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MEASURING THE RISK OF STOCK PRICE VOLATILITY IN INSURANCE COMPANIES WITH APPLICATION TO THE INSURANCE SECTOR IN THE KINGDOM OF SAUDI ARABIA

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Abstract

Our research aims to develop a quantitative model that describes the fluctuations in the stock prices of insurance companies by modeling the behavior of the variable in the time series of stock prices. This enables us to estimate the level of risk and provides highly accurate predictions of price variations. Irregular fluctuations in stock prices represent one of the most important measures of risk associated with stock ownership, as their increase leads to a lack of confidence among investors, which results in a decrease in the market value of companies. Insurance companies are more affected than others by these fluctuations, which negatively impact their business results, as the insurance business depends on the state of trust that exists between the insured and the company. The research concluded that the most appropriate model to reflect stock price fluctuations is the GARCH(1,1) model, which reflects the influence of both prior information derived from the time series of stock prices (ARCH Effect) and the impact of prior fluctuations in the series (GARCH Effect). The study recommended that insurance companies adopt the proposed model, which helps them develop a model that describes stock price fluctuations. This enables them to accurately predict stock movements, thereby reducing the unsystematic risks associated with this type of financial asset for insurance companies.

Keywords

Risk measurement, Saudi insurance companies, stock prices, conditional variance models, unsystematic risk.

1. Introduction

Given the importance of the insurance sector as a pillar of the financial sector, it is essential to focus on quantitative methods used to measure and analyze the risks associated with insurance company stock prices. This risk can be identified and measured by identifying trends in the price time series. The wider the range of the curve representing the probability distribution of price rates, as reflected by the variance, the greater the risk to the security, and consequently, the lower the market value of the stock (Chowdhury & Stasi, 2022). The problem of instability in stock price time series, resulting from irregular fluctuations in the price time series of insurance companies, is one of the most significant challenges facing these companies (Smales, 2021).

This challenge requires predicting the value of these stocks, which would achieve greater stability. To study the uncertainty factor, it was necessary to address quantitative models that describe the irregular fluctuations in the values of financial assets over time. Several models are used to describe the fluctuations associated with stock price time series observations, allowing for high-degree prediction accuracy. These models include the Box-Jenkins model, the autoregressive model with conditional error heteroscedasticity, and the artificial neural network model. Heteroscedastic autoregressive models have been of great importance in studying and modeling this type of irregular fluctuation (Fang & Shao, 2022).

Heteroscedastic autoregressive models are used as a mechanism for predicting volatility to model the variance that accompanies the time series of stock prices. These models' use of a conditional variable makes them better at describing the behavior of economic phenomena than models based on the unconditional mean. This additional feature provides greater accuracy in predicting future economic phenomena (Shahzad & Bouri, 2021). GARCH models have become one of the most important statistical tools used in analyzing time series data, particularly for financial phenomena, due to their ability to analyze the irregular fluctuations of time series data. Recently, the contributions of heteroscedastic autoregressive models have had a significant impact on estimating the level of financial risk, in addition to providing highly reliable predictive values for stock price variations in financial markets (Liu & Liu, 2022).

GARCH models aim to model the heterogeneity of time series variance. They are most commonly used in financial statement models, as the modern trend among investors focuses not only on analyzing and predicting the expected prices of stocks and bonds in financial markets, but also on the element of risk or uncertainty. To study uncertainty, we need special models that address the volatility of stock values across a time series, or what can be called the variance of the series (Upreti & Jia, 2022).

By attempting to develop a quantitative model that describes the volatility of stock prices in cooperative insurance companies in the Kingdom of Saudi Arabia, the behavior of the conditional variance of the stock price time series can be modeled using ARCH and GARCH conditional variance models. This enables us to estimate the level of risk and make highly accurate predictions of price variances. Therefore, this research presents a method for modeling the irregular volatility of stock price time series (Koijen & Yogo, 2022). The remainder of this paper is organized as follows. Section 2 Data and Methodology, Section 3 Empirical Findings & Results. Finally, