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FORECASTING THE VOLATILITY OF REAL RESIDENTIAL PROPERTY PRICES IN MALAYSIA: A COMPARISON OF GARCH MODELS

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ABSTRACT

The presence of volatility in residential property market prices helps investors generate substantial profit while also causing fear among investors since high volatility implies a high return with a high risk. In a financial time series, volatility refers to the degree to which the residential property market price increases or decreases during a particular period. The present study aims to forecast the volatility returns of real residential property prices (RRPP) in Malaysia using three different families of generalized autoregressive conditional heteroskedasticity (GARCH) models. The study compared the standard GARCH, EGARCH, and GJR-GARCH models to determine which model offers a better volatility forecasting ability. The results revealed that the GJR-GARCH (1,1) model is the most suitable to forecast the volatility of the Malaysian RRPP index based on the goodness-of-fit metric. Finally, the volatility forecast using the rolling window shows that the volatility of the quarterly index decreased in the third quarter (Q3) of 2021 and stabilized at the beginning of the first quarter (Q1) of 2023. Therefore, the best time to start investing in the purchase of real residential property in Malaysia would be the first quarter of 2023. The findings of this study can help Malaysian policymakers, developers, and investors understand the high and low volatility periods in the prices of residential properties to make better investment decisions.

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1. Introduction

Volatility modeling and forecasting of financial time series data have attracted the attention of researchers in the last two decades owing to its variety of applications in financial markets (Mohammed et al., 2020; Capelli et al., 2021; Yu et al., 2016; Glaeser & Nathanson, 2017; Gupta et al., 2010). The existence of volatility in the market price helps investors generate substantial profit while also causing fear among investors since high volatility implies a significant return with significant risk (Dixit & Agrawal, 2020). Volatility refers to the rate at which a given set of the market returns increases or decreases during a particular period (Stock & Watson, 2004, Wang et al., 2014). It is calculated as the standard deviation of the returns over a certain period and provides the range within which the returns might rise or fall. In addition, volatility assesses the security risk and helps in the forecasting of short-term variations (Balaji et al., 2023). Therefore, if the return of a security fluctuates swiftly over a short period, it is said to have high volatility, whereas if it swings slowly over a long period, it is said to have low volatility.

The residential market has grown rapidly during the last decades, although this depends on the geographical region and type of property (Mohd Daud & Marzuki, 2019; Milunovich, 2020; Bork & Møller, 2015). This type of financial market contributes to the economic growth of many countries in the world (Gupta et al., 2011; Kokot, 2022, Hong et al., 2022). For example, the Malaysian property market is divided into six sub-sectors which include residential, agricultural, industrial, commercial, development, and others. Malaysian residential properties account for about 60% of all property units (Zull Kepili & Masron, 2016). Consequently, the prices of this sector have received a lot of attention in recent years due to its unprecedented dynamic changes (Xu & Zhang, 2021; Glaeser & Nathanson, 2017). The residential property price volatility is essential for understanding the fluctuation of changes in property prices since prices remained volatile over the years (Gerek, 2014).

The importance of understanding residential property price volatility cannot be over-emphasized since it provides opportunities for property investors and individuals to enhance their investment decisions. An investor may decide to purchase properties at a low price and sell them when they are overpriced. However, the randomness trend exhibited by volatility influences stock markets (Zekri & Razali, 2019). Investors continue to be affected by the uncertainty of volatility, and forecasting volatility is always a challenging task. Therefore, forecasting the volatility of this market price is important since it helps future investments by giving a clear picture of when to allocate funds to the resources at a reasonable cost (Idrees et al., 2019; Alpha Kabine, 2022; Olayemi et al., 2021). Volatility forecasting helps in the protection of property trade between investors and buyers, as well as the reduction of risk. As a result, it is essential to understand and model residential property price volatility (Lee & Reed, 2014).

Numerous research about stock market volatility exists (Akhtar & Khan, 2016; Dufitinema, 2022; Kinateder & Wagner, 2014; Doszyń, 2022), yet there is a lack of detailed studies on volatility forecasting of residential prices, despite its importance. For example, (Crawford & Fratantoni, 2003) evaluated the accuracy of three types of models in forecasting the United States (U.S.) housing prices. Autoregressive Integrated Moving Average (ARIMA), Regime-Switching, and GARCH were the three models employed. Another study conducted by (Miles, 2008) compared the performance of a Markov-Switching model with the autoregressive-moving average (ARMA), generalized autoregressive (GAR), and generalized autoregressive conditional heteroscedastic (GARCH) models on U.S. housing prices. Recent research on forecasting market volatility includes (Xiao et al., 2021; Zhang et al., 2022; Liang et al., 2021; Dai & Chang, 2021; Capelli et al., 2021; Wang, 2022; Alfeus & Nikitopoulos, 2022; Koo & Kim, 2022). However, previous studies on Malaysian residential property investments have focused on property prices in various geographical regions. For instance, (Hui, 2010; Shahid et al., 2017; Soon & Tan, 2019; Kok et al., 2018) found Malaysian residential property price movements in both the short-run and long-run, due to environmental changes, policymaking, exchange rate, and monetary liquidity. Hence, these irregular changes in residential property prices indicate a need for a volatility forecasting approach to determine future changes in prices for proper decision-making. The objective of this research is to suggest a suitable model and forecast the volatility of the residential property price index in Malaysia using GARCH models.

