And it does not need to be serially independent, like the EGARCH, GJR also processes through maximizing log likelihood. The function performs specific parametric form for conditional heteroskedasticity, and therefore $\varepsilon\text{t} = \sigma\text{tzt}$.

The conditional log-likelihood of normal random variable is

$$\ln f(rt \mid \mu, \sigma 2t) = \\ = -12\left(\ln 2\pi + \ln\sigma 2t + \left(rt - \mu\right) 2\sigma 2t\right). \quad (10)$$

which confirms following conditions;

$$It - 1 \cdot \{0 \, if \; rt - 1 \geq \mu \mid 1 \; if \; rt - 1 < \mu. \quad (11)$$

GJR process confirms that their unconditional distribution presents excess kurtosis (leptokurtic effect) proves that distribution of Gaussian remains unconditional. In the GJR functions, γ signifies the irregular parameter (asymmetric parameter); whereas, d_{t-1} represents specimen variables when $\varepsilon_{t-1} < 0$, $d_{t-1} = 1$ and when $\varepsilon_{t-1} \geq 0$, $d_{t-1} = 0$.

3. EMPIRICAL ANALYSIS AND RESULTS

The assumption process regarding the variance equation focuses on strengthening the fact that the value of constant is higher than 0, considering the value of α + β. In other words, GARCH (1,1) model plays the role of the asymmetric model whose primary purpose is to estimate volatility in financial time series returns.

This empirical study also examined specific representative statistical indicators, such as skewness and kurtosis, using the distribution of selected databases. To correctly interpret the results and ensure the robustness of the empirical results, the paper explores some of their characteristic features. Thus, the skewness represents a measure of the asymmetry of the distribution, which characterizes financial data series around its mean. However, the skewness of asymmetric distribution is equal to zero.

On the other hand, considering the implications of the efficient markets hypothesis (EMH) and the impact of normal distribution, there can be only the inherent conclusion that the skewness has zero value, so it is null. However, the positive skewness suggests the presence of a long right tail in the case of statistical distribution. At the same time, vice versa is also valid such as negative skewness indicates the existence of a long-left tail for the distribution. The second statistical indicator, kurtosis, measures the flatness or peakedness of the distribution exhibited by the financial returns obtained based on the selected data series. Practically, the kurtosis of a normal distribution is equal to 3. However, if the kurtosis exceeds 3, the distribution peaks; it is also known as leptokurtic relative to the normal. Otherwise, if the kurtosis is less than the value 3, the distribution is flat or platykurtic relative to normal.

The GARCH (1,1) model represents an extension of the ARCH model that considers the effect of ARCH and GARCH terms. Hawaldar et al. (2020) suggested that the ARCH effect is based on time-varying conditional volatility. The sum of ARCH and GARCH terms provides information about persistence in the selected series returns. However, the GARCH model cannot capture stylized facts in sample returns. Thus, the paper explores asymmetric models such as the EGARCH and GJR models, capturing the stylized facts. Moreover, those models can also identify whether the sample series returns exhibit any leveraging effect for the covered period.

Figures 1, 2, and 3 provide necessary information about selected stock market index series movement (daily closing prices). In addition, they show stationary series returns considering the first log difference and place of the autocorrelation function and partial autocorrelation function, respectively.

Source: Authors' computations based on selected financial data series.

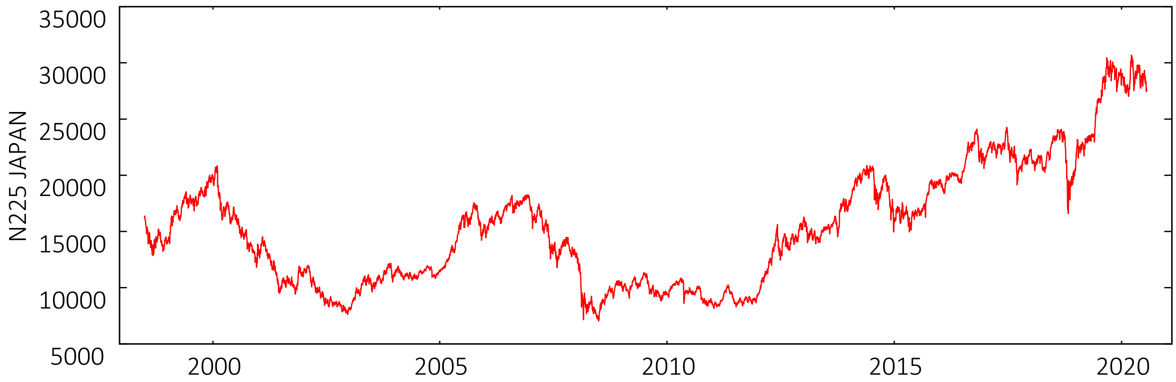

Figure 1. The trend of the NIKKEI 225 index using daily closing prices during the sample period

Source: Authors' computations based on selected financial data series.

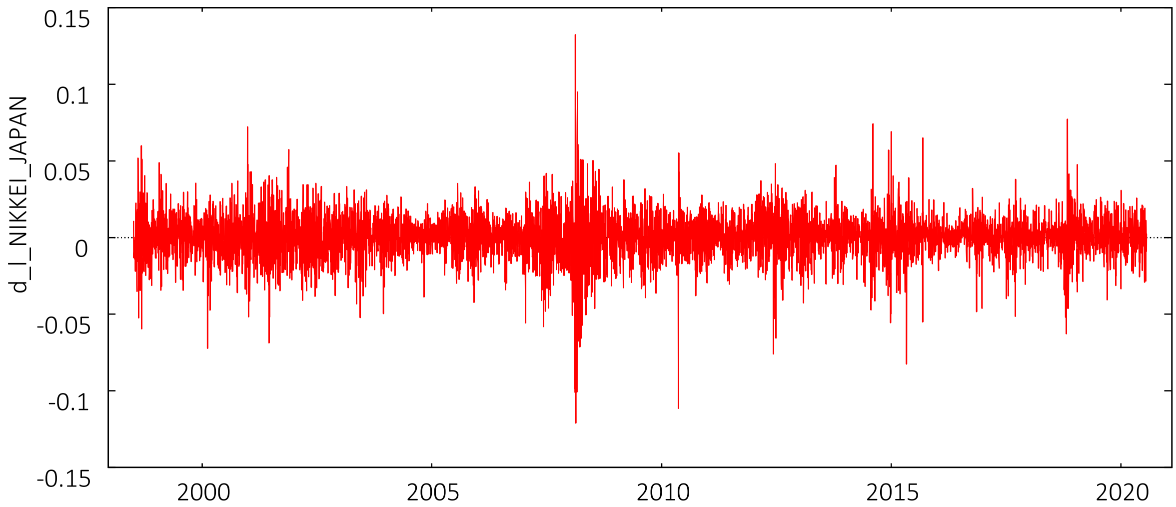

Figure 2. The log-returns of the NIKKEI 225 index using daily closing prices during the sample period

The impact of the global financial crisis, also known as GFC, which erupted in the US in mid-2007, is visible in the graphical trend of selected daily observations. Nevertheless, the COVID-19 pandemic impalso appears significant, as shown in Figure 1. It provides information about loss of asset value more than 56% during the GFC and over 23% during the COVID-19 pandemic appears in the sample series returns. The ACF and PACF tests provided helpful information on the stationarity of results supported by the Augmented Dickey-Fuller test. The Augmented Dickey-Fuller test is used to establish the stationarity of the NIKKEI index sample data series. The augmented Dickey-Fuller test, which is testing down from 4 lags, uses criterion AIC, which indicates the test results with constant. It suggests zero lags of (1 – *L*), applied on the first difference of log returns with the following model:

$$(1-L)y=\beta_0+(\alpha-1)\cdot y(-1)+\varepsilon. \qquad (12)$$

In this regard, the empirical findings found the estimated value of (α– 1): –1.03347 and tau_c(1) = –78.421 at 1% significance level.

Figure 4 provides the graphical conversion of a frequency distribution in Table 1.

In the statistical property of Table 1, the mean value is 9.25068e-005, which indicates merely zero throughout the entire sample duration with the degree of the standard deviation of 14%. In addition, the property provides interval difference,

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Source: Authors' computations based on selected financial data series.

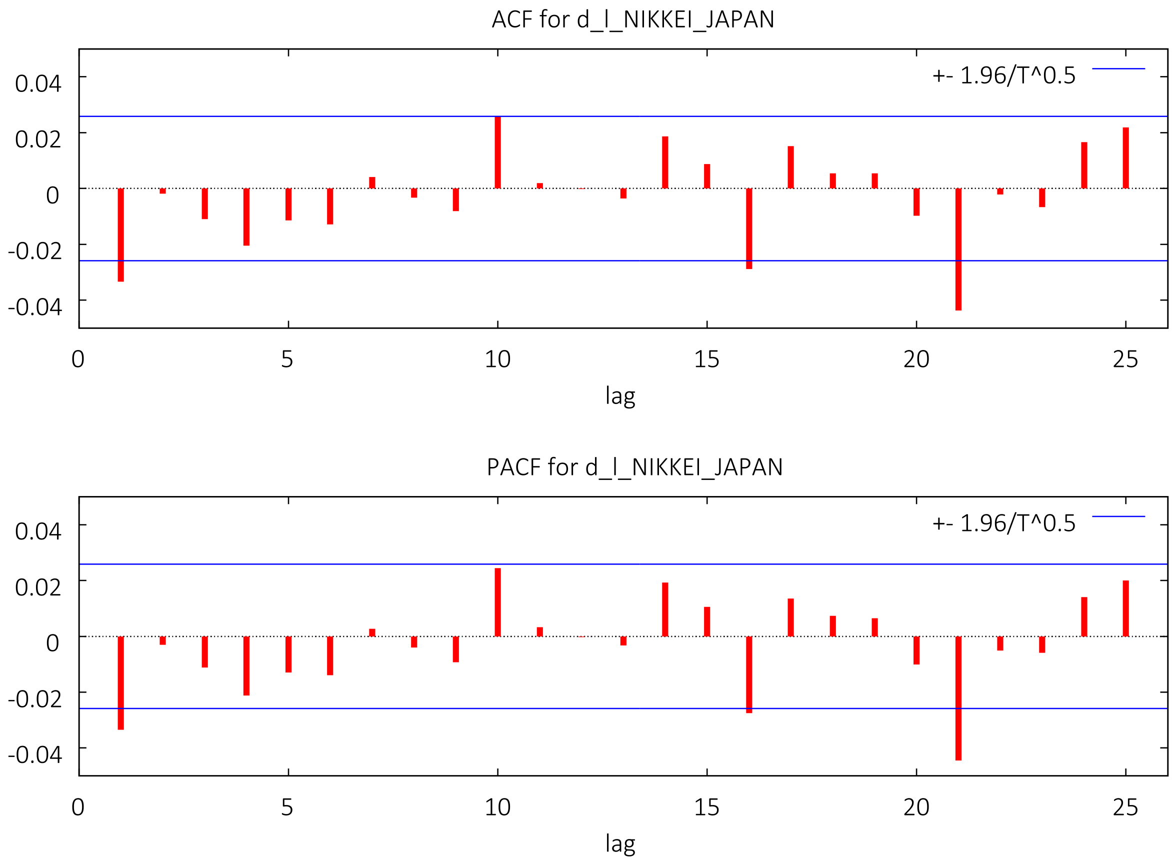

Figure 3. Evidence on autocorrelation and partial autocorrelation tested for NIKKEI 225 index during the sample period

Source: Authors' computations based on selected financial data series.

