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Asymmetric Volatility and Market Efficiency: Evidence from Asian Pacific Stock Exchanges Using GARCH Family Models

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ABSTRACT
The study is conducted with aim to analyze and examine the behavior of Asian Pacific stock market by analyzing the volatilities of five chosen stock markets; Karachi Stock Exchange (KSE) 100, Jakarta Stock Exchange (JKSE), Nikkei 225 Stock (N225), Shanghai Stock Exchange (SSE) and Taiwan Stock Exchange (TWSE) indices. This study takes 25 years, 2000 till 2024 of data by taking daily prices of the markets. The prices were transformed to log returns. In the descriptive statistics N225 index had recorded the highest positive return and highest negative return. Similarly, TWSE index recorded the lowest positive and lowest negative returns. Furthermore, modeling the volatilities, the study first estimated the ARCH effect for heteroscedasticity, the results are significant for all the series. The outcomes of GARCH model for all the series are significant. The study finds that past volatilities are significantly affecting the current volatilities and empirically the future returns and volatilities can be predicted by using past volatilities. The EGARCH model found that all the indices are having asymmetric volatilities. Thus, it is concluded that Asian pacific stock markets behave in similar way.

Key words: *ARCH, GARCH, EGARCH, Asymmetric Volatility*

INTRODUCTION

Stock returns are hard to predict, as due to fluctuation in the stock market (Balvers, Cosimano, & McDonald, 1190). Therefore, the stock returns often have time varying behavior, also called return volatility. The deviation from mean value of a given set of returns is called volatility (Fassasa & Siriopoulosb, 2021). Typical investors often fail to forecast the stock returns, which is due to the time varying variance property of the stock prices and the risk associated with it (Marobhe & Pastory, 2019). Volatility measures the risk of given stock prices, if the prices of an index fluctuate rapidly the stock market is said to be risky or high volatile market and vice-versa (Ahmed & Suli, 2011).

The volatility of stock return is time varying and can be forecasted, however estimating the future volatility of stock return is complicated due certain reasons (Ali, Hassan, & Nasir, 2005). First, often volatility model's specification is sensitive to the volatility estimates, therefore specifying the patterns and features of data is important to find the right fit between specific volatility model and the data (Caiado, 2004). Corresponding to the mentioned reason, a simple regression may not be able to forecast the volatility because it fails to capture the error term and its relationship with the lag term, it can only be possible when the error term is zero (Moura, Zio, Lins, & Droguett, 2011). Second, the non-linear and asymmetric behavior of stock prices, because most often stock market responds aggressively to the bad news than good news. Therefore, measuring asymmetry in the time series and its relationship with the error term is important, while capturing the volatility (Badeeb & Lean, 2016). Last, most of the models anchor the volatility of stock returns with the current level of estimates; however, risk is surrounded by the volatility parameter, which is independent of forecasting process (Poon & Taylor, 1992).

This leads to the introduction of auto regression models i.e. the development of Engle (1982)'s ARCH model. Further, the development Bollerslev (1986)'s GARCH model to capture the linear symmetric behavior and the long-term relationship properties. Other contribution to GARCH family models was EGARCH Nelson (1991) model, GJR-GARCH Glosten, Jagannathan, and Runkle (1993), AGARCH Engle R. (1990), APARCH Ding, Granger, and Engle (1993), TGARCH Zakoian (1994), and QGARCH Sentana, (1995) in order to improve the flexibility ARCH model and capture for the afore mentioned problems in simple regression model. The volatility models have been widely used in past finance literature, but since last decade the authors divert their focus from this phenomenon. This study is extension of the work of Su and Knowles, (2006), that further add to the existent literature by investigating the efficiency of Asian pacific countries stock markets over the last 25 years. To test the efficiency, the study expends the discussion toward the Efficient Market Hypothesis (EMH) theory.

The concept of Efficient Markets hypothesis can be found in Roberts (1967) and Fama (1970). The concept states that the market is said to be efficient, where large number of investors optimizing their profits in order to compete with each other driving the price toward equilibrium through demand and supply. The investors try predict the future market prices of stocks, using information that is freely available in the market regarding relevant stock prices. Furthermore, the concept of EMH states that in market rational investors compete with each other, which drives the market to a new equilibrium. The new equilibrium, where the prices of individual securities reflect the relevant information that is used by investors to predict the future prices. Most of the time securities reflect the information of past events that already been occurred and the news regarding future events that are relevant to the market. The main assumption in such situation is that the information is freely available to the investors and policy makers as well. Similarly, in efficient market the information is a good technique for estimating the future price, which lead to the argument that actual prices do reflect the intrinsic value of a stock.

Fama (1970) identified three forms of market where it is efficient at different level. The first one is Strong-form EMH, which states that the market is strongly efficient when relevant information of intrinsic value of stock, which might not be available to all investors but the intrinsic value of a stock with respect to relevant information shall reflect the market value of stock. Similarly, if the information of a specific stock is held private by a group of investors and the value of that stock is justified by that information, they will cease the opportunity to exploit the market and will enjoy the pricing anomaly by buying or selling the specific stock. Further the investors will involve themselves in that specific stock by creating excess demand until they achieve their incentive and then they will withdraw their funds and the market will be on a new equilibrium. This whole phenomenon in the market is called strong form of EMH. This form of EMH is the most compelling, however due one big drawback it is difficult to evaluate this phenomenon in practice. It is difficult for research to justify this form of EMH empirically, the cooperation from investors' groups is unlikely to get.

The second form of EMH is semi strong form, this form of market is a bit rigorous and competitive. It states that the market is said to be efficient if the publicly available relevant information justifies the quickly the market prices. This phenomenon is said to be Semi-strong form of EMH. The problem with this form of market, it is hard to identify the relevant information that drives the market prices. In reality things are not that much straight forward and clear, the information does not arrive with label of being relevant. Most of the time responding to irrelevant information may lead to worst consequences. The last form of Efficient Market Hypothesis is weak-form, which states that a market is said to be efficient when historical or cyclical information of a stock reflects a subset of the market price and the intrinsic value is justified by the market value. Similarly, cyclical information alone does not reflect market prices of the stock. This concludes that Prediction of stock prices and its volatility are subject to privately relevant held information, publicly relevant information and cyclical information. However, in weak-form of EMH the future prices and volatilities are also subject to a random walk.

Many authors have criticized the theoretical argument of EMH; however, this concept has dominated the academic, and business practices for over a decade after its publication. Banz (1981) took the stock prices of list firm and segregated those firms into small and large firm. The standard of segregation was market capitalization of each firm. The study attempted to find the long-run stock return of small firm and large firm simultaneously. The study found that the firms having lower market capitalization tends to have higher stock return and the larger firms were having lower stock returns. Banz (1981) further criticized the efficient market hypothesis by presenting the argument that stock prices are not only determined by information, there may be some other factors that determine the stock prices and predict the market volatilities.

The argument that Banz (1981) presented was the small firm affect, which dismantle the argument of EMH. Further the concept of small firm effect was backed by January effect, which states that firms having small market capitalization are having higher returns in January (Thaler, 1987).The theoretical discussion of small firm effect indicate that future stock prices are not the sole reflection of information, other factors such as small firm effect and calendar anomalies are also the cause of future prices.