2. Literature

To forecast the volatility of a given market stock, one must first consider the volatility behavior of the return assets of the time series data. The variance of these asset returns fluctuates over time, forming what is known as volatility clusters, which indicates that the time series will be heteroskedastic. The autoregressive conditional heteroskedasticity (ARCH) developed by (Engle, 1982) considers the variance fluctuation, and no homoskedasticity assumption is required. The model has received considerable attention in modeling the asset returns of time series data over the years. The studies by (Bollerslev, 1986; Nelson, 1991; Glosten et al., 1993) have contributed significantly to the extension of the family of ARCH models, yielding the generalized ARCH (GARCH), exponential GARCH (EGARCH) and Glosten, Jagannathan and Runkle-GARCH (GJR-GARCH) models, respectively. Therefore, many other extensions of GARCH-type models exist in

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the literature.

In forecasting practice, a large amount of literature applies GARCH-type models for the volatility forecasting performance of these models on asset returns. The competing models are assessed based on their ability to forecast volatility, and the best model is chosen using statistical criteria for further forecasting.

The study performed by (Liu & Hung, 2010) examined the daily volatility forecasting in Taiwanese stock index futures markets, which were significantly affected by the global financial crisis in 2008. From April 24, 2001 to December 31, 2008, the study used various GARCH-type models to forecast daily volatility, including GARCH, GJR-GARCH, quadratic GARCH (QGARCH), EGARCH, integrated GARCH (IGARCH), and component GARCH (CGARCH). The findings of this study show that the EGARCH gives the best volatility forecast for the daily index, whereas the other competing GARCH models perform poorly.

The study conducted by (Akhtar and Khan, 2016) compared the performance of various volatility models in modeling the volatility patterns of the Karachi Stock Exchange (KSE), which covered the index of daily, weekly, and monthly data recorded from November 2, 1991, to December 31, 2013. In the study, the ARCH, GARCH, GARCH in mean (GARCH-M), EGARCH, threshold GARCH (T-GARCH), P-GARCH, and exponentially weighted moving average (EWMA) models have been compared to determine the best volatility forecasting model. The outcomes have shown non-normality, stationarity, and volatility clustering in the return index. Furthermore, their results revealed that EWMA captured the volatility pattern in the monthly index. However, the P-GARCH model adequately described the volatility pattern in the daily data, while the GARCH model has proven to be the most suitable for weekly data. Moreover, they found a leverage effect for the weekly returns. The daily series of the Karachi Stock Exchange KSE 100 index, on the other hand, shows a considerable leverage effect.

Other extensions of the GARCH model including the EGARCH and power GARCH, P-GARCH have been employed by (Dixit & Agrawal, 2020) to determine the best fit model for estimating and forecasting the volatility of daily closed returns of the Bombay Stock Exchange (BSE) and National Stock Exchange (NSE). The data used in this study was obtained from the period April 1, 2011 to March 31, 2017. The authors concluded that the P-GARCH is the best-suited model to estimate the volatility of all markets.

A hybrid sliding window and GARCH model has been developed in a study conducted by (Hanapi et al., 2018) to forecast the prices of crude oil in Malaysia covered from January 2009 to December 2017. The monthly data in their study was obtained from the official database of the Malaysian Palm Oil Board. The performance of the developed hybrid model was compared with the GARCH model based on the mean percentage of absolute error (MPAE) and mean squared error (MSE). The results revealed that the developed hybrid model performed better than the GARCH model.

The GARCH, The EGARCH, and GARCH-M are among the volatility models employed (Tegtmeier, 2022). The study examines the characteristics of stochastic volatility processes using weekly data from globally listed private equity (LPE) markets from January 2011 to December 2020. The results from GARCH show that the long-run volatility persistence is larger than the short-run volatility persistence. EGARCH confirmed the existence of a leverage effect for all LPE series.

Recently, (Zekri & Razali, 2019) analyzed the behavior of the volatility of Malaysian recognized property institutions for the last 2 decades. The study compared several volatility models such as EGARCH and Markov-switching, MSEGARCH for analyzing the dynamics of volatility in series. The study revealed that the MSEGARCH model provided a better fit for the volatility behavior in the series than other competing models. However, the study focused mainly on the behavior of the volatility of Malaysian recognized property institutions, yet the study failed to explore the volatility forecasting approach to determine the volatility forecasting for the real residential property price (RRPP) index, which is the focus of the present research.

The present research compared the performance of volatility models such as GARCH, EGARCH and GJR-GARCH on the Malaysian RRPP index, covering the first quarter of 1981 through the third quarter of 2021. The research contributed to the knowledge by evaluating the characteristics of volatility in the Malaysian RRPP index and presented the best model for forecasting return volatility among competing models. Moreover, the research forecasted the period at which the volatility became stable.