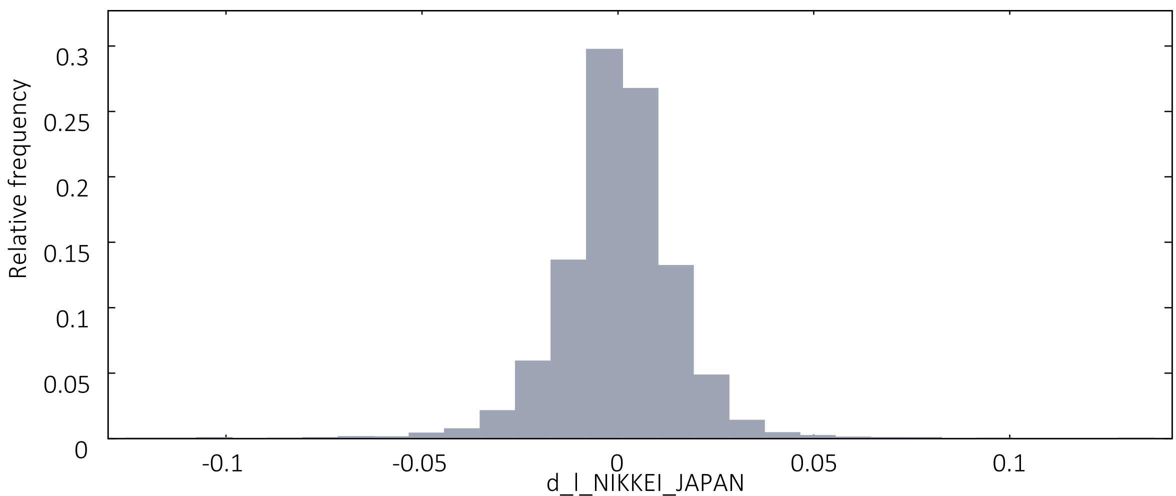

Figure 4. Relative frequency distribution for NIKKEI 225 index during the sample period

distribution of frequency levels with relative distribution in percentile and significance of cumulative significance. Table 2 summarizes statistics that provide essential information about how the series has performed over time.

Property of conditional variance equation for both asymmetric models only provide results at the significance of 1% excluding property of conditional mean equation that resulted overestimated despite alternate parameterization. The

Table 1. Frequency distribution for NIKKEI 225 index

Source: Authors' computations based on selected financial data series.

Interval	Midpt	Frequency	Rel.	Cum.
(–0.026064)-(–0.017012)	–0.021538	340	5.91%	9.58% **
(–0.017012)-(–0.0079601)	–0.012486	784	13.63%	23.20%****
(–0.0079601)-0.0010919	–0.0034341	1710	29.72%	52.92%**********
0.0010919-0.010144	0.0056179	1539	26.75%	79.67%*********
0.010144-0.019196	0.014670	760	13.21%	92.87%****
0.019196-0.028248	0.023722	278	4.83%	97.71%*

Note: Cumulative frequency indicates and incorporates sum of its predecessors provided in frequency (Colum no-3) into percentiles. The (*) indicates that the frequency of first-class interval being added to frequency of the second class, and so on. The highest number of (*) indicates most relevant frequency distributions.

Table 2. Summary statistics

Source: Authors' computations based on selected financial data series.

Mean	Min	Max	St. dev	Skewness	Ex. kurtosis
9.25E-05	–0.1211	0.13235	0.0148	–0.3371	5.9641

Table 3. Statistical property of GARCH (1, 1), GJR (1, 1), and EGARCH (1, 1) models

Source: Authors' computations based on selected financial data series.

	Const	Omega	Alpha	Gamma	Beta	Sign.
GARCH (1, 1)	0.0005	0.0000	0.1094	N/A	0.8704	1%
GJR (1, 1)	0.0002	0.0000	0.0937	0.3465	0.8661	E
EGARCH (1, 1)	0.0001	–0.4799	0.1959	–0.1003	0.962	E

GJR (1,1) and EGARCH or Exponential GARCH models confirmed the leverage effect in the sample period's Japanese stock market series returns. This means that the stock returns followed long memory over the sample period and demonstrated history in the future returns. The significance of the GARCH (1,1) model provides evidence that volatility remained persistent over a sample period (0.1094 + 0.8704). It means that the return will have a more significant effect on the unconditional variance for future trades.

