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# An Empirical Investigation of Comparative Performance of GARCH Family Models and EWMA Model in Predicting Volatility of TSEC Weighted Index of Taiwan

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## Abstract

The act of modeling and forecasting stock market volatility has become essential to risk management practice; it has emerged as one of the most popular themes in financial econometrics and has been mainly and constantly used in the valuation of financial assets and the Value at Risk, as well as the pricing of options and derivatives, are all part of the process. The purpose of this paper is to contrast the GARCH (Generalized Auto Regressive Conditional Heteroscedasticity) family models – GARCH, PGARCH, EGARCH, GJR-GARCH, MGARCH, and IGARCH – with the EWMA (Exponentially Weighted Moving Average) models in the prospect of establishing the best algorithm to forecast TSEC volatility weighted index from Taiwan stock market. We employ daily returns for the range between July 1997 and July 2023. The sample data spans a long time period i.e. 26 years of data with 6375 observations, which includes dramatic events such as the financial crisis of 2008, the COVID-19 epidemic, and the war between Russia and Ukraine. We observe that the asymmetric model PGARCH with a Student's t distribution develops the best model for assessing the volatility of the chosen index, but PGARCH with a normal error distribution produces the best estimating performance outcomes and hence outperforms the EWMA model. The present empirical investigation also seeks to illustrate the potential for investment returns as well as the associated risk. Our findings may have implications for risk management in Taiwan, together with a deeper exploration of the TSEC weighted index from Taiwan stock market volatility dynamics, given the scarcity of prior such studies.

**Keywords**: volatility spillovers, GARCH family models, forecasting stock market volatility, EWMA, stock index, emerging stock market, risk, international diversification of the portfolio

**JEL Code**: B26, C19, C58, G10, G11, and G17.

## Introduction

Forecasting the volatility of indices is of paramount importance in the world of finance and investment. Volatility, often measured by indicators such as the VIX (Volatility Index), refers to the degree of fluctuation or uncertainty in the prices of financial instruments (Pindyck, 2004). Understanding and predicting volatility allows shareholders, merchants, and risk managers to make well-versed decisions and commendably manage their portfolios. Accurate volatility forecasts provide valuable insights into market behavior, enabling market participants to anticipate potential risks and adjust their strategies accordingly (H. Liu et al., 2020)(Onali, 2020). By analyzing historical patterns and employing statistical models, experts can estimate the future volatility of indices, allowing investors to allocate their assets appropriately and optimize their risk-return trade-offs (Glosten et al., 1993) (Hawaldar et al., 2022). Additionally, volatility forecasting is essential for derivative pricing and trading strategies. Derivative instruments, such as options and futures, are heavily influenced by volatility (Hawaldar et al., 2020)(Abounoori & Zabol, 2020)(Manera et al., 2013) (Meher et al., 2020). Accurate volatility forecasts allow traders to assess the fair value of these instruments and develop effective trading strategies to profit from volatility swings.

Forecasting the volatility of the TSEC Weighted Index of Taiwan holds significant importance in financial research and market analysis(C.-L. Chang et al., 2012). The TSEC Weighted Index, also termed as the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX), is a key benchmark for the Taiwanese stock market. Understanding and accurately predicting its volatility can yield several benefits. Financial institutions and portfolio managers need accurate volatility estimates to assess the risk associated with their Taiwanese investments. This information helps them determine appropriate risk management strategies, set risk limits, and allocate capital effectively. Understanding the potential volatility of the TAIEX allows these entities to evaluate the potential downside risk of their portfolios and take preventive measures to safeguard against adverse market movements.