Asymmetric and non-linear behavior of stock market fails the investors to forecast the volatility. Due to which the Efficient Market Hypothesis Fama (1970) introduces the fair game model, which states that volatility follows the random walk hypothesis in at autoregressive process or not and can the volatility be captured? The theoretical background of Random Walk hypothesis is associated with Efficient Market Hypothesis. The EMH states that prices of stocks are associated with information, the information spreads very quickly which is then reflected in the prices of stocks. Similarly, individual prices of stocks and stock market both perform efficiently in terms of reflecting information in the stock prices. The use of past data to predict the future prices and the fundamental analysis, which to study the financial position of the company, both analysis holds no value in view of EMH while predicting the individual stock and whole stock market index.

The theoretical reasoning of EMH backed the Random Walk hypothesis. Random Walk hypothesis stated that any change in the series prices of an index is subsequent to a random destination and thus it cannot be predicted through past data (Godfrey, Granger, & Morgenstern, 1964). Similarly, the prices reflect the information of that concerned day, likewise tomorrow’s information is independent of today’s prices. However, news is unpredictable, which will result in random changes in prices of an index. The emergence of new technologies and intellectual dominance after 90s the theoretical argument of efficient market hypothesis has become less objective and is not accepted widely. Similarly, at the start of 21st century economists and financial analysts began to change their perspectives from that stock prices respond to only the concerned news, to that stock prices can be partially forecasted.

The stock market is highly volatile and frequently appears in the news. Investment and business opportunities in the stock market can increase with an efficient algorithm to predict short-term stock prices. This study aims to predict stock market volatility in Asian Pacific countries. The GARCH model is widely used for modeling and forecasting stock market volatility (Karmakar, 2005; Hansen & Lunde, 2005). EGARCH is noted for capturing asymmetric behavior (Hamid & Hasan, 2016; Kamal, Ghani, & Khan, 2012). Su and Knowles (2006) found GARCH (1, 1) effective for Asian Pacific markets. This study extends their work by examining asymmetric behavior in additional markets, including KSE 100, SEE, TWSE, Nikkei 225, and JKSE.

EMPIRICAL REVIEW

Modeling Volatility

Modeling and estimation of volatilities has practical implications in economics and finance, supported in wide range of literature. The ARCH and GARCH family models are the most suitable model for modeling volatility. In case of modeling FOREX volatilities these models are widely used, as previously used Mohnot, (2011); Kamal et al. (2012). The substantial GARCH effect is disclosed as the announcement outcome in the stock market reveals. This effect considers the influence of past returns and the impact of previous volatility on present volatility as well as move toward a vast dismissal of stable variance and future volatilities. The Q-GARCH models offers as long as more substantial reports about the estimated volatility has been investigated and inquired.

Booth, Martikainen, and Tse (1997) took the data of period duration May 1, 1998 to June 1, 1994 to study the stock price, behavior, and volatility in Scandinavian stock markets by using E-GARCH model. The conclusion of the study expresses abnormal statistical distribution with significant ARCH effect and return clustering in every stock market excluding Denmark stock market. The Denmark stock market show less reaction to good news than bed news, which proves the asymmetric behavior of stock markets. Using ten separate model to study the estimate volatility and to examine the performance of UK stock market that consist of symmetric and asymmetric variation. McMillan, Speight, and Apgwilym (2010) argue that generalize linear model in contrast to other models give more accurate volatility forecast. With respect to weekly returns data, the performance of moving average, and generalize linear model is better in case of symmetric data. Furthermore, GARCH model, exponential smoothing, and MA model have given better volatility forecast in case of daily returns series having asymmetry. The analysis concluded that the GARCH model and MA model were the most persistent models for volatility estimation of volatility.

Caiado (2004) analyze the Portuguese stock market by study the PSE-20 index in accordance with daily and weekly return for period range from January 1995 to November 2001. The discussion expresses that data had features of asymmetry, high value kurtosis and negative value skewness is represented in daily and weekly data. The high consistency of volatility along with high consistency in the subject of daily returns data that remarked a growing market trend and as well as substantial GARCH effect is observed. Whereas the daily data returns particularly gave the affirmative risk premium along with substantial leverage effect.

Volatility in Emerging Markets

Brandt and Jones (2012) express the return series gave the characteristics of time series financial data, for instance volatility clustering, huge kurtosis, negative skewness and asymmetry, and also express the presence of a leverage effect in some situation in the developed market. Whereas the ultimate discussion as regard to the analysis of volatility behavior is analyzed in developed markets. Ahmed and Zakaria (2011) a small attempt concerning to emerging markets is first attempt in the literature. Siourounis (2002) studied Ethen capital market in Greece in the period of 1988 to design volatility in a developing market by concentrating on the daily price of stocks. The results state that high kurtosis, abnormal distribution with heavy tails, positive skewness and the stationary features showed from the series of returns. The conclusion provides long, consistent, and growing trend of volatility due to political uncertainty, also with a substantial leverage effect. The unsubstantial leverage effect is proposed by EGARCH model.

Ali, Hassan, and Nasir (2005) investigate capital market of Kuala Lumpur Malaysia through GARCH model, for stock returns. The conclusion expresses that for representing the volatility of returns, the GARCH is the suitable model, and that the previous volatility could describe the present volatility. Karmakar (2007) explains behavior of the Indian capital market, taken the data of the time span of July 1990 to December 2004. A time varying property in the stochastic volatility and expressed return clustering indicated by the given conclusion. The leverage effect, no risk premium in the market, high consistency and furthermore explaining the estimated volatility were recommended by the conclusion. Bahadur G.C

(2009) examine the operation in the Nepalese capital market from time July 2003 to February 2009. The series expressed the properties of financial time series, the conclusion reveals that good or bad news having no symmetric effect on volatility. It was revealed in the result that the GARCH was the most appropriate model for representing return clustering.

Nyamongo and Misati (2010) studied the capital market of Nairobi Kenya for the time span of January 2006 till April 2009, a substantial GARCH effect was expressed by the GARCH model conclusion and as well as a huge consistency in the volatility. Furthermore, the conclusion express that the unsubstantial leverage parameter reported through the TGARCH and EGARCH models and for the missing of asymmetric effects on volatility in the returns. Using the GARCH symmetric and asymmetric models, Ahmed and Suli (2011) studied the daily return of capital market of Khartoum Sudan of the time span from January 2006 to November 2010. The affirmative skewness, huge kurtosis, non-normal statistical data distribution, volatility clustering, and heteroscedasticity is observed in the result of return series. The conclusion also gave the substantial GARCH effects, for undefined span of time expressing consistency of volatility along with the existence of risk premium and leverage effect. The presence of huge volatility the study recommends volatility asymmetric models as best suited.

Kalu (2012) explores capital market of Nigeria for daily returns from 1996 to 2011. The huge kurtosis, affirmative skewness, stationarity and volatility clustering was shown by return series. The finding of GARCH model (1, 1) furnish toward the presence of huge consistence volatility. It was concluded that there is no leverage effect but a substantial asymmetric effect concern to volatility was exist in the returns. It is recommended that the negative disturbance having less effect than positive disturbance.

All above discussion forms the basis for GARCH (1, 1). The literature for using GARCH model for volatility is not observed in the last decade that’s why the study extend its use to check for the recent data and compare the performance of Asian pacific markets with previous studies. This indicates toward the direction toward gap in the literature in the recent years.