4. DISCUSSION

The findings of this paper are in line with the results of Spulbar et al. (2020), Nguyen and Le (2021), Spulbar and Birau (2019), Kahraman and Keser (2022), Zulfiqar et al. (2020), Du (2021), and others. The observed series trend provides information about the reaction of the leverage effect. For instance, the index traded above the level of 20000 points in the year 2000, which re-established a trading level of less than 9,000 in forty-four months. The aggressive recovery was evident much later than the GFC impact, after 2011 until the index remained less than the trading level of 10000 or around. Then, aggressive recovery appeared and filled a gap of over 10000 points in 39 months with quick corrections. The impact of the COVID-19 pandemic generates a sharp pattern like a "V" letter shape, providing information about unpredictable sudden fall and similar recovery that delivered gain for more than 50% in index trading from about 17,000 to 30,000. Summary of the series sample suggests that the mean value is positive but close to zero with negative statistics for skewness and leptokurtic impact by excess kurtosis. It means the return creates a fat left tail. During careful analysis of empirical results, it is concluded that the impact of the COVID-19 pandemic (though very sharp and quick) is approximately 61% less volatile than in the global financial crisis. Further, the leverage effect remained for a much longer time, which is more than 26 months during the global financial crisis, while it is just less than 3 months for COVID-19 pandemic duration.

Frequency distribution indicates –0.00796 – 0.00109 (negative to positive event) with highest relativity 29.72% occurred at least 1710 times, confirming abnormal distributions to normal distributions. Statically, this indicates that the series of

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NIKKEI 225 has at least 1710 repeatable events where negative mean to positive mean occurred during the sample period. Furthermore, despite overestimating the asymmetric property of mean-variance, the variance equation significantly confirms the leverage effect in series returns, indicating that the NIKKEI 225 index continued to react based on a higher number of negative responses than the positive.

One of the limitations of this study is the consideration of a single market (Japan) for analysis. Instead, it is worth considering a cluster of Asian stock markets (for instance, India, China, Japan, Pakistan, and others). In addition, the timeframe selected for the analysis should be exceptionally long, at least 25 years of daily data to examine the impact of certain extreme events, including the Asian financial crisis of 1997.

CONCLUSIONS

This empirical study contributes to expanding the existing literature on investigating the very long-term behavior (over two decades) of the developed stock market in Japan. The GARCH (1,1) model has been applied on the series stock returns at a significance of 1% and fitted for mean and variance equations. The empirical findings revealed that innovation has scope for more than 10%, and about 90% of the stock market is dominated by past volatility. The empirical evidence confirms the presence of leverage effect, but also high and persistent volatility in the sample stock returns. The return is negatively skewed, creating a leptokurtic impact, demonstrating the long fat left tail. The degree of standard deviation approaches 14%, the sum of$\alpha + \beta$ indicates 0.9798, confirming the return is persistent for NIKKEI 225 index during the sample period from July 30, 1998, to January 24, 2022. The empirical findings suggested that the symmetric GARCH (1, 1) model designed by Bollerslev (1986) remains the most suitable for modeling and forecasting the volatility for the selected sample, such as NIKKEI 225 index. Observed volatility during the COVID-19 pandemic has been demonstrated to form a “V” shape pattern where an unpredictable, sharp negative slope is generated. This was entirely different from the pattern created during the global financial crisis. The sample series reacted for a much longer and evident most extended duration for the carry-forwarding leverage effect. Asymmetric GARCH model property for variance equations (GJR and EGARCH models) confirms that series still perceive leverage effect and retained pattern to repeat more negative shocks than positive ones. The empirical results are helpful to both government decision-makers, investors, and financial regulators.