Volatility forecasting using GARCH (Generalized Autoregressive Conditional Heteroskedasticity) family models and EWMA (Exponentially Weighted Moving Average) are two popular approaches for estimating and predicting volatility in financial markets. GARCH models are widely used for volatility forecasting due to their ability to capture time-varying volatility patterns. GARCH models assume that volatility is influenced by past volatility and squared residual errors. These models estimate the conditional variance of a time series, which can then be used to forecast future volatility. On the other hand, EWMA is a simpler method that assigns exponentially decreasing weights to historical volatility observations. It places more weight on recent observations and less weight on older observations, assuming that recent volatility is more relevant for future volatility forecasting. The paper is an effort to examine the effectiveness of GARCH Family and EWMA by taking into consideration TSEC Weighted Index of Taiwan. Ultimately, the choice between GARCH family models and EWMA depends on the specific requirements of the analysis and the intended forecasting horizon. GARCH models are better suited for capturing longer-term volatility patterns and more intricate dynamics, while EWMA is advantageous for shorter-term forecasting and simplicity in implementation. This paper is an effort to examine the effectiveness of GARCH Family prototypes and EWMA model using the data of index values of TSEC.

# Review of Literature

The review of literature section is divided into three sub sections. The first subsection highlights the major researches on forecasting volatility. The second section reflects the studies specifically related to GARCH model and the last sub-section throws the light on the researches related to EWMA model.
(Yang et al., 2019) investigate how stockholder sentiment and spillover affect the predictability of crude oil futures market volatility over the course of a day, a week, and a month. (Cristi, Birau, Kumar, et al., 2023) have developed the study of volatility pattern using GARCH family model for USA and Netherland, (Cristi, Birau, Trivedi, Iacob, et al., 2023) have developed the study of volatility pattern using GARCH family model for grouping of advanced stock markets that includes Austria, France, Germany, and Spain, (Meher et al., 2023) have developed the study of volatility analysis of OMX Tallinn Index in the case of Estonia's new and promising stock exchange using PARCH model, (Kumar et al., 2023) have developed the an empirical case study of volatility analysis of Toronto Stock Exchange using PGARCH Model, (Cristi, Birau, Trivedi, Simion, et al., 2023) have developed the study of volatility pattern using GARCH family model for Italy and Poland. (Tan et al., 2019) In order to estimate daily volatility, we propose the quantile Parkinson (QPK) measure and demonstrate how it can strengthen the Parkinson (PK) measure when dealing with intraday extreme returns.(Jawadi et al., 2019)using high frequency data, try to model and predict volatility in both the oil and USD exchange rate markets. (Wang et al., 2020) bolster the GARCH-MIDAS model's predictive power by incorporating asymmetric and extreme volatility effects into its framework. (Sharma et al., 2021)aspire to evaluate and contrast the volatility forecasting abilities of the symmetric and asymmetric GARCH models applied China, India, Indonesia, Brazil, and Mexico. Using univariate volatility models like GARCH (1, 1), E-GARCH (1, 1) and T-GARCH-(1, 1), this study empirically examines the volatility of financial markets in five major emerging countries over a period of two decades, from January 2000 to December 2019. (Lyócsa & Todorova, 2020)check out the pros and cons of modeling the stock volatility over the next one to twenty-two days using trading and non-trading period market volatilities. Since then, many new theoretical advancements and methodologies have emerged, vastly enhancing our ability to predict and analyze market volatility and other forms of risk. Following this line of thinking there are other works of significance (Ramos-Pérez et al., 2019)(Capelli et al., 2021).

(Dhankar, 2019) (Meher et al., 2022) examine various VaR estimation techniques and their uses. (C.-W. Chang, 2020)in order to address the costs associated with diabetes hospitalization and treatment, suggest an early warning payment algorithm that uses data analytics technology. (Chamizo & Novales, 2021) try out hedging in three distinct ways: with single stocks, with sectoral portfolios, and with regional investments. Other influential work includes (Hendrych & Cipra, 2019), (Jeng et al., 2020), (Araneda, 2021).