Volatilities in Asian Pacific Stock Markets

The volatility occurs in stock exchange continuously with great confusion (Whitelaw, 1994). The too much up and down in share prices occur due to the abrupt circulation of knowledge and assets movement, which influence the stock market returns (Shiller, 2003). This is the action of interrelationship and inter induction. The developing China’s exchange market are still volatile from its origin and frequently showing abrupt ups and downs (Girardin & Joyeux, 2013). The empirical analysis concluded through GARCH model and cut up this composite index property in the context of econometric. It also gave some recommendations on the basis of SSE composite index present level fluctuation. The conclusion expresses that from the perspective of financial time series, the index of SSE having substantial features of clustering and alteration. Furthermore, it was examined that the EGARCH performed better than those of GARCH and TARCH. Except these the government of China should overcome its intermingling in the Securities and Exchange Commission and should built a powerful system in which rational investment thinking is supported (Lin, 2018).

Takahashi, Watanabe, and Omori (2021) analyzed N225 index to relate the alteration estimated capability of the models like GARCH, EGARCH models and stochastic fluctuation by using the daily returns data. The indirect co-relation between return of today and fluctuation of tomorrow, this familiar situation is well adjusted by these models. The study further used QML (Quasi likelihood) technique are used to evaluate the REGARCH and EGARCH models and OLS (ordinary least squares) are used to estimate HAR model. Furthermore, it explores that the best performer among models is stochastic volatility, whereas the HAR could contest with it. It means that the stochastic volatility is competing with HAR models for better performance. To capture the volatilities of Asian Pacific stock markets, Su and Knowles (2006) that used

GARCH for capturing the volatilities. The results illustrated that Taiwan Indonesia and South Korea stock markets are exhibiting high volatilities.

The international investors have been captured by Asia Pacific market due to exchange market potentiality (Chang, He, & Xiaoqiang, 2015). Although, you will confront to higher risk for attaining higher returns and higher growth (Boyd & Nicolo, 2005). Sharma (2017) applied VAR (Value at Risk) analysis in the Asia pacific market. The volatility modeling is imperative to perform (GARCH) models, mixture switch or by using EWMA (Exponentially Weighted Moving Average). The VaR value can be measure for system as well as individual risk later the appraisal of volatility limitation. The empirical result concluded that the highest VaR value is of Indonesia and Korea, while the lowest is that of Australia accordingly. The highest level of volatility in Asian pacific markets is that of Taiwan. Furthermore, the conclusion of the kupiec test stated that the delta normal Value at Risk is inferior to mixture switch Value at Risk.

Hamid and Hasan (2016) investigated the behavior of KSE, pattern of the returns and estimate the future volatilities. In case of Asian real estate investment trust, Tsai (2013) applied the (ARCH)-family models, to estimate the future volatilities of REIT, the study found the EGARCH model was the least error causing forecasting model, as well as the study results were significant enough for investors to derive the future returns and price of Asian REIT. The FOREX volatilities are also modeled through GARCH family model, in which the most robust model that show high forecasting potential is EGARCH. Kamal et al, (2011) stated that EGARCH based estimation showed asymmetric behavior of the series, however TARCH showed insignificant results. Thus, the empirical results of Kamal et al, (2011) and Tsai (2013) proves that EGARCH model is more likely to predict the future price than other conditional volatility model.

Boateng, Sasu, and Frempong (2015) modeled volatilities of stock market by taking the return of three indices on the Ghana Stock Exchange (GSE), taking daily historical data of seven years, the study applied GARCH (p, q) model for fitting the residuals of all indices, the study found that GARCH model and recommended that the of other variants of GARCH model for comparison. Mustapa and Ismail (2019) attempted to capture the volatility of index prices, initially the study applied conventional ARIMA model for forecasting and then applied GARCH, the diagnostics the empirical results showed that GARCH (1,1) is adequate for forecasting volatility, using Akaike Information Criterion and Schwarz Bayesian Criterion. Thus, it proves that GARCH (1,1) model is more likely to capture the volatility of time series as compared to other models, as previously proved (Boateng, Sasu, & Frempong, 2015); Mustapa & Ismail 2019).

volatility and its relationship with stock price in developed financial markets has been well studied, little attention has been paid towards an extensive study of the volatility of the Asian pacific stock markets in the last decade. This study attempts to investigate the volatility in the recent years and compare the appropriateness of volatility models to present the best to the academic researchers.

Efficient Market Hypothesis

The efficient market hypothesis (EMH) is a backbreaker for forecasters. In its simplest form it positively says that series we would very much like to forecast, the returns from speculative assets, are unpredictable. This is a venerable thesis, its earliest form appearing a century ago as the random walk theory (Bachelie, 1964). This theory was confirmed empirically in the 1960s (Granger, 1965) and many times since. Soon after the empirical evidence appeared, the EMH was pro-posed based on the overpowering logic that if returns were predictable, many investors would use them to generate unlimited profits. The behavior of market participants induce returns that obey the EMH, otherwise there would exist a ‘money-machine’ producing unlimited wealth, which cannot occur in a stable economy. Intellectually, that might appear to be the end of the story. However, despite the force of the argument, it seems not to be completely convincing for many forecasters. Everyone with a new prediction method wants to try it out on returns from a speculative asset, such as stock market prices, rather than series that are known to be forecastle. Papers continue to appear attempting to forecast stock returns, usually with very little success.

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DESIGN

Data and Methods

The sample for the current study includes the primary stock index in each of the five countries in Asia, i.e. the KSE index for the Pakistan, the NSE index for the India, the Nikkei 225 index for Japan, the SSE Composite Index for China, the JKSE index Indonesia. Data for the study are collected from Asia & Pacific Indices web site that include all daily close prices for the five indices, for the period 2000-2024. In addition, the price datasets are converted into returns series using the natural log of relative prices for all close prices.

The following is the systematic process:

1. Auto-Regression estimation of time series and finding the residuals
2. Unit root test for stationary of data
3. Augmented Diki-Fuller test
4. Hetroskedecity test for ARCH effect
5. Estimation of ARCH and GARCH models
6. Estimation of EGARCH model to capture the asymmetric effect

Specification of Models

The study first applied the unit root test on the series. When the series are integrated on levels or at first difference then the study will have a green signal to apply auto-regressive model for modeling volatility. If this is the case, the study will apply GARCH-family models. The below discussion is for model specification which shall be used in the study.

Unit Root Specifications

The Augmented Dickey Fuller test, Dickey Fuller test, and Phillips Perron test. Here is this study we have used ADF test for stationary.

The general procedure for the ADF test is given here. The test is based on simple AR (1) process.

$$Y_t = \varphi Y_{t-1} + \mu_t$$

Now subtracting Y_{t-1} from both sides we get

$$\Delta Y_t = \gamma Y_{t-1} + \mu_t$$

$\Delta Y_t = Y_t - Y_{t-1}$and $\gamma = \varphi - 1$

The augmented form of the model is given as

$$\Delta Y_t = \gamma Y_{t-1} + \sum_{i=1}^{n} \pi_i \Delta Y_{t-i} + \mu_t$$

In the data there is also certain linear time trend and intercept (drift). In such cases, we have to include the intercept term and a time trend term in the model.

Model with drift/intercept

$$\Delta Y_t = \alpha_0 + \gamma Y_{t-1} + \sum_{i=1}^{n} \pi_i \Delta Y_{t-i} + \mu_t$$

Model with drift and time trend

$$\Delta Y_t = \alpha_0 + \gamma Y_{t-1} + \alpha_1 T + \sum_{i=1}^{n} \pi_i \Delta Y_{t-i} + \mu_t$$

In Augmented Dickey Fuller (ADF) test, we tested the Ho that the variable is non stationary (have a unit root) and the alternative hypothesis $H_1\colon \gamma < 0$or $\varphi < 1$ means that the variable is stationary.