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REFERENCES

1. Baek, S., Mohanty, S. K., & Glambosky, M. (2020). COVID-19 and stock market volatility: An industry-level analysis. *Finance Research Letters, 37,* 101748. https://doi.org/10.1016/j.frl.2020.101748
2. Birau, R., Spulbar, C., Trivedi, J., & Florescu, I. (2021). Modeling volatility in the stock markets of Spain and Hong Kong using GARCH family models in the context of COVID-19 pandemic. *Revista de Ştiinţe Politics. Revue des Sciences Politiques, 72,* 13-21. Retrieved from https://cis01.ucv.ro/revistadestiintepolitice/files/numarul72_2021/2.pdf
3. Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*(3), 307-327. https://doi.org/10.1016/0304-4076(86)90063-1
4. Du, W. (2021). News and Market Efficiency in the Japanese Stock Market. *Journal of Behavioral Finance, 22*(3), 306-319. https://doi.org/10.1080/15427560.2020.1774886
5. Duttilo, P., Gattone, S. A., & Di Battista, T. (2021). Volatility Modeling: An Overview of Equity Markets in the Euro Area during COVID-19 Pandemic. *Mathematics, 9*(11), 1212. https://doi.org/10.3390/math9111212
6. Ejaz, A., Birau, R., Spulbar, C., Buda, R., & Tenea, A. C. (2020). The impact of domestic portfolio diversification strategies in Toronto stock exchange on Canadian textile manufacturing industry. *Industria Textila, 71*(3), 215-222. http://doi.org/10.35530/IT.071.03.1696
7. Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of UK Inflation. *Econometrica, 50*(4), 987-1007. https://doi.org/10.2307/1912773
8. FTSE Russell. (2021). *FTSE Equity Country Classification, September 2021, Annual Announcement.* FTSE Classification of Equity Markets. Retrieved from https://research.ftserussell.com/products/downloads/FTSE-CountryClassification-Update_latest.pdf
9. Gillani, D. Q., Gillani, S. A. S., Naeem, M. Z., Spulbar, C., Coker-Farrell, E., Ejaz, A., & Birau, R. (2021). The Nexus between Sustainable Economic Development and Government Health Expenditure in Asian Countries Based on Ecological Footprint Consumption. *Sustainability, 13*(12), 6824. https://doi.org/10.3390/su13126824
10. Glosten, L., Jagannathan, R., & Runkle, D. (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *The Journal of Finance, 48*(5), 1779-1801. https://doi.org/10.1111/j.1540-6261.1993.tb05128.x
11. Hamori, S. (2003). *An Empirical Investigation of Stock Markets: The CCF Approach.* New York: Kluwer Academic Publisher.
12. Hamzaoui, N., & Regaieg, B. (2016). The Glosten-Jagannathan-Runkle-Generalized Autoregressive Conditional Heteroscedastic approach to investigating the foreign exchange forward premium volatility. *International Journal of Economics and Financial Issues, 6*(4), 1608-1615. Retrieved from https://www.econjournals.com/index.php/ijefi/article/view/2740
13. Hawaldar, I. T. (2014). Seasonal analysis of abnormal returns after quarterly earnings announcements. *International Journal of Accounting and Financial Reporting, 4*(2), 501-519. http://dx.doi.org/10.5296/ijafr.v4i2.6622
14. Hawaldar, I. T. (2015). Empirical Testing of Capital Asset Pricing Model on Bahrain Bourse. *Asian Journal of Finance & Accounting, 7*(2), 107-119. http://doi.org/10.5296/ajfa.v7i2.8356
15. Hawaldar, I. T. (2016). The Cross-Sectional Variations in Portfolio Returns: Evidence from Bahrain Bourse. *British Journal of Economics, Finance and Management Sciences, 12*(2), 1-11. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3504527
16. Hawaldar, I. T., Birau, R., Spulbar, C., Rohit, B., Pinto, P., Rajesha, T. M., & Di Sciorio, F. (2020). Further evidence on the efficiency of Bahrain Bourse: A high challenge for other industries. *Industria Textile, 71*(5), 458-466. http://doi.org/10.35530/IT.071.05.1732
17. Hawaldar, I. T., Mallikarjunappa, T., & Nayak, P. (2007). Stock Price Adjustments to Quarterly Earnings Announcement: A Test of Semi-Strong Form of Efficiency. *Gyan Management, 1*(2), 25-42.
18. Higashide, T., Tanaka, K., Kinkyo, T., & Hamori, S. (2021). New Dataset for Forecasting Realized Volatility: Is the Tokyo Stock Exchange Co-Location Dataset Helpful for Expansion of the Heterogeneous Autoregressive Model in the Japanese Stock Market? *Journal of Risk and Financial Management, 14*(5), 215. https://doi.org/10.3390/jrfm14050215
19. Kahraman, S., & Keser, M. (2022). Volatility Transmission Between the Japanese Stock Market and the Western Stock Market Indices: Time & Frequency Domain Connectedness Analysis with High-Frequency Data. *Applied Economics, 54*(6), 670-684. http://doi.org/10.1080/00036846.2021.1967868
20. Kumar, A., Soni, R., Hawaldar, I. T., Vyas, M., & Yadav, V. (2020). The Testing of Efficient Market Hypotheses: A Study of Indian Pharmaceutical Industry. *International Journal of Economics and Financial Issues, 10*(3), 208-216. https://doi.org/10.32479/ijefi.9764
21. Mazur, M., Dang, M., & Vega, M. (2021). COVID-19 and the March 2020 stock market crash. Evidence from S&P 1500. *Finance Research Letters, 38,* 101690. https://doi.org/10.1016/j.frl.2020.101690
22. Meher, B. K., Hawaldar, I. T., Mohapatra, L., & Sarea, A. M. (2020a). The Impact of COVID-19 on Price Volatility of Crude Oil