(Guesmi et al., 2019) look into the legitimacy of Bitcoin in the market for financial services. because of the significance of geopolitical risk and its potential to predict oil price volatility. (J. Liu et al., 2019) intend to conduct a quantitative study of geopolitical risk (GPR), and more specifically, serious geopolitical risk (GPRS), in predicting oil volatility. (Troster et al., 2019) modeling and predicting bitcoin yields and risk requires performing a general GARCH and GAS analysis. (Bangar Raju et al., 2020)the use of EGARCH models to investigate and analyze market volatility in GOI and GOFI countries. Focusing on measuring the inherent correlation (Sun et al., 2020)to settle the heated argument over whether or not the maritime industry is exposed to extreme risk from the commodity market, a GARCH-Copula-CoVaR analysis is recommended. Other influential work includes(Gronwald, 2019), (Pal & Mitra, 2019).

*Research Gap*

The existing studies are not enough that could throw light on the effectiveness of both GARCH family and EWMA model using the Taiwan Index. Hence, this study is conducted taking into consideration this feasible research gap to provide ample analysis to compare both the models and measure its effectiveness using TSEC Weighted Index of Taiwan.

## Significance of the Study

A research study that compares the effectiveness of GARCH and EWMA (Exponentially Weighted Moving Average) models using the TSEC (Taiwan Stock Exchange Corporation) Weighted Index of Taiwan can provide significant benefits to society. Firstly, such research is invaluable for investment decision-making. The TSEC Weighted Index is a crucial indicator of the performance of the Taiwanese stock market. By comparing the predictive capabilities of GARCH and EWMA models in estimating volatility or risk in the index, the study offers valuable insights to investors and financial professionals. This information enables them to make more informed investment decisions, effectively manage risk, and optimize portfolio allocations. Secondly, risk management is a vital aspect of financial markets. Evaluating the performance of different volatility models, such as GARCH and EWMA, in the context of the TSEC Weighted Index helps market participants, including financial institutions, regulators, and policymakers, gain a deeper understanding of market risks. Insights from this study can help with development of more effective risk management approaches and policies, enhancing stability and resilience within the financial system. Furthermore, the research study advances financial modeling and forecasting methodologies. By comparing GARCH and EWMA models, it improves modeling techniques for capturing market dynamics not only in Taiwan but also globally. This enhances the accuracy and reliability of predictions, scenario analysis, and stress testing, benefiting financial analysts, economists, and researchers in their work.

## Research Methodology

This investigation examines the changes in volatility parameters and movement performance of a selected illustration of Taiwan stock market indices, namely the TSEC weighted index. Studies investigate whether or not there is asymmetry in the transmission of volatility, the path taken by shocks of greater positive and negative magnitudes, and the overall model's viability. Traditional heteroskedastic models either specify the conditional variance as in(Bollerslev, 1986) or describe the conditional standard deviation directly as in (Taylor, 1987). ADF and PP test statistic have been used to determine whether the data is stationary in nature in order to apply the GARCH family's models (Kumar et al., 2023). To choose the most appropriate asymmetric volatility model for stock markets, numerous criteria have been used to examine the results of the models after they had been created using different distributions. E-Views 10 and 12 has been applied to the creation of models for selected stock indexes.

Following are the main equation which has been used for estimation the best model and analysis.

**A.** The following formula is for EGARCH model (Hassan, 2012)&(Dhamija & Bhalla, 2010).

$$\log(\sigma_t^2) = \omega + \sum_{j-i}^{p} \beta i \log(\sigma_{t-i}^2) + \sum_{j-1}^{q} \alpha i \langle \frac{\varepsilon i - t}{\sigma_{i-t}} \left| \frac{-\sqrt{2}}{n} \right| - yi \frac{\varepsilon i - t}{\sigma i - t} \rangle$$

**B.** The following formula is for MGARCH model which was proposed by (Engle, 1986)

$$y_t = \varphi + \sum_{k=1}^{p} \theta_k h_{t-k} + \sum_{i=1}^{q} b_i u_{t-i}^2$$

**C.** For the GJR- GARCH

$$\sigma_t = \omega + \alpha \iota [\varepsilon_{t=1} \geq 0] \varepsilon_{t=1} + \gamma \iota [\varepsilon_{t=1} < 0] \varepsilon_{t=1} \beta \alpha_{t-1}$$

Here, if $\gamma > 0$, there is an asymmetry, showing that the impression of positive and negative news on conditional volatility is different.