3. Data and methods

The present research involved the usage of three GARCH-type models, such as the standard GARCH, EGARCH and GJR-GARCH models to forecast the volatility of the RRPP index in Malaysia. For optimum forecasting accuracy, the research considered five main steps as shown in (Fig.1). All computations in this work were performed using RStudio (version 2022.2.1.0).

This study uses quarterly Malaysia residential property prices time series data from the first quarter (Q1) of 1988 to the third quarter (Q3) of 2021 obtained through the publication of the Economic Research Division, Federal Reserve Bank of St. Louis in the form of an index and is publicly accessible retrieved from (https://fred.stlouisfed.org/series/QMYR628BIS, May 02, 2022). The dataset was reported based on units (index 2010=100, Not Seasonally Adjusted).The present study evaluates an appropriate GARCH model and volatility prediction on the Malaysian residential property prices index. The algorithm of the research is depicted in (Fig.1).

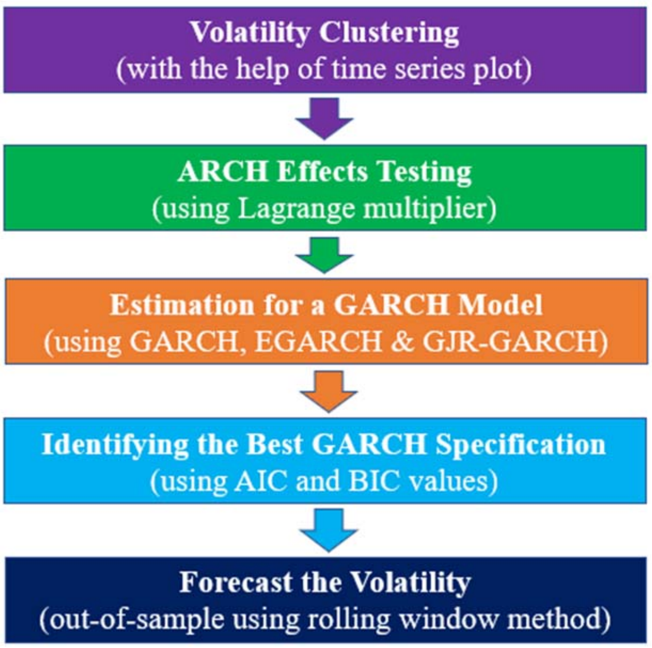

Fig.1. Steps for volatility forecasting. *Source: own study.*

Brief reviews of these models are discussed in the following subsections.

3.1. GARCH model

The study (Merton, 1980), proposed a model that takes heteroskedasticity into account when estimating volatility, resulting in the establishment of the ARCH model (Engle, 1982), which estimated the volatility of inflation data in the United Kingdom more accurately. The ARCH model considers that the error variance term is influenced by the previous error variance term. The ARCH(q) model can be expressed in its general form as follows:

$$h_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \quad (1)$$

where q represents the number of the previous ε_t^2 terms, the coefficient $\alpha_i$quantifies how the shock of today's volatility will affect the volatility of the next period.

Following the development of the ARCH model, (Bollerslev, 1986) improved on it and developed the GARCH model. The general form of the GARCH(p,q) model can be represented by:

$$h_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}^2 \quad (2)$$

where $\omega > 0$is the intercept, $\alpha_i \geq 0$is the coefficient of ε_{t-i}^2 and $\beta_j \geq 0$ is the coefficient of h_{t-j}^2 of the parameters for ARCH and GARCH, respectively. Value p represents the number of previous ε_t^2 terms. If the condition $\alpha_1 + \beta_1 < 1$ is satisfied, the GARCH (1,1) process is stationary. As a result, the conditional variance in the long run will converge to the unconditional variance, yielding the following expression $\frac{\omega}{1-(\alpha_1+\beta_1)}$.

A GARCH (1,1) model's forecast equation for the next period, that is, the future forecasted value, is expressed by:

$$h_{t+1}^2 = \omega + \alpha_1 \varepsilon_t^2 + \beta_1 h_t^2 \quad (3)$$

3.2. EGARCH model

One modification to this model is its use of the natural log value of conditional variance that yields a positive value of the conditional variance observed. To enable the model to examine the leverage effects on the conditional variance caused by negative and positive shocks, (Nelson, 1991) proposed the EGARCH. The model enables negative market news to have a greater influence on conditional variance than positive market news, known as the leverage effect. Asymmetric effects mean that negative shocks have a greater impact on volatility than positive shocks. The study defines the model as presented by (Akhtar and Khan, 2016).