and Natural Gas Listed on Multi Commodity Exchange of India. *International Journal of Energy Economics and Policy, 10*(5), 422-431. https://doi.org/10.32479/ijeep.10047

23. Meher, B. K., Hawaldar, I. T., Mohapatra, L., Spulbar, C., & Birau, R. (2020b). The Effects of Environment, Society and Governance Scores on Investment Returns and Stock Market Volatility. *International Journal of Energy Economics and Policy, 10*(4), 234-239. https://doi.org/10.32479/ijeep.9311
24. Meher, B. K., Hawaldar, I. T., Spulbar, C. M., & Birau, F. R. (2021). Forecasting Stock Market Prices Using Mixed ARIMA Model: A Case Study of Indian Pharmaceutical Companies. *Investment Management and Financial Innovations, 18*(1), 42-54. http://dx.doi.org/10.21511/imfi.18(1).2021.04
25. Nelson, D. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica, 59*(2), 347-370. https:/doi.org/10.2307/2938260
26. Nguyen, M. K., & Le, D. N. (2021). Return Spillover from the US and Japanese Stock Markets to the Vietnamese Stock Market: A Frequency-Domain Approach. *Emerging Markets Finance and Trade, 57*(1), 47-58. http://doi.org/10.1080/1540496X.2018.1525357
27. Ohmura, H. (2022). The connection between stock market prices and political support: evidence from Japan. *Applied Economics Letters, 29*(1), 1-7. http://doi.org/10.1080/13504851.2020.1854660
28. Palma-Ruiz, J. M., Castillo-Apraiz, J., & Gómez-Martínez, R. (2020). Socially Responsible Investing as a Competitive Strategy for Trading Companies in Times of Upheaval Amid COVID-19: Evidence from Spain. *International Journal of Financial Studies, 8*(3), 41. https://doi.org/10.3390/ijfs8030041
29. Poon, S. H., & Granger, C. W. J. (2003). Forecasting Volatility in Financial Markets: A Review. *Journal of Economic Literature, 41*(2), 478-539. https://doi.org/10.1257/002205103765762743
30. Rabbani, M.R., Kayani, U., Bawazir, H.S., & Hawaldar, I. T. (2022). A Commentary on Emerging Markets Banking Sector Spillovers: Covid-19 Vs GFC Pattern Analysis. *Heliyon, 8* (3), 1-8. https://doi.org/10.1016/j.heliyon.2022.e09074
31. Sajeev, K. C., Afjal, M., Spulbar, C., Birau, R., & Florescu, I. (2021). Evaluating the linkage between Behavioral Finance and Investment Decisions Amongst Indian Gen Z Investors Using Structural Equation Modeling. *Revista de Ştiinţe Politice. Revue des Sciences Politiques, 72,* 41-59.
32. Sakamoto, S., & Sengoku, S. (2021). Predictability of Stock Price Fluctuations Based on Business Relationships: A Comparison of Normal and the COVID-19 Pandemic Periods in Japan. *Sustainability, 13*(18), 10146. https://doi.org/10.3390/su131810146
33. Shen, J., & Shafiq, M. O. (2020). Short-term stock market price trend prediction using a comprehensive deep learning system. *Journal of Big Data, 7,* 66. https://doi.org/10.1186/s40537-020-00333-6