**D.** PGARCH models (Salamat, et al., 2019)& (Alsharkasi, Crane, & Ruskin, 2016).
The variance in a PGARCH model (Ding, Granger, & Engle, 1993) (general) is written as:

$$\sigma_t^\delta = \omega + \sum_{i=1}^{p} (\alpha_i \, |y_{t-i}| - y_i \; y_{t-i})^\delta + \sum_{j=1}^{q} \beta_j \, \sigma_{t-j}^\delta$$

**E.** In the last following equation is used for estimation of IGARCH model:
IGARCH models are considered volatile because present knowledge stays valid for anticipating volatility across all time spans.

$$h_t^2 = \alpha_0 + \sum_{i=0}^{q} \alpha \, u_{t-1}^2 + \sum_{i=0}^{p} \beta \, h_{t-1}^2$$

**F.** For the main objective of the paper following formula is used for calculation of the EWMA

The EWMA model (Exponentially Weighed Moving Average) is one of the oldest statistical models, and it is in response to the shortcomings of both the basic and historical volatility models, which place equal emphasis on past observations, this model was developed.
In reality, the importance of new knowledge tends to outweigh that of very old data. And it is because of this that, despite its simplicity, EWMA is a very powerful model. Many academics find GARCH models lacking, but EWMA has the advantage of not reverting to the mean. This is why there is a substantial body of research showing that EWMA can provide better volatility forecasts than GARCH models. The EWMA may be outlined as

$$\sigma^2(EWMA) = \lambda \sigma_{n-1}^2 + (1-\lambda) \gamma_{n-1}^2$$

Where $\sigma^2$n signifies volatility at time n, $\sigma_{N-1}^2$ is the initial volatility lag, and λ is known as the smoothing coefficient. When the occurrence of observations is daily, the value of λ was set to 0.94. Term $(1-\lambda)\gamma_{n-1}^2$ measures the variance's response intensity to market news, whereas $\lambda \sigma_{n-1}^2$ is utilised to capture volatility persistence.

## Empirical Results, Discussion and Findings

We start out by conducting descriptive statistics study to understand the value of the shareholder return in chosen stock market indexes from July 1997 to July 2023. Table 1 summarizes the economic viability of the sample stock index. The mean return of stock index is 9.85 whereas standard deviation is 0.013 and Skewness is negative .021879. This means that, while stock indexes present more substantial returns, their volatility (risk) is also higher than usual. The presence of leptokurtic influence on the series returns is shown by the aberrant pattern of kurtosis.

**Table 1 - Descriptive statistics and Normality of PGARCH model residues.**

| x̄ | Md | Max | Min | σ | Skew[X] | K | J-B | Sum Sq. Dev. | Obs |
|---|---|---|---|---|---|---|---|---|---|
| 9.85E-05 | 0.000429 | 0.085198 | -0.09936 | 0.013546 | -0.21879 | 6.689 | 3665.509 | 1.169 | 6375 |

*Source: Own computations of the author using particular financial data series*

TSEC weighted index from Taiwan stock market contains a significant number of normal volatility rates. Series returns provide a definite and obvious indicator of the market decline as a result of the worldwide economic downturn (see Fig.1). Investors, academics, and researchers ought to keep careful consideration to the post-financial crisis scale and positive returns ratios. It unequivocally demonstrates how seriously investors take long-term investing.

Log returns for financial data series, such as the TSEC weighted index from Taiwan stock market has been determined for the six asymmetric GARCH prototype, Simple GARCH, EGARCH, GJR- GARCH, MGARCH, PGARCH and IGARCH. The sample data of the Taiwan stock price were again tested for stationarity using the unit root test (Table 2).