The EGARCH (p,q) model can be expressed by the following equation:

$$ln(h_t^2) = \omega + \sum_{i=1}^{q} \alpha_i \left\{ \left| \frac{\varepsilon_{t-i}}{h_{t-i}} \right| - \sqrt{\frac{2}{\pi}} \right\} - \gamma_i \frac{\varepsilon_{t-i}}{h_{t-i}} + \sum_{j=1}^{p} \beta_j \, ln\left(h_{t-j}^2\right) \quad (4)$$

The asymmetric effect is represented by the coefficient γ, reflecting the leverage effect. If the value of $\gamma = 0$, then it implies that the model is symmetric, whereas if $\gamma < 0$, negative news has a greater influence on volatility than positive news (Lim and Sek, 2013).Theα_i and$\alpha_i + \gamma_i$ represent the effects of good market news and bad market news, respectively. $I_{t-i}$is the indicator function, with a value of one if $\varepsilon_{t-1} < 0$ and zero otherwise. Implying a greater degree of influence $(\alpha_i + \gamma_i)\varepsilon_{t-i}^2$ with $\gamma_i > 0$ of a negative shock ε_{t-i}, while a positive shock ε_{t-i} has little impact $\alpha_i \varepsilon_{t-1}^2$ to h_t^2(Dufitinema, 2022). The process is stationary if $\beta_j < 1$(Enders, 2015). The specifications of the EGARCH (1,1) model can represent as:

$$ln(h_t^2) = \omega + \alpha_1 \left\{ \left| \frac{\varepsilon_{t-1}}{h_{t-1}} \right| - \sqrt{\frac{2}{\pi}} \right\} - \gamma_1 \frac{\varepsilon_{t-1}}{h_{t-1}} + \beta_1 \, ln(h_{t-1}^2) \quad (5)$$

For the EGARCH (1,1) model, the forecasted equation for the forecasted value for the next time period is expressed by:

$$ln(h_{t+1}^2) = \omega + \alpha_1 \left\{ \left| \frac{\varepsilon_t}{h_t} \right| - \sqrt{\frac{2}{\pi}} \right\} - \gamma_1 \frac{\varepsilon_t}{h_t} + \beta_1 \, ln(h_t^2) \quad (6)$$

3.3. GJR-GARCH model

The model was developed to account for asymmetric effects by adding a dummy variable. The GJR-GARCH model, unlike the standard GARCH model, does not assume that if a shock occurs, the shock's sign will be independent of the response variable. It would only depend on the magnitude of the shock (Glosten et al., 1993). The general form of GJR-GARCH model, GJR-GARCH (p,q) can be presented as:

$$h_t^2 = \omega + \sum_{i=1}^{q} (\alpha_i + \gamma_i I_{t-i}) \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}^2 \quad (7)$$

where α_i, β_j and γ_i are positive parameters. The dummy variable I_{t-i} assumes to be equal to one when γ_i is negative and zero when γ_i is positive. In the GJR-GARCH model, the impact of ε_{t-i} on the conditional variance h_t^2 differs when ε_{t-i} is positive or negative. The leverage effect is represented by the coefficient γ_i. If the value of $\gamma_i = 0$, the model shows symmetry and converts to the standard GARCH model. If it is large, it means a leverage effect exists (Danielsson, 2011). The parameter β_j represents the effect of volatility clustering, while persistence in relation to the market news is represented by $\alpha_1 + \beta_1 + \frac{\gamma_1}{2}$ (Akhtar and Khan, 2016).

The specification of the GJR-GARCH (1,1) model can be presented as:

$$h_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 I_{t-1} \varepsilon_{t-1}^2 + \beta_1 h_{t-1}^2 \quad (8)$$

For the GJR-GARCH (1,1) model, the forecasted equation for the next period of time forecasted value is expressed by:

$$h_{t+1}^2 = \omega + (\alpha_1 + \gamma_1 I_t)\varepsilon_t^2 + \beta_1 h_t^2 \quad (9)$$

3.4. Statistical equation for the return index

The quarterly Malaysian real residential property price index is transformed for the needs of fitting the model to a logarithmic returns index. Suppose the price index is represented by P_t, then the log returns index r_t is calculated by

$$r_t = log\left(\frac{P_t}{P_{t-1}}\right) \quad (10)$$

whereP_t is the Malaysian real residential property prices at time t and P_{t-1} represents real residential property prices at time $t-1$. The r_t is the quarterly log returns at time t. The log return is the natural log of the returns at time t divided by the previous return from the last quarter. The log return has desirable statistical properties, such as stationarity and ergodicity, which are favorable for statistical analysis (Perlin et al., 2020).

4. Empirical results

4.1. Descriptive statistics

In descriptive statistics, the mean, variance, skewness, and kurtosis values are fundamental properties of a time series. A high value of deviation indicates significant volatility in the price log returns. Skewness value signifies the symmetry behavior of the distribution of a time series. The kurtosis coefficient value indicates the peakedness or flatness of the tail of the density compared to normal density. A skewness value of 0 implies that the time series data is normally distributed, while a value greater than one implies extreme skewness (Dixit and Agrawal, 2020). An asymmetry coefficient of 0 implies a symmetric distribution. For the distribution to be normal, the kurtosis must be at the appropriate level. The descriptive statistics of the quarterly price index and quarterly log returns are presented in Table 1. These statistics indicated that the distribution of the quarterly log returns index is a non-normal distribution.