3.2.2 Return

The daily returns are calculated by

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) * \ 100$$

Where r_t refers to the daily return at time *t*. The return: $\ln\left(\frac{P_t}{P_{t-1}}\right)$ is simply taking the natural log of adjusted closing prices of each day. Then multiplying than which the division of current day price and previous day price at time *t*. The return series is supposed to be into two parts:

$$R_t = E(R_t | I_{t-1}) + \ \varepsilon_t$$

The conditional mean return$E(R_t | I_{t-1})$ is considered to be an Autoregressive process, where the return at rt of each series is taken with the constant, which makes it the auto regression, that captures the expected returns at time; t given all the available information.

The 2nd part is believed to unpredicted part i.e. ε_t that can be defined by the

$$\varepsilon_t = z_t \sigma_t ,$$

Where $\sigma_t$is the conditional standard deviation of ε_t while the sequence of $z_t$is an independent and identically distributed (iid) with average value equal to zero and a unit variance (Angelidis, Benos, & Stavros, 2004)

Volatility Models

Conditional variance models can estimate the unpredicted part. In 1982, (Engle) introduced the ARCH model, as a way to forecast the variance property of a time series. The ARCH model is believed to be the bench mark model of the GARCH-Family models. The ARCH model assumes that the error term of a series is the autoregressive process and the significance of this model b, just as the error terms in a regular AR process, the variance of the

The GARCH-Family models

The ARCH type models common form are given below:

$$y_t = \mu_t + \epsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

$$\epsilon_t = \sigma_t z_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

$$\mu t = C(ŋ|\Omega_{\tau-1}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

$$\sigma_t = h(ŋ|\Omega_{\tau-1}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

Whereas the function of$(\Omega_{\tau-1})$ is $C(ŋ|\Omega_{\tau-1})$ and $h(ŋ|\Omega_{\tau-1})$, at time t-1 the information set and rely on some unspecified vector parameters ŋ, z_t which is i.i.d. process. The ARCH type model expansion are as under:

i. GARCH Model

This model was presented by Bollerslev in 1986. The models we use here as

$$\sigma^2{}_t = \omega + \alpha\epsilon^2{}_{t-1} + \beta\sigma^2{}_{t-1},\ \omega > 0,\ \alpha, \beta > 0 \ldots\ldots\ldots\ldots\ldots (5)$$

ω, β and α are whereas the parameters, these are supposed to be non-negative and assure that the volatility being positive all the time. The capturing of volatility clustering is enabled through this model. The volatility is stationary and the movement of shock of volatility decays are slower when $\beta + \alpha$ is moving toward one. These all are indicated by $|\beta + \alpha| < 1$.

ii. EGARCH Model

It has been accepted before that the common GARCH model cannot represent the popular volatility asymmetry phenomenon in share market. We use EGARCH model proposed by Nelson in 1991 to represent this phenomenon. Especially EGARCH (1, 0) model is using here.

$$\ln(\sigma^2_{t-1}) = \omega + \phi[\ln(\sigma^2_{t-1}) -] + \theta z_{t-1} + y(|z_{t-1}| - E|z_{t-1}|, |\phi| < 1 \ldots\ldots\ldots\ldots\ldots (6)$$

Whereas $E|z_{t-1}| = \sqrt{2/\pi}$, it is suggested that standard normal distribution is followed by z_{t-1}. As the logarithm of volatility is set out by EGARCH model.

ANALYSIS AND DISCUSSION

Descriptive Statistics of Stock Markets

Table 4.1: Descriptive Statistic of ASIAN Pacific Stock Market

	LKSE	LJKSE	LN255	LSSE	LTWSE
Mean	0.000699	0.000551	0.000129	0.000105	0.000195
Median	0.000969	0.001114	0.000524	0.000556	0.000591
Maximum	0.085071	0.097042	0.132346	0.094010	0.065246
Minimum	-0.097379	-0.113060	-0.121110	-0.092561	-0.069124
Std. Dev.	0.013343	0.013306	0.014981	0.015565	0.012656
Skewness	-0.390801	-0.623305	-0.384391	-0.390091	-0.264813
Kurtosis	7.410970	10.57684	9.531005	7.951490	6.493489
Jarque-Bera	4067.862	8766.133	5093.236	2530.807	11952.18
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	4865	4865	4865	4865	4865

The descriptive statistics of all Asian Pacific markets are shown in Table 4.1. The mean value for KSE is 0.06%, JKSE is 0.05%, N225 is 0.012%, SSE is 0.01%, and TWSE is 0.019%. The average value of each market indicate that the mean return of each market is positive in long run. The maximum return of KSE is 8.5%, JKSE is 9.7%, N225 is 13%, SSE is 9.4%, and TWSE is 6.5%. Among the five markets N225 has recorded the highest maximum return and TWSE has recorded the lowest maximum return. The minimum value of return for KSE is -9.7%, JKSE is 11%, N225 is -12%, SSE is -9.2%, TWSE is 6.9%. N225 has recorded the highest negative return among all markets and TWSE has recorded the lowest negative return. The Standard deviation of all series is rare and show a normal pattern. The Skewness of all the series is negative, which indicate that all the series are having left tail and negatively skewed.

Jarque-Bera Test

To check the normality of the data, the study will attempt to observe the Jarque-Bera results. The Ho of this test is that the distribution is normal. The P-values of all series are significant, which leads to the rejection of Ho. All the series are not from the normal distribution. The study will proceed because the study is interested in volatility and asymmetric behavior of the markets. Therefore, the study will further proceed to apply unit root test on the series.

Unit root of Individual stock markets

The unit root test for individual market as shown as below. The study has applied ADF test for each stock market.

Table 4.2: JKSE Unit Root

Ho: LJKSE has a unit root

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-62.93652	0.0001
Test critical values:	1% level	-3.431512	
	5% level	-2.861939	
	10% level	-2.567025	

*MacKinnon (1996) one-sided p-values.

Table 4.3: KSE Unit Root Test

Ho: LKSE has a unit root

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-62.29773	0.0001
Test critical values:	1% level	-3.431512	
	5% level	-2.861939	
	10% level	-2.567025	

*MacKinnon (1996) one-sided p-values.

Table 4.4: N225 Unit Root

H: LN255 has a unit root

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-72.09406	0.0001
Test critical values:	1% level	-3.431512	
	5% level	-2.861939	
	10% level	-2.567025	

*MacKinnon (1996) one-sided p-values.

Table 4.5: SSE Unit Root

Ho: LSSE has a unit root

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-68.40787	0.0001

Test critical values:	1% level	-3.431512
	5% level	-2.861939
	10% level	-2.567025

*MacKinnon (1996) one-sided p-values

Table 4.6: TWSE Unit Root

Ho: LTWSE has a unit root

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-66.49004	0.0001
Test critical values:	1% level	-3.431512	
	5% level	-2.861939	
	10% level	-2.567025	

*MacKinnon (1996) one-sided p-values.

The study has conducted unit root test of each market individually. From table 2 till 6, the ADF test was conduct on these five-stock market. According to the results portrayed in Tables from 2 till 6 all, the series are stationary at level 1(0). Furthermore, ADF test suggest that all series are integrated at level and became stationary therefore, the study will proceed to volatility models.

Volatility Models

In this section the study will attempt to apply volatility models on the five stock markets. The study will carry out the econometric analysis of each market individually. In this section the study will go through the following systemic process.