**Table 2 - Outcomes of Unit root test**.

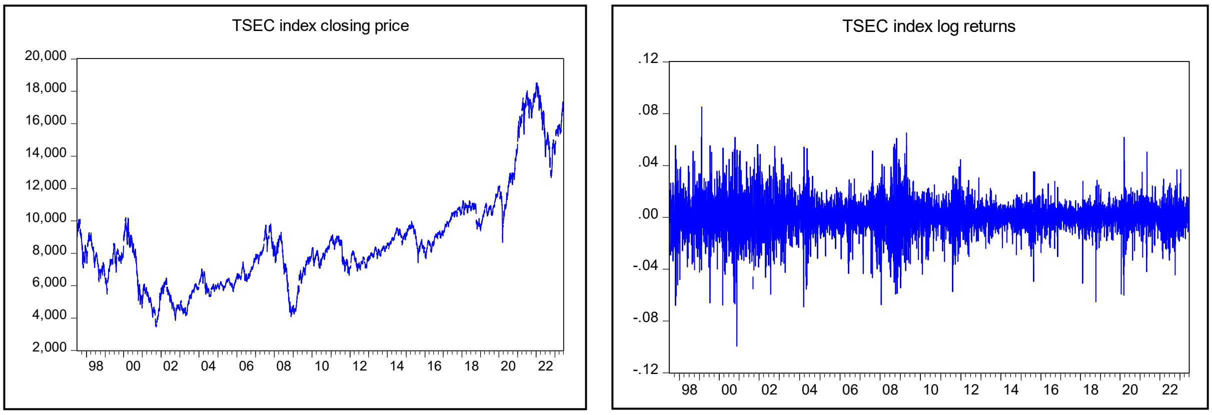
| Null Hypothesis: TSEC_INDEX_LOG_RETURNS has a unit root | | | | |
|---|---|---|---|---|
| | | | t-Statistic | Prob.* |
| **AD test outcomes** | | | -17.86059 | 0.0000 |
| A critical values: | 0.01 level | | -3.431200 | |
| | 0.05 level | | -2.861800 | |
| | 0.10 level | | -2.566951 | |
| | | | Adj. t-Stat | Prob.* |
| **PP test results** | | | -76.60359 | 0.0001 |
| A critical values: | At 0.01 level | | -3.431197 | |
| | 0.05 level | | -2.861799 | |
| | 0.10 level | | -2.566950 | |

Source: Authors' own computations using Eviews10

The following sections are built on evaluating the relevant hypotheses needed to create the GARCH family models. Following figure shows graphs with the log returns of the selected index displayed to show the presence of volatility clustering (Fig.1)

The property of Fig.1 indicates there are different clusters in this diagram because we can see that in Line graphs Fig.1, sometimes volatility is high and sometimes volatility is less.

It is evident that the returns of the selected stocks of Taiwan Stock Exchange markets were highly variable. These significant changes during 2020 and 2022 are a blatant sign that the pandemic and Russia Ukraine war having a leveraging impact on market values, and asymmetric GARCH prototype would be suitable for simulating the spillover of the stock prices of a chosen index.




SSource: - Authors own computation using Eviews

**Figure 1 - Movement pattern of selected index of Indian stock markets**

Now, there are six asymmetric GARCH models have been developed using three distinct error distribution constructs. It is necessary to analyze the outcomes of the developed models with the different distinct distributions in order to select an optimal model. "The standard method for selecting a prototype is for the ARCH and GARCH coefficients to be significant." Furthermore, a model with a lower Akaike Information Criterion (AIC) and Schwartz Information Criterion (SIC) and a higher Log Likelihood statistics is preferred."