Table 1

Descriptive statistics for the quarterly price index and quarterly log returns

Descriptive	Quarterly Index	Quarterly Log Returns
Observation	135	135
Mean	104.3400	0.0076
Median	94.4100	0.0052
Variance	900.7841	0.0004

Standard deviation	30.0130	0.0192
Skewness	0.7111	0.1415
Kurtosis	-0.5736	1.9341
Minimum	59.4700	-0.0530
Maximum	167.9300	0.0743
Jarque-Bera test	83.2152	6.8417
p-value	0.0015	0.0000

Sources: http://www.bis.org/statistics/pp.htm.

4.2. Autocorrelation

It is usually essential to examine the autocorrelation pattern of the measured market index, which will determine whether log returns at period t are associated with log returns at period $t-k$. The autocorrelation plot, also known as autocorrelogram, can help detect abnormalities in time series, which will aid the future stage of the modeling procedure. An autocorrelogram displays the values of the autocorrelation function (ACF) and partial autocorrelation function (PACF) on the vertical axis, while the magnitude of the lag between the variables of the time series is shown on the horizontal axis of the autocorrelogram. The ACF and PACF plots for the quarterly log returns are displayed in (Fig. 2a) and (Fig. 2b), respectively. As expected, the plots have shown that the log of quarterly log returns provides low values of autocorrelation for lags up to 21, which indicates that the log returns were not highly correlated. It means that the quarterly log returns are significantly independent of each other. Moreover, (Fig. 2b) illustrates that the log return is stationary, which is suitable for time series analysis (Akhtar & Khan, 2016).

4.3. Volatility clustering

When the market is calm, price fluctuations are relatively slow. When not, they change quickly in the presence of uncertainties, increased trade, and the delivery of new information to the market. The fluctuations of the price index in Malaysia from 1988 to 2021 are depicted in (Fig. 3a). It can be seen in the graph that the price index has been continuously growing during the first decade. The index began to increase dramatically in 1990 and continued to rise until mid-1999, when the Asian financial crisis occurred. From 2000 to 2008, there was a progressive increase in prices, followed by a big drop in 2009. The prices began to rise again between 2010 to mid-2020, but still, another financial crisis impacted the market negatively, causing the market to collapse for the second time in less than a decade because of the COVID-19 epidemic.

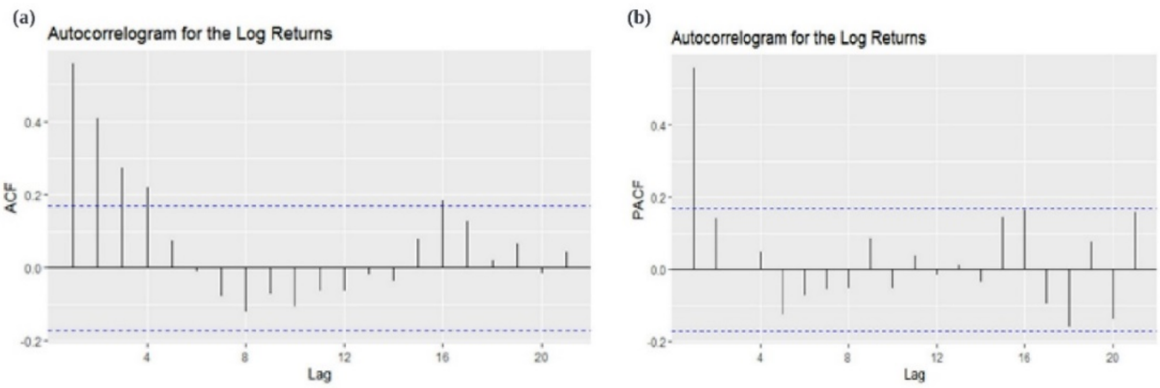

Fig. 2. (a) ACF of quarterly log returns and (b) PACF of quarterly log returns.*Source*: own study.

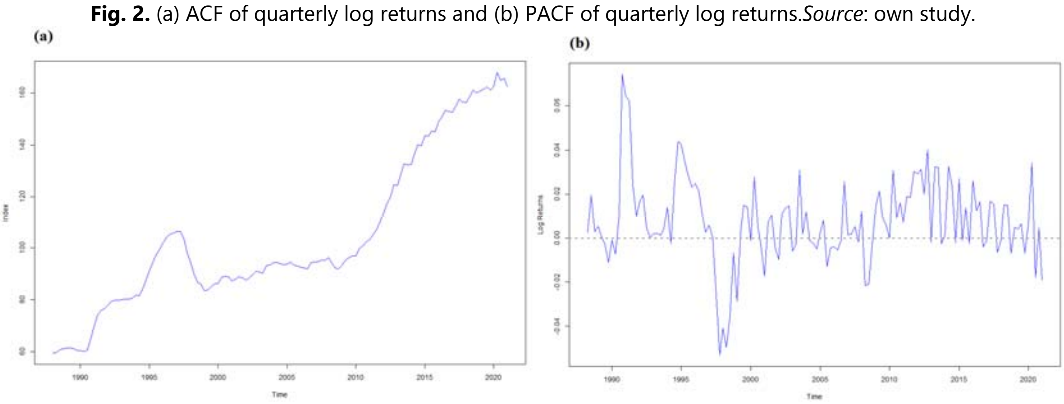

Fig. 3. (a) Quarterly price index of residential properties in Malaysia (b) Quarterly log returns of residential property price index (1988–2021)(2010=100).*Source*: https://fred.stlouisfed.org/series/QMYR628BIS.