- Run the auto regression on the series to identify the clusters from residual graph
- Run residual diagnostic to check the ARCH effect through heteroscedasticity test
- Run the ARCH and GARCH model
- Run EGARCH model to check the asymmetric effect

The above figure 1 it can be observed that the volatility clusters from 2001 till mid-2002 and from 2004 mid 2009. The cluster from mid-2018 till 2020, the COVID-19 shock can be clearly observed. The cluster has been identified; the study will check the ARCH effect.

The purpose of testing for ARCH effect is, if the possible presence of ARCH effect is found then the study will require estimate ARCH and GARCH model for volatility modeling. If there is no ARCH effect, then there is no need to estimate the GARCH-Family models.

Table 4.7
ARCH Effect

Heteroscedasticity Test: ARCH Effect

F-statistic	328.2114	Prob. F (1,4862)		0.0000
Obs*R-squared	307.5829	Prob. Chi-Square (1)		0.0000
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000133	6.73E-06	19.80593	0.0000
RESID^2(-1)	0.251475	0.013881	18.11661	0.0000
R-squared	0.063237	Mean dependent variance		0.000178
Adjusted R-squared	0.063044	S.D. dependent variance		0.000451
S.E. of regression	0.000436	Akaike info criterion		-12.63575

Sum squared residuals	0.000926	Schwarz criterion	-12.63308
Log likelihood	30732.15	Hannan-Quinn criteria.	-12.63481
F-statistic	328.2114	Durbin-Watson stat	2.101885
P-Value(F-statistic)	0.000000		

Table 4.7, the mean equation of ARCH effect Test, the p-value of F-statistics is significant at 99% confidence interval level. The variance equation of the model states that the constant and coefficient of ARCH effect (RESID^2(-1)) both are significant at 99% confidence interval level. The significant ARCH effect is witnessed, the study proceeds to estimate the volatility if KSE 100 through ARCH and GARCH model. The result support the estimation of Daly (2008).

1) ARCH Effect

Table 4.8 Output of GARCH models on KSE 100 index

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001177	0.000148	7.952504	0.0000
Variance Equation				
C	7.85E-06	5.29E-07	14.81936	0.0000
RESID (-1) ^2	0.155431	0.009368	16.59150	0.0000
GARCH (-1)	0.802601	0.009765	82.19362	0.0000
R-squared	-0.001285	Mean dependent variance		0.000699
Adjusted R-squared	-0.001285	S.D. dependent variance		0.013343
S.E. of regression	0.013352	Akaike info criterion		-6.090930
Sum squared residuals	0.867140	Schwarz criterion		-6.085594
Log likelihood	14820.19	Hannan-Quinn Criteria.		-6.089057
Durbin-Watson stat	1.772706			

Table 4.8 illustrate the output of GARCH model on KSE 100 index. The results show that the constant of mean equation in the model is statistically significant at 99% interval, since the p-value of constant is less than 0.00. The constant of variance equation along with ARCH (RESID (-1) ^2) and GARCH (GARCH (-1)) term are significant at 99% confidence interval. The ARCH term significance of indicate that the past volatility of KSE 100 index is significantly influencing the current volatility. The significance of GARCH (-1) term is an indication that the past volatilities are influencing the current volatilities in the market and it also portray that large number of volatilities in the KSE 100 are followed by larger volatilities and vice versa. Previous literature has found significance results, while modeling volatilities of KSE 100 index (Akhtar & Khan 2016; Kim , Shephard, & Chib, 1998).

3) EGARCH

The study has attempted to check the asymmetric effect of KSE 100 index. EGARCH model the ARCH and GARCH term along with the asymmetric term. The asymmetric term will indicate the impact of shocks dues to news and losses on current volatilities of KSE 100 index.

Table 4.9 EGARCH Model on KSE 100 Index

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001104	9.77E-05	11.29975	0.0000
Variance Equation				
C 2	-0.866770	0.046688	-18.56522	0.0000
C 3	0.288995	0.014071	20.53815	0.0000
C 4	-0.093994	0.007090	-13.25676	0.0000
C 5	0.927004	0.004512	205.4672	0.0000
R-squared	-0.000923	Mean dependent var		0.000699
Adjusted R-squared	-0.000923	S.D. dependent var		0.013343
S.E. of regression	0.013350	Akaike info criterion		-6.104237
Sum squared resid	0.866826	Schwarz criterion		-6.097567
Log likelihood	14853.56	Hannan-Quinn Criteria.		-6.101896
Durbin-Watson stat	1.773348			

Table 4.9 portray the results of EGARCH model on KSE 100 Index. The constant of mean equation statistically significant at 99% confidence. In variance equation C (2) represent the constant term, C (3) is ARCH term (RESID (-1) ^2), C (4) is asymmetric term and C (5) is GARCH (-1) term. In variance equation all of the coefficients are statistically significant. The significant results are an indication that the past volatilities are affecting the current volatilities. The significant asymmetric term illustrate that the positive shock is affecting the market less than the negative shock. Similarly, the asymmetric behavior of KSE 100 indicate that bad news and losses in the market are followed by more negative shock, previously witnessed by the study conducted in context of KSE 100 index (Akhtar & Khan, 2016).

JKSE Index

The study will run an auto regression on the returns of JKSE index and observe the clusters. The cluster will be identified, which will enable the study whether to check the Heteroskedasticity for ARCH effect.

1) ARCH Effect

Table 4.10 ARCH Effect
Heteroscedasticity Test: ARCH Effect

F-statistic	187.6519	Prob. F (1,4862)		0.0000
Obs*R-squared	180.7528	Prob. Chi-Square (1)		0.0000
Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.000143	8.10E-06	17.63708	0.0000
RESID^2(-1)	0.192773	0.014072	13.69861	0.0000
R-squared	0.037161	Mean dependent var		0.000177
Adjusted R-squared	0.036963	S.D. dependent var		0.000548
S.E. of regression	0.000538	Akaike info criterion		-12.21820
Sum squared resid	0.001406	Schwarz criterion		-12.21553
Log likelihood	29716.66	Hannan-Quinn Criteria.		-12.21726
F-statistic	187.6519	Durbin-Watson stat		2.105021
Prob(F-statistic)	0.000000			

Table 4.10 portray the results of ARCH effect for JKSE index. The p-value of F-statistic is significant with 99% confidence interval the constant and ARCH term (RESID^2(-1)) are also significant, which indicate the estimation of ARCH and GARCH models is required.

2) GARCH

Table 4.11: GARCH Model for JKSE Index

Mean Equation of the Model

Variable	Coefficient		Std. Error	z-Statistic	P-value
C	0.000778		0.000149	5.207244	0.0000
Variance Equation					
C	4.06E-06		4.28E-07	9.486590	0.0000
RESID (-1) ^2	0.129293		0.006944	18.61951	0.0000
GARCH (-1)	0.853193		0.007640	111.6701	0.0000
R-squared	-0.000292	Mean dependent var			0.000551
Adjusted R-squared	-0.000292	S.D. dependent var			0.013306
S.E. of regression	0.013308	Akaike info criterion			-6.098664
Sum squared resid	0.861418	Schwarz criterion			-6.093328
Log likelihood	14839.00	Hannan-Quinn Criteria.			-6.096792
Durbin-Watson	1.794968				

Table 4.11 illustrate the results of GARCH model on JKSE index. The coefficient of mean equation is significant at 99% confidence interval. In the variance equation the constant along with RESID (-1) ^2 and GARCH (-1) term are significant. The past residual square is statistically affecting the current volatilities of JKSE. Similarly, the GARCH (-1) term indicate that the past volatilities are significantly affecting the current returns of JKSE. Furthermore, high volatilities in past are followed by higher risk volatilities. A study conducts by Sharma S. (2021), found similar results in case JKSE index, while model the volatilities of JKSE index and other emerging markets, using non-linear GARCH model.