## Implementation of Various GARCH family Models for the TSEC weighted index from Taiwan stock market

TSWE owns the "Taiwan stock exchange capitalization weighted stock Index" (TAIEX), which assesses the performance of all listed stocks on the Taiwan stock exchange (TWSE). The TWSE's first self-compiled index, TAIEX, is the most important benchmark for Taiwan's securities market. Based on its level in 1966, the index has a base value of 100. The TSEC Index is another name for this index.

**Table 3 - Choosing an appropriate model of the TSEC weighted index from Taiwan stock market with Normal distribution**

| Estimated model | C α0 | ARCH(-1) α | GARCH(-1) β | AIC | SIC | Log Likelihood |
|---|---|---|---|---|---|---|
| GARCH(1,1) | 0.000490 (0.0002)* | 0.085823 (0.0000)* | 0.906442 (0.0000)* | -6.065242 | -6.059939 | 19334.93 |
| GJR-GARCH | 0.000235 (0.0727)* | 0.098036 (0.0000)* | 0.905026 (0.0000)* | -6.082877 | -6.076514 | 19392.13 |
| EGARCH | 0.000204 (0.1075)*** | 0.158245 (0.0000)* | 0.981611 (0.0000)* | -6.091875 | -6.085512 | 19420.81 |
| MGARCH | ------- | 0.086421 (0.0000)* | 0.905750 (0.0000)* | -6.065294 | -6.058930 | 19336.09 |
| ***PGARCH*** | ***0.000218 (0.0822)**** | ***0.085976 (0.0000)**** | ***0.917747 (0.0000)**** | ***-6.092481*** | ***-6.085057*** | ***19423.74*** |
| IGARCH | 0.000254 (0.1890)*** | 0.086586 (0.0000)* | 0.905548 (0.0000)* | -6.065395 | -6.059032 | 19336.41 |

*Source: - Authors calculation using Eviews*
*Note: The values in brackets are p-values.*

For the normal distribution (Table 1), the best prototype of the conditional spillover of the TSEC weighted index is PGARCH, which has significant parameters and the lowest AIC (-6.092481) and

SIC (-6.085057) values while having a higher maximum-likelihood value (19423.74). This paradigm is closely followed by EGARCH and GJR-GARCH (1.1.1). So, these are the models that will be tested and compared later.

**Table 4 - Choosing an appropriate model for TSEC weighted index based on the results of the regressions following Student t's Distribution**

| Estimated model | C α 0 | ARCH(-1) α | GARCH(-1) β | AIC | SIC | Log Likelihood |
|---|---|---|---|---|---|---|
| GARCH (11) | 0.000629 (0.0001)* | 0.062653 (0.0000)* | 0.934733 (0.0000)* | -6.114078 | -6.107714 | 19491.57 |
| GJR-GARCH | 0.000471 (0.0001)* | 0.072475 (0.0000)* | 0.931917 (0.0000)* | -6.124377 | -6.116953 | 19525.39 |
| EGARCH | 0.000459 (0.0001)* | 0.130275 (0.0000)* | 0.989163 (0.0000)* | -6.131038 | -6.123614 | 19546.62 |
| MGARCH | ---------- | 0.062950 (0.0000)* | 0.934400 (0.0000)* | -6.113789 | -6.106366 | 19491.65 |
| ***PGARCH*** | ***0.000457 (0.0001)**** | ***0.072671 (0.0000)**** | ***0.933925 (0.0000)*** | ***-6.131498*** | ***-6.123013*** | ***19549.08*** |
| IGARCH | 0.000560 (0.0014)* | 0.063104 (0.0000)* | 0.934234 (0.0000)* | -6.113810 | -6.106386 | 19491.71 |

*Source: - Authors calculation using Eviews*
*Note: The figures in brackets are p-values.*

The findings found when a Student error distribution is used are quite comparable to those obtained when a normal distribution is used. For this error distribution, we can evidently see that the model PGARCH (1.1.1) does the best job of capturing and predicting our index's conditional volatility (see Table 4).