Figure 3b represents the log returns of the corresponding real residential property price log returns. It can be observed that many of the log returns are located around zero. The figure shows that large positive and large negative observations in the price log return appear in clusters. This is known as volatility clustering.

4.4. ARCH effects testing

Before estimating a GARCH model, the time series data must show non-constant variance. That data must exhibit the characteristic of heteroskedasticity. The existence of ARCH effects can be measured using the Lagrange multiplier (LM) statistic introduced by (Engle, 1982). The null hypothesis for the LM test statistic asserts that there are no ARCH effects in the data. It proceeds by regressing the squared error on its lag and verifying that all lagged regression coefficients are equal to zero. The log returns of the price index and lag are provided in the test. Using the log returns index, the results indicated that the test coefficients are close to zero. The p-values determined the tendency of having no ARCH effects in the data. The lower the p-value, the higher the chances of detecting the ARCH effect. The results of the ARCH LM test for five lags are presented in Table 2. The p-value is lower in all cases, confirming that ARCH effects are present in the data. As a result, the null hypothesis is rejected, validating the use of the GARCH volatility model.

Table 2

ARCH LM test results for quarterly return index

Lag	LM statistic	p-value
1	46.116	1.114e-11
2	45.791	1.139e-10
3	49.36	1.094e-10
4	49.043	5.721e-10
5	48.861	2.369e-09

Source: own study.

4.5. Estimations for GARCH models

Following (Perlin et al., 2020), the first step in estimating a GARCH model is to define the number of lags, the variance equation, and the model parameters. In this study, three different GARCH-type models such as GARCH, EGARCH, and GJR-GARCH were estimated, each with a different number of lags and distribution assumptions. Multiple estimations for various autoregressive moving averages (ARMA-GARCH) were performed under normal and student distribution (std) as probability distribution assumptions. GARCH-type models with std distribution, such as GARCH (1,1), EGARCH (1,1), and GJR-GARCH (1,1), were shown to have the lowest Akaike information criteria (AIC) and Bayesian information criterion (BIC) values among their respective benchmark models, and their estimation results are given in Table 3. The parameters of the three estimated models are statistically significant at the 5% level. The intercept (μ) in the mean equation has a positive value. This means that, as expected, the RRPP index will have a significant positive log return in the long run.

Table 3

Results of GARCH models estimation with corresponding standard errors (in parentheses) for the quarterly log returns of the Malaysian real residential property price index

Parameter	GARCH (1,1)	EGARCH (1,1)	GJR-GARH (1,1)
μ	0.0070^{***}	0.0062^{***}	0.0069^{***}
	(0.0011)	(0.0010)	(0.0002)
ω	0.0001^{***}	-0.4790^{***}	0.0000^{***}
	(0.0000)	(0.0009)	(0.0000)
α_1	0.4575^{**}	0.0023^{***}	0.6000^{***}
	(0.0068)	(0.0012)	(0.0057)
β_1	0.1887^{***}	0.4238^{*}	0.3720^{***}
	(0.0041)	(0.0193)	(0.0034)
γ_1		0.4414^{**}	0.0418^{***}
		(0.0201)	(0.0031)
Distribution	Std	Std	Std
Log-likelihood	362.4596	354.3924	364.2828
AIC	-5.3858	-5.2938	-5.4134
BIC	-5.2329	-5.1846	-5.2605
R-square	0.8906	0.8917	0.8938

Note. $^{***}p<0.001$; $^{***}p<0.01$; $^{*}p<0.05$.

Source: own study.

4.5.1.GARCH (1,1) model estimation

The GARCH (1,1) in Table 3 revealed significant parameters for quarterly log returns. The significant values of α_1 and β_1 indicated the fact that log returns from the previous period and volatility from the past period have predictive power over the present volatility. The existence of volatility clustering was inferred by the positive β_1. The persistence of volatility, as evidenced by the fact that the sum of ARCH and GARCH terms $(\alpha_1 + \beta_1)$ is 0.65, suggests that if a shock occurs today, future log returns will be affected for a long time (Hameed et al., 2006). High volatility allows for more profit potential, which contributes to market inefficiencies. Consequently, investors are influenced by sudden price swings that cause them to unwillingly engage in the market (Akhtar & Khan, 2016).