3) EGARCH

Table 4.12: EGARCH Model on JKSE Index

Mean Equation of the Model

Variable	Coefficient		Std. Error	z-Statistic	Prob.
C	0.000613		0.000149	4.114407	0.0000
Variance Equation					
C 2	-0.45190		0.030579	-14.77795	0.0000
C 3	0.22512		0.011082	20.31413	0.0000
C 4	-0.06037		0.005985	-10.08884	0.0000
C 5	0.96830		0.002945	328.8030	0.0000
R-squared	-0.00002	Mean dependent var			0.000551
Adjusted R-squared	-0.00002	S.D. dependent var			0.013306
S.E. of regression	0.01330	Akaike info criterion			-6.110283
Sum squared resid	0.86118	Schwarz criterion			-6.103613
Log likelihood	14868.2	Hannan-Quinn Criteria.			-6.107942
Durbin-Watson	1.79545				

Table 4.12 illustrate the result of EGARCH model on JKSE. The constant term of mean equation is significant at 99% confidence interval. The variance equation is having four coefficients. C (2) is the constant term, C (3) is the (RESID^2(-1)), C (4) is the asymmetric term (λ). All the coefficients are statistically significant with 99% confidence interval. The ARCH and GARCH term illustrate that past volatilities are affecting the current volatilities and the future volatilities can be estimated through past volatilities of JKSE index. The asymmetric term portrays that negative shock have high impact on the series than the positive shock. Similarly, bad news and losses are affecting the current volatilities higher than good news and gains. This confirms the weak form efficiency of efficient market hypothesis in JKSE index. The study conducts by Sharma S. (2021) also attempted to apply the EGARCH model to check for asymmetric effect on JSKE and other emerging markets and the results of this study are similar with it.

1) ARCH Effect

Table 4.13: ARCH Effect
Heteroskedasticity Test: ARCH

F-statistic	414.0921	Prob. F (1,4862)		0.0000
Obs*R-squared	381.7492	Prob. Chi-Square (1)		0.0000
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000161	9.54E-06	16.93071	0.0000
RESID ^2 (-1)	0.280153	0.013767	20.34925	0.0000
R-squared	0.078485	Mean dependent var		0.000224
Adjusted R-squared	0.078295	S.D. dependent var		0.000656
S.E. of regression	0.000629	Akaike info criterion		-11.90330
Sum squared resid	0.001926	Schwarz criterion		-11.90064
Log likelihood	28950.83	Hannan-Quinn Criteria.		-11.90237
F-statistic	414.0921	Durbin-Watson stat		2.169717
Prob(F-statistic)	0.000000			

Table 4.13 illustrate the result of heteroscedasticity test for ARCH effect of N225. The F-statistics of ARCH effect is significant since its p-value is less than 1%. The constant and RESID^2(-1) are also significant. The significant RESID^2(-1) the presence of ARCH effect, thus the study has a green signal to estimate GARCH model on N225 Index.

2) GARCH

Table 4.14: GARCH Model for N225 Index

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000584	0.000168	3.482533	0.0005
		Variance Equation		
C	4.25E-06	5.79E-07	7.346141	0.0000
RESID (-1) ^2	0.112861	0.006644	16.98596	0.0000
GARCH (-1)	0.870794	0.007821	111.3429	0.0000
R-squared	-0.000921	Mean dependent var		0.000129
Adjusted R-squared	-0.000921	S.D. dependent var		0.014981
S.E. of regression	0.014988	Akaike info criterion		-5.842858
Sum squared resid	1.092706	Schwarz criterion		-5.837522
Log likelihood	14216.75	Hannan-Quinn Criteria.		-5.840986
Durbin-Watson stat	2.064160			

Table 4.14 illustrate the output of GARCH model on N225 index. The constant in the mean equation is significant. In the variance equation the constant along with ARCH term RESID (-1) ^2 and GARCH (-1) term. The ARCH and GARCH term indicate the past shocks are significantly affecting the current volatilities of N225 index. Similarly, past volatility is significant enough to predict the future volatilities of N225 index. A study conducted by Takahashi et al. (2021), on N225 modeling its volatilities, found similar results.

3) EGARCH

Table 4.15: EGARCH Model for N225 Index

Mean Equation

Variable	Coefficient	Std. Error	z-Statistic	Prob.

C (1)	0.000613	0.000149	4.114407	0.0000
Variance Equation				
C (2)	-0.458790	0.033125	-13.85010	0.0000
C (3)	0.197748	0.010933	18.08709	0.0000
C (4)	-0.101230	0.005056	-20.02253	0.0000
C (5)	0.964535	0.003264	295.5441	0.0000
R-squared	-0.000075	Mean dependent var		0.000129
Adjusted R-squared	0.000131	S.D. dependent var		0.014981
S.E. of regression	0.014981	Akaike info criterion		-5.869475
Sum squared resid	1.091781	Schwarz criterion		-5.864139
Log likelihood	14281.50	Hannan-Quinn Criteria.		-5.867602
Durbin-Watson stat	2.065908			

Table 4.15 illustrate the output of EGARCH model for N225 index. The constant of mean equation is statistically significant at 99% confidence interval. In the variance equation C (2) represent the constant, C (3) is ARCH term, C (4) is asymmetric term and C (5) is GARCH term. All the coefficients of variance equation are statistically significant. The asymmetric term indicates that not only past volatilities are affecting the current volatilities, negative shocks that are caused by bad news and losses, this asymmetry also affect the current and future volatilities of N225 index. Similarly, negative shocks caused by bad news and losses affect the market more than good news and gains. This asymmetric behavior of N225 index is also witnessed by a group of researchers from Japan (Takahashi et al, 2021).

1) ARCH Effect

Table 4.16: ARCH Effect
Heteroskedasticity Test: ARCH

F-statistic	130.9294	Prob. F (1,4862)		0.0000
Obs*R-squared	127.5485	Prob. Chi-Square (1)		0.0000
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000203	9.67E-06	21.00081	0.0000
RESID^2(-1)	0.161936	0.014152	11.44244	0.0000
R-squared	0.026223	Mean dependent var		0.000242
Adjusted R-squared	0.026023	S.D. dependent var		0.000639
S.E. of regression	0.000630	Akaike info criterion		-11.90016
Sum squared resid	0.001932	Schwarz criterion		-11.89749
Log likelihood	28943.19	Hannan-Quinn Criteria.		-11.89922
F-statistic	130.9294	Durbin-Watson stat		2.039354
Prob(F-statistic)	0.000000			

Table 4.16 provide the results of heteroscedasticity test. The p-value of F-statistics is significant at 99% confidence interval. In the variance equation the constant is significant along RESID^2(-1) are significant. Since the ARCH effect is witnessed in SSE index the study will now estimate GARCH model on SSE to model its volatilities.