**Table 5 - Choosing an appropriate model for TSEC weighted index with generalized error distribution (GED)**

| Estimated Model | C α0 | ARCH(-1) α | GARCH(-1) β | AIC | SIC | Log Likelihood |
|---|---|---|---|---|---|---|
| GARCH(1,1) | 0.000570 (0.0000)* | 0.069738 (0.0000)* | 0.925186 (0.0000)* | -6.113728 | -6.107364 | 19490.45 |
| GJR-GARCH | 0.000424 (0.0003)* | 0.081327 (0.0000)* | 0.920966 (0.0000)* | -6.124441 | -6.117017 | 19525.59 |
| EGARCH | 0.000408 (0.0000)* | 0.141359 (0.0000)* | 0.986168 (0.0000)* | -6.130858 | -6.123434 | 19546.04 |
| MGARCH | --------- | 0.069771 (0.0000)* | 0.925149 (0.0000)* | -6.113414 | -6.105990 | 19490.45 |
| ***PGARCH*** | ***0.000410 (0.0004)**** | ***0.077726 (0.0000)**** | ***0.927419 (0.0000)**** | ***-6.131297*** | ***-6.122812*** | ***19548.44*** |
| IGARCH | 0.000537 (0.0018)* | 0.069975 (0.0000)* | 0.924921 (0.0000)* | -6.113425 | -6.106002 | 19490.49 |

*Source: - Authors calculation using Eviews*
*Note: The figures in brackets are p-values.*

In the context of this model, the PGARCH prototype represents the optimum technique to simulate the conditional volatility of the sample index in the case of the generalized error distribution (see Table 5).

The aforementioned table shows that in all eighteen GARCH family models with normal, student t's distribution error construct, and generalized error distribution (GED). It was determined that PGARCH (1.1.1) with Student t's Distribution has the lowest AIC (-6.131498) and SIC (-6.123013) when compared to the other seven models when the AIC and SIC of all the aforementioned eight models are compared. Aside from having the highest Log

Likelihood (19549.08). As a result, this model is thought to be the best one. The table below lists the outcomes of the chosen PGARCH (1.1.1) Model for the TSEC_INDEX.

**Table 6 - Results of PGARCH (1, 1, 1) with Student's t distribution Error Construct**

| Dependent Variable: TSEC_INDEX_LOG_RETURNS | | | | |
|---|---|---|---|---|
| Sample data: 6374 total | | | | |
| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
| C | 0.000457 | 0.000117 | 3.893572 | 0.0001* |
| TSEC_INDEX_LOG_RETURNS(-1) | 0.034734 | 0.012837 | 2.705773 | 0.0068* |
| | Variance Equation | | | |
| C(i) | 0.000201 | 0.000117 | 1.716750 | 0.0860** |
| C(ii) | 0.072671 | 0.005942 | 12.22993 | 0.0000* |
| C(iii) | 0.556610 | 0.063002 | 8.834808 | 0.0000* |
| C(iv) | 0.933925 | 0.005327 | 175.3302 | 0.0000* |
| C(v) | 0.915237 | 0.118405 | 7.729711 | 0.0000* |
| T-DIST. DOF | 6.981438 | 0.576778 | 12.10420 | 0.0000 |
| $R^2$ | 0.000947 | MDV | | 9.57E-05 |
| Adj $R^2$ | 0.000790 | S.D. dep. v | | 0.013545 |
| S.E.R | 0.013539 | AIC | | -6.131498 |
| Sum squared resid | 1.168093 | SIC | | -6.123013 |
| Maximum Log likelihood | 19549.08 | HQC | | -6.128560 |
| DBS | 1.987503 | | | |

Source: Author's own computations using EViews 10

The TSEC weighted index from Taiwan stock market is represented in the following table as the output of the PGARCH (1,1,1) model using Student t's Distribution Construct. The outcomes come in two sections. The variance equation is represented in the lower area, while the main equation is shown in the upper portion. The constant (C) in the primary equation is significant at 5 %. Every coefficient in the variance equation is considered significant except C (i). Focus should be placed on the fact that the co-efficient of the asymmetric term is positive, or 0.5566100 and statistically significant. This suggests that there is a leverage effect on the company's stock price volatility. From estimation results of this model in Table 5, the coefficient of the leverage effect is significant. According to the PGARCH estimation results in Table 5, indicates that bad news, i.e., the spread of COVID-19 and Russia Ukraine war, has a larger effect on the volatility of the company's stock price.