4.5.2. EGARCH (1,1) model estimation

As for the EGARCH (1,1) model in Table 3, it indicated the GARCH effects and the existence of volatility clustering in the quarterly log returns from the RRPP index. Volatility persistence($\alpha_1 + \beta_1$) in the quarterly log returns was estimated to be 0.43 using the EGARCH (1,1) model. Since the persistence was estimated to be less than one, it indicated that volatility would remain stable in the long run (Perlin et al., 2020). The leverage or asymmetry parameter is positive and significant, showing that bad news did not influence volatility more than good news.

4.5.3. GJR-GARCH (1,1) model estimation

The GJR-GARCH is an alternative to the conditional volatility model for investigating a leverage effect. The results of GJR-GARCH (1,1) in Table 3 verified the existence of the GARCH effects and volatility clustering for the quarterly log return index. The estimated persistence as measured by $\alpha_1 + \beta_1 + \lambda_1/2$, is 0.993. Since the persistence value was below one, the mean reversion process was used, revealing that a significant amount of volatility eventually moved to average (normal) values. The asymmetry parameter (γ_1) had a positive value, indicating the presence of a leverage impact, showing that bad news did not influence volatility more than good news.

4.6. Identifying the best GARCH specification

In practice, researchers often employ various measures of goodness of fit to compare and select the most suitable GARCH model for a given dataset (Fakhfekh and Jeribi, 2020). To avoid bias in selecting the best GARCH model, associated lags, and the underlying probability distribution assumption, researchers conducted an algorithmic search for parameters, since it removes the researcher's possible bias.

The most commonly used statistical criteria for selecting the best models are the Akaike information criterion (AIC) and Bayesian information criterion (BIC) which can be obtained using the equations below (Tsay, 2005).

$$Log - likelihood = log(\sum_{i=1}^{N} f(x_i/\theta)) \quad (11)$$

$$AIC = -2(loglik) + 2K \quad (12)$$

$$BIC = -2(loglik) + K.ln(N) \quad (13)$$

where$loglik$ is the associated log-likelihood of the forecasted model, K is the number of estimated parameters, and N is the number of observations. The guideline is that the model with higher log-likelihood values and smaller AIC and BIC values for each estimated model is known as the best model (Singh et al., 2020; Auwalu et al., 2021).

In Table 3, the results of log-likelihood, AIC, and BIC values are presented for the three competing models estimated from the log returns index. Comparing these statistical measures revealed that the GJR-GARCH (1,1) with student distribution is the best forecasting model for the Malaysian real residential property price log returns index.

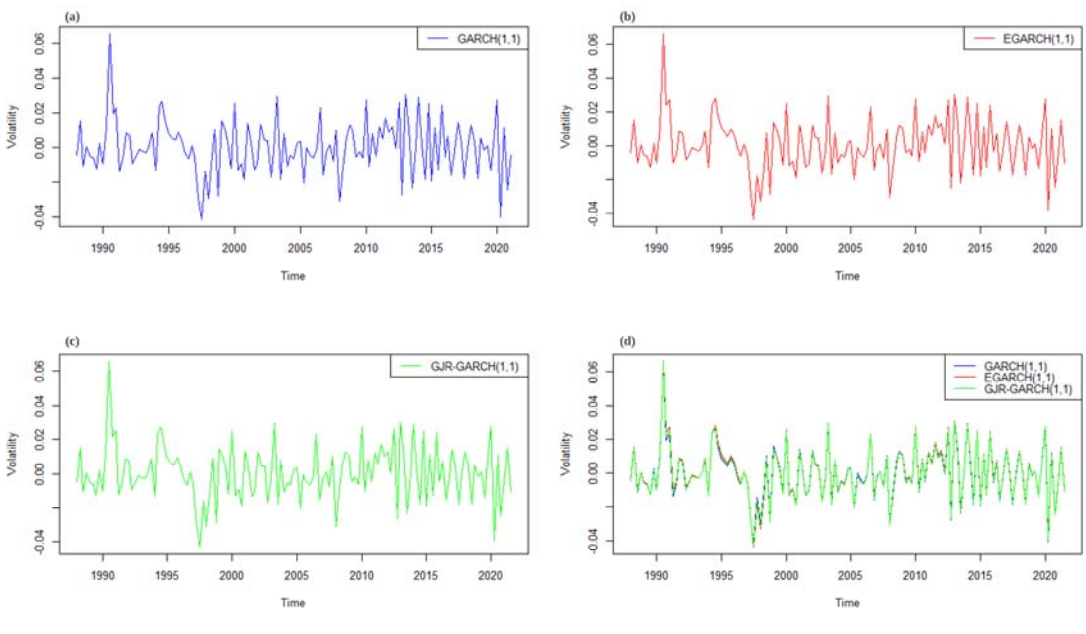

Fig. 4. Plot of various volatility models for the quarterly log return index (1988-2021). *Source*: own study.