2) GARCH

Table 4.17: GARCH Model for SSE Index

Mean Equation

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Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000196	0.000157	1.252630	0.2103
Variance Equation				
C	1.81E-06	2.46E-07	7.385737	0.0000
RESID (-1) ^2	0.081369	0.003812	21.34479	0.0000
GARCH (-1)	0.915437	0.003529	259.4167	0.0000
R-squared	-0.000034	Mean dependent var		0.000105
Adjusted R-squared	-0.000034	S.D. dependent var		0.015565
S.E. of regression	0.015565	Akaike info criterion		-5.774034
Sum squared resid	1.178378	Schwarz criterion		-5.768698
Log likelihood	14049.34	Hannan-Quinn Criteria.		-5.772161
Durbin-Watson stat	1.961554			

Table 4.17 illustrate the output of SSE index for GARCH model. The constant of mean equation is not statistically significant since it p-value is great than 1% of significance level. Since the main concern of the study is to model the volatility of the index so the study is more interested in variance equation of GARCH model. In the variance all of the coefficients are significant. The significant ARCH and GARCH term indicate that the past volatilities are significantly affecting the current volatilities of SSE index. The RESID (-1) ^2 represent the past residual square and GARCH (-1) is it generalize form. A study was conduct which modeled the volatility of SSE and applied the GARCH family model (Lin, 2018).

3) EGARCH

Table 4.18: EGARCH Model for SSE Index

Mean Equation

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000143	0.000159	0.895872	0.3703
Variance Equation				
C (2)	-0.255136	0.015158	-16.83167	0.0000
C (3)	0.184037	0.007535	24.42549	0.0000
C (4)	-0.023104	0.004160	-5.553485	0.0000
C (5)	0.986040	0.001628	605.5009	0.0000
R-squared	-0.000006	Mean dependent var		0.000105
Adjusted R-squared	-0.000006	S.D. dependent var		0.015565
S.E. of regression	0.015565	Akaike info criterion		-5.783725
Sum squared resid	1.178344	Schwarz criterion		-5.777055
Log likelihood	14073.91	Hannan-Quinn Criteria.		-5.781384
Durbin-Watson stat	1.961610			

Table 4.18 illustrate the result of EGARCH model for SSE asymmetric effect. The constant of mean equation is insignificant, since its p-value is greater than 5% significance level. However, already discuss in the interpretation of Table 17 the main concern is to study the variance equation. In the variance equation all the coefficients are significant. To check the asymmetric effect, the study will observe the coefficient of C (4). The significant asymmetric term indicates the current and future volatilities are affected by the news and losses. Similarly, negative shock caused by bad news and losses in the market are negatively affecting the market with higher intensity than good news and gain. Thus, negative shock is badly affecting the SSE index than positive shock. A study attempted to model the volatility of SSE using GARCH-Family models, also witnessed the asymmetry in volatilities of SSE (Lin, 2018).

1) ARCH Effect

Table 4.19: ARCH Effect for TWSE

Heteroskedasticity Test: ARCH

F-statistic	133.8138	Prob. F (1,4862)		0.0000
Obs*R-squared	130.2831	Prob. Chi-Square (1)		0.0000
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000134	5.77E-06	23.19772	0.0000
RESID^2(-1)	0.163663	0.014148	11.56779	0.0000
R-squared	0.026785	Mean dependent var		0.000160
Adjusted R-squared	0.026585	S.D. dependent var		0.000375
S.E. of regression	0.000370	Akaike info criterion		-12.96371
Sum squared resid	0.000667	Schwarz criterion		-12.96104
Log likelihood	31529.75	Hannan-Quinn Criteria.		-12.96278
F-statistic	133.8138	Durbin-Watson stat		2.046194
Prob(F-statistic)	0.000000			

Table 4.19 portray the results of TWSE for ARCH effect. The p-value of F-statistics is significant, which indicate that the model is significant. In the variance equation constant and RESID^2(-1) are significant at 99% confidence interval. Since the ARCH effect is found, the study will proceed to estimate GARCH and EGARCH model.

2) GARCH

Table 4.20: GARCH Model for TWSE

Mean Equation				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000504	0.000141	3.561356	0.0004
Variance Equation				
C	1.61E-06	1.95E-07	8.275877	0.0000
RESID (-1) ^2	0.073988	0.004484	16.49940	0.0000
GARCH (-1)	0.916274	0.005025	182.3347	0.0000
R-squared	-0.000595	Mean dependent var		0.000195
Adjusted R-squared	-0.000595	S.D. dependent var		0.012656
S.E. of regression	0.012659	Akaike info criterion		-6.192621
Sum squared resid	0.779507	Schwarz criterion		-6.187285
Log likelihood	15067.55	Hannan-Quinn Criteria.		-6.190748
Durbin-Watson stat	1.903661			

Table 4.20 illustrate the output of GARCH model for TWSE. In the mean equation the constant is significant. In the variance equation the constant along with ARCH term and GARCH term are significant. The significant results in variance portray that past volatilities are significantly affecting the current volatilities. Similarly, the past volatilities can be used to predict the future volatilities of TWSE. Sharma (2017), attempted to model the volatility of Asia Pacific Market usnig GARCH family model, took TWSE as sample market, the results of the study are similar with this research.

3) EGARCH

Table 4.21: EGARCH Model for TWSE

Mean Equation				
Variable	Coefficient	Std. Error	z-Statistic	Prob.

C	0.000264	0.000140	1.891715	0.0585
Variance Equation				
C (2)	-0.250859	0.017218	-14.56972	0.0000
C (3)	0.142349	0.007796	18.25838	0.0000
C (4)	-0.069136	0.005054	-13.67888	0.0000
C (5)	0.984189	0.001591	618.6098	0.0000
R-squared	-0.000030	Mean dependent var		0.000195
Adjusted R-squared	-0.000030	S.D. dependent var		0.012656
S.E. of regression	0.012656	Akaike info criterion		-6.214869
Sum squared resid	0.779067	Schwarz criterion		-6.208199
Log likelihood	15122.67	Hannan-Quinn Criteria.		-6.212528
Durbin-Watson stat	1.904736			

Table 4.21 illustrate the result of EGARCH model for TWSE index. The mean equation of the model is significant. In variance equation the constant along with ARCH GARCH and asymmetric term, all of the coefficients are significant. The significant asymmetric term indicates that TWSE index is having asymmetric volatilities. Similarly, the results portray that negative shocks in the series are causing more negative shock. However, positive shocks are not causing any significant positive impact on TWSE index. The results are significant, it can be generalized that all the stock markets in Asia pacific are having the same behavior. This can also be confirmed from a previous study conducted by Sharma (2017) on Asia Pacific stock market.

Summary of Results

The study attempts to model volatility of Asian pacific regions. They are KSE, JKSE index, N225 index, SSE index, and TWSE. For KSE, the constant of variance equation along with ARCH (RESID (-1) ^2) and GARCH (GARCH (-1)) term are significant at 99% confidence interval. The ARCH term significance of indicate that the past volatility of KSE 100 index is significantly influencing the current volatility. The significance of GARCH (-1) term is an indication that the past volatilities are influencing the current volatilities in the market. Results of EGARCH model on KSE 100 Index. The constant of mean equation statistically significant at 99% confidence. In variance equation C (2) represent the constant term, C (3) is ARCH term (RESID (-1) ^2), C (4) is asymmetric term and C (5) is GARCH (-1) term. In variance equation all of the coefficients are statistically significant. The significant results are an indication that the past volatilities are affecting the current volatilities. The significant asymmetric term illustrate that the positive shock is affecting the market less than the negative shock.

Discussing JKSE index, the GARCH (-1) term indicate that the past volatilities are significantly affecting the current returns of JKSE. Furthermore, high volatilities in past are followed by higher risk volatilities. The results of EGARCH model on JKSE shows constant term of mean equation significant at 99% confidence interval. The variance equation is having four coefficients. C (2) is the constant term, C (3) is the (RESID^2(-1)), C (4) is the asymmetric term (λ). All the coefficients are statistically significant with 99% confidence interval. The ARCH and GARCH term illustrate that past volatilities are affecting the current volatilities and the future volatilities can be estimated through past volatilities of JKSE index. The asymmetric term portrays that negative shock have high impact on the series than the positive shock. Similarly, bad news and losses are affecting the current volatilities higher than good news and gains. This confirms the weak form efficiency of efficient market hypothesis in JKSE index.