At this point, after reviewing and comparing the models of the GARCH family in the hope of discovering the best adaptations of these models, we will proceed to the final phase, which constitutes the goal and object of this essay. This step will examine the following models: GARCH (1.1), GJR-GARCH, EGARCH, PGARCH (1.1.1), MGARCH, IGARCH, and, of course, EWMA.

**Table 7 - Table for forecasting performance evaluation.**

| Volatility model | RMSE | MAE | TIC |
|---|---|---|---|
| GARCH(1,1) Gs | 0.013550 | 0.009452 | 0.963877 |
| GARCH (1,1)-St | 0.013555 | 0.009437 | 0.955028 |
| GARCH (1,1)-GED | 0.013552 | 0.009436 | 0.959292 |
| GJR-GARCH-Gs | 0.013544 | 0.009437 | 0.982016 |
| GJR-GARCH-St | 0.013549 | 0.009435 | 0.965466 |
| GJR-GARCH- GED | 0.013548 | 0.009435 | 0.969022 |
| EGARCH- Gs | 0.013544 | 0.009437 | 0.984418 |
| EGARCH- St | 0.013549 | 0.009435 | 0.966391 |
| EGARCH- GED | 0.013548 | 0.009435 | 0.970192 |
| *MGARCH- Gs* | *0.013563* | *0.009442* | *0.943714* |
| MGARCH- St | 0.013560 | 0.009440 | 0.947841 |

| | | | |
|---|---|---|---|
| MGARCH- GED | 0.013553 | 0.009436 | 0.958835 |
| ***PGARCH - Gs*** | **0.013544** | **0.009437** | **0.983452** |
| *PGARCH - St* | 0.013549 | 0.009435 | 0.965466 |
| *PGARCH – GED* | 0.013548 | 0.009435 | 0.970104 |
| *IGARCH- Gs* | 0.013562 | 0.009441 | 0.945014 |
| IGARCH- St | 0.013561 | 0.009441 | 0.945768 |
| IGARCH- GED | 0.013554 | 0.009437 | 0.946586 |
| **EWMA** | **0.013551** | **0.009438** | **0.958837** |

The information in Table 7 shows that the eighteen stipulated models are reasonably close, but an examination of the RMSE, MAE, and TIC statistics leads us to the conclusion that the PGARCH with a normal error distribution is the best model for forecasting the volatility of the TSEC weighted index, followed by the EGARCH and GJR-GARCH models. As a result, conditional volatility models beat exponentially weighted volatility models for the TSEC weighted index.

## Conclusion

The key objective of this research-study is to see if there is an asymmetric influence in the conditional spillover of the TSEC weighted index using the Normal, generalized error distribution, and Student-t density functions, as well as to evaluate the precision of the simple GARCH, GARCH-in-Mean, EGARCH, GJR-GARCH, PGARCH, and IGARCH models. According to the findings of the study, the volatility of stock returns of selected indices behaves asymmetrically. Moreover, significant results of various GARCH family models indicating the existence of leverage effects (asymmetry) in specified financial series. Forecasting volatility in the financial markets, on the other hand, is a key topic. We also tried to find the best prototype to forecast and estimate the spillover of the TSEC weighted index throughout this research. To do this, we used GARCH models, which have been well investigated and scrutinized, and whose performance is well acknowledged in the financial writing. The EWMA model was also included in our example models. Among the findings of this study, we discovered that the GARCH prototype are more successful than the EWMA prototype in modelling and explaining the volatility of the TSEC weighted index.

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