From (Fig. 4), the GARCH (1,1), EGARCH (1,1), and GJR-GARCH (1,1) models performed reasonably in estimating the quarterly log return index. However, comparatively, the GARCH (1,1) model shows high persistence of volatility, suggesting that future log returns will be affected for a long time (Hameed et al., 2006). On the other hand, the EGARCH (1,1) and GJR-GARCH (1,1) indicated low asymmetric volatility, indicating that the volatility would remain stable in the long run (Danielsson, 2011).

It can be observed from (Fig. 4) that the GJR-GARCH (1,1) model provides a better volatility forecasting model than the other competing models. Thus, the GJR-GARCH (1,1) model is considered the most appropriate forecasting model for the quarterly log returns index.

4.7. Forecasting performance measure

To assess the forecasting accuracy of the competitive models, we used a goodness-of-fit measure called the root mean squared error (RMSE) of the square of the out-of-sample observations using the true volatility h_t as defined by (Souza et al., 2002). The best forecasting model is the one with the lowest RMSE of the squared out-of-sample observations given by

$$RMSE = \sqrt{\frac{1}{T-t_0}\sum_{t=t_0+1}^{T}\left(h_t - \hat{h}_{jt}\right)^2} \quad (14)$$

where $\hat{h}_{jt}$ is the estimated volatility at the time t, t_0 is the total observations in the in-sample period and T is the total number of observations.

4.8. Forecasting performance measure

The estimated GARCH (1,1), EGARCH (1,1), and GJR-GARCH models are selected based on the first 135 quarterly log returns indices in the sample covering the period from the first quarter of 1988 to the third quarter of 2021.. Finally, the rolling window approach is then applied to forecast the out-of-sample period, which corresponds to the volatility forecast for 10 horizons of the quarterly log returns index. The forecast starts from the fourth quarter (Q4) of 2021 and the latest observation corresponds to the first quarter (Q1) of 2024. The forecasted volatility will determine the period at which the volatility in the price index will be stable. Table 4 shows the log returns and volatility forecasts for the quarterly log return of the Malaysian real residential property price index with forecast horizon=10 based on the GARCH (1,1), EGARCH (1,1), and GJR-GARCH (1,1) models with student distribution. Moreover, it is evident from the table that the volatility of the price index will become stable in the first quarter of 2023.

Table 4

Volatility forecasts for the quarterly log returns of the Malaysian real residential property price index based on the GARCH (1,1), EGARCH (1,1), and GJR-GARCH (1,1) forecasting models

Model	Period	2021 Q4	2022 Q1 – Q4				2023 Q1 – Q4			2024 Q1
	Horizon	1	2	3	4	5	6	7	8	9	10
GARCH	Return	-0.008	-0.001	0.002	0.004	0.005	0.006	0.006	0.007	0.007	0.007
	Volatility	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017
EGARCH	Return	-0.006	0.002	0.003	0.004	0.006	0.006	0.006	0.006	0.006	0.006
	Volatility	0.019	0.017	0.016	0.016	0.016	0.015	0.016	0.016	0.016	0.016
GJR-GARCH	Return	-0.007	-0.001	0.003	0.005	0.006	0.006	0.007	0.007	0.007	0.007
	Volatility	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015

Source: own study.

Table 5

The goodness-of-fit metric of competitive volatility forecasting models for the quarterly log returns of the Malaysian real residential property price index

	GARCH (1,1)	EGARCH (1,1)	GJR-GARCH (1,1)
RMSE	0.0047	0.0063	0.0034

Source: own study.

The statistical metrics, RMSE for the forecasting models is provided in Table 5. From this table, the GJR-GARCH (1,1) model revealed the smallest values of the RMSE metric in comparison to the GARCH (1,1) and EGARCH (1,1) models. Thus, the GJR-GARCH (1,1) model can be selected as the best volatility forecasting model for the quarterly log returns of the Malaysian real residential property price index.

5. Discussion and conclusions

Three different volatility models were considered in the present study on the quarterly log returns index for the Malaysian residential property prices index covering the first quarter of 1981 to the third quarter of 2021. The volatility forecasting models, such as GARCH (1,1), EGARCH (1,1), and GJR-GARCH (1,1) were estimated from the quarterly log return index to determine the most appropriate volatility forecasting model. The GJR-GARCH (1,1) with the underlying student distribution, produces the best-suited forecasting model based on log-likelihood, AIC, and BIC values. Further, these models were applied to forecast the volatility for ten periods ahead using a rolling window technique. The results showed that the GJR-GARCH (1,1) outperformed the GARCH (1,1) and EGARCH (1,1) based on the goodness-of-fit measure. The forecasts indicated that the quarterly RRPP volatility decreases in the first quarter of 2022 and stabilizes at the beginning of the first quarter of 2023. The findings of this study could help Malaysian policymakers, property developers, and investors to understand the high and low volatility periods in the prices of residential properties and help citizens to plan when to buy their properties at reasonable periods. Therefore, the best time to start investing in the purchase of real residential property in Malaysia would be the first quarter of 2023. However, some interesting results could emerge if more volatility models would be used for different price log returns in different geographical settings of Malaysia, as the residential property prices change from region to region and from time to time.

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