The constant in the mean equation is significant for GARCH model on N225 index. In the variance equation the constant along with ARCH term RESID (-1) ^2 and GARCH (-1) term. The ARCH and GARCH term indicate the past shocks are significantly affecting the current volatilities of N225 index. Similarly, past volatility is significant enough to predict the future volatilities of N225 index. The output of EGARCH model for N225 index shows constant mean equation as statistically significant at 99% confidence interval.

All the coefficients of variance equation are statistically significant. The asymmetric term indicates that not only past volatilities are affecting the current volatilities, negative shocks that are caused by bad news and losses, this asymmetry also affect the current and future volatilities of N225 index. Similarly, negative shocks caused by bad news and losses affect the market more than good news and gains.

Output of SSE index for GARCH model shows constant mean equation not statistically significant since it p-value is great than 1% of significance level. Since the main concern of the study is to model the volatility of the index so the study is more interested in variance equation of GARCH model. In the variance all of the coefficients are significant. The significant ARCH and GARCH term indicate that the past volatilities are significantly affecting the current volatilities of SSE index. The result of EGARCH model for SSE asymmetric effect shows the constant mean equation as insignificant, since its p-value is greater than 5% significance level. However, already discuss in the interpretation of Table 17 the main concern is to study the variance equation. In the variance equation all the coefficients are significant. The significant asymmetric term indicates the current and future volatilities are affected by the news and losses. Similarly, negative shock caused by bad news and losses in the market are negatively affecting the market with higher intensity than good news and gain. Thus, negative shock is badly affecting the SSE index than positive shock.

Lastly, output of GARCH model for TWSE, the mean equation of constant is significant. In the variance equation the constant along with ARCH term and GARCH term are significant. The significant results in variance portray that past volatilities are significantly affecting the current volatilities. Similarly, the past volatilities can be used to predict the future volatilities of TWSE. For EGARCH model, TWSE index mean equation of the model is significant. In variance equation the constant along with ARCH GARCH and asymmetric term, all of the coefficients are significant. The significant asymmetric term indicates that TWSE index is having asymmetric volatilities. Similarly, the results portray that negative shocks in the series are causing more negative shock. However, positive shocks are not causing any significant positive impact on TWSE index.

Since all results of Asian pacific region are significant, it can be generalized that all the stock markets in Asia pacific are having the same behavior. The results also confirm the weak form efficiency (discussed in detail in first chapter) of efficient market hypothesis theory in the Asian pacific regions. So, testing the EMH is justifies in Asian pacific regions.

CONCLUSION

The study is undertaken in order to observe the volatilities and risk in Asian Pacific Markets. In the first chapter the study attempted to discuss the theoretical background of stock market behavior through Efficient Market Hypothesis. The study also discussed the theoretical background of volatility models and its evolution throughout the time. The study critically reviews volatility model that were developed over the time. Then the best model was chosen based on literature. Previously, these markets were studied individually and were not covered in a single study. In chapter two of the study, the literature was critically reviewed. The study first reviewed the literature on the volatilities in the developed market, then the literature about developed studies were discussed and then the volatilities in Asia pacific market were studied through literature. In the third chapter the study discussed the data collection and the sample markets. The study took five stock markets across the region, KSE 100, JKSE, N225, SSE and TWSE markets were taken as sample to study the Asian pacific markets and generalize the results for the region.

In the methodology section the study discussed the econometric tools that were used in the research. First, the model's specification for unit root test was discussed and estimated. Then, the volatility models were specified and estimated. The study used ARCH, GACRH and EGARCH model for modeling the Volatility of Asia pacific markets. In the fourth chapter the study applied some econometric and statistically tools on the sample stock markets. In the descriptive statistics the study witnessed that among the five markets N225 has recorded the highest maximum return and TWSE has recorded the lowest maximum return. N225 has recorded the highest negative return among all markets and TWSE has recorded the lowest negative return. In normality test the P-values of all series were significant, which lead to the rejection of Ho. All the series were not from the normal distribution. However, study proceeded because the study was interested in volatility and asymmetric behavior of the markets. The study then tests the markets for unit root and found significant results that all of the series were integrated at level.

The last phase of the analysis the study applied the volatility models. The study found that all of the series were having ARCH effect and are having Heteroscedasticity. While estimating the GARCH model for the markets the study found similar results and all of the results were similar with the literature in case of TWSE Sharma (2017); in case of SSE Lin (2017); in case N225 Takahashi et al. (2021); in case of KSE 100 Akhtar and Khan, (2016); in case of JKSE Sharma et al, (2020). The study found that all of the stock markets are having asymmetric behavior through the output of EGARCH model of all the stock market.

It is concluded that all the Asian Pacific markets behaving in same manner. To forecast the future return and volatilities in Asian Pacific markets, past volatilities can be used. The study also made it clear that past volatilities are affecting the current volatilities of these stock markets. Thus, it is empirically proved that past volatilities are significant enough to predict the future return of Asian Pacific stock markets. The study also witnessed that negative shocks caused by bad news and losses, bring more negative shocks, and harm the stock market. In contrast positive shocks caused by good news and gain do not bring significant positive impact on the stock market.

RECOMMENDATIONS

The recommendation for investors is that holding any security on the Asia Pacific Stock Markets are not risky the volatilities can be forecasted. Since these markets are predictable which makes them less risky. Therefore, the investors can hold the security for long-run. However, other factors should be taken into consideration like political and economic situations of the country. Recently the rupees lost its value due to political instability in the country that brought a huge impact on the Pakistan stock exchange. Relying on single study result is not recommended for investors.

IMPLICATION OF THE STUDY

The study provides following implications for investors in Asian pacific stock markets.

- The various GARCH models provide good forecasts of volatility and are useful for portfolio allocation, performance measurement, option valuation, etc.
- Given the anticipated high growth of the economy and increasing interest of foreign investors towards the regions, it is important to understand the pattern of stock market volatility in Asian pacific countries that are time-varying, persistent, and predictable. This may help diversify international portfolios and formulate hedging strategies.
- Our results have important implications for index investing and option pricing. The index investing approach is generally considered a passive strategy. However, our results suggest that major events may lead to volatility shifts and may alter the risk-return trade-off.
- Investors and market participants such as traders are highly recommended to be cautious and better understand the risk factor originated from the volatility observed in the Asian pacific regions.
- It is crucial for investors and traders to re-weight their international stock holding portfolios.

LIMITATIONS AND FUTURE RESEARCH DIRECTION

One of the limitations of our study is that the GARCH models used in the study do not take account of the issues of long memory (Baillie, Bollerslev, & Mikkelsen, 1996) and scale consistency (Drost & Werker, 1996), which are commonly found in the recent literature of asset prices. This problem could be overcome by alternatively applying a multifractal model, which can simultaneously incorporate the properties of long memory and scale consistency in the data series (Mandelbrot, Fisher, & Calvet, 1997). Since multifractal models are substantially different from GARCH-type models, we leave this approach as one of the research directions for the future. Furthermore, the main limitations of our research study is due to the relatively small number of only 5 selected Asian pacific countries for the sample. A future extension of this research study will include a much larger number of countries.

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