34. Spulbar, C., & Birau, R. (2019). *Emerging Research on Monetary Policy, Banking, and Financial Markets* (322 p.). USA: IGI Global. http://doi.org/10.4018/978-1-5225-9269-3
35. Spulbar, C., Birau, R., Oluwi, V., Ejaz, A., Gorun, T. H., Calugăru, T., Zulfiqar, A. I., & Minea, E. L. (2021). Diversification opportunities in European stock markets and their impact on textile industry development based on a financial education approach. *Industria Textila, 72*(5), 528-537. http://doi.org/10.35530/IT.072.05.1819
36. Spulbar, C., Trivedi, J., & Birau, R. (2020). Investigating abnormal volatility transmission patterns between emerging and developed stock markets: a case study. *Journal of Business Economics and Management, 21*(6), 1561-1592. https://doi.org/10.3846/jbem.2020.13507
37. Spulbar, C., Trivedi, J., Birau, R., Tenea, C. A., & Ejaz, A. (2019). Estimating volatility spillovers, dynamic causal linkages, and international contagion patterns between developed stock markets: An empirical case study for USA, Canada, France, and UK. *Annals of the "Constantin Brâncuşi" University of Târgu Jiu, Economy Series, 3,* 44-62. Retrieved from https://ideas.repec.org/a/cbu/jrnlec/y2019v3p44-62.html
38. Sultonov, M. (2020). The Impacts of International Political and Economic Events on Japanese Financial Markets. *International Journal of Financial Studies, 8*(3), 43. https://doi.org/10.3390/ijfs8030043
39. Takaishi, T. (2022). Time Evolution of Market Efficiency and Multifractality of the Japanese Stock Market. *Journal of Risk and Financial Management, 15*(1), 31. https://doi.org/10.3390/jrfm15010031
40. Trivedi, J., Spulbar, C., Birau, R., & Mehdiabadi, A. (2021a). Modelling volatility spillovers, cross-market correlation, and co-movements between stock markets in European Union: an empirical case study. *Business, Management and Economics Engineering, 19*(1), 70-90. https://doi.org/10.3846/bmee.2021.13588
41. Trivedi, J., Spulbar, C., Birau, R., & Minea, E. L. (2021b). Assessing the changes in the statistical property of selected stock markets behavior before and after COVID-19 pandemic: A case study. *Research and Science Today, 22*(2), 63-72. Retrieved from https://www.rstjournal.com/rst-222-2021/
42. Watanabe, T. (2020). *Heterogeneous Autoregressive Models: Survey with the Application to the Realized Volatility of Nikkei 225 Stock Index.* Hiroshima University of Economics, Keizai Kenkyu.
43. Zulfiqar, A. I., Ejaz, A., Spulbar, C., Birau, R., & Nethravathi, P. S. R. (2020). Measuring the Impact of Governance Quality on Stock Market Performance in Developed Countries. *Economic Research-Ekonomska Istraživanja, 33*(1), 3406-3426. https://doi.org/10.1080/1331677X.2020.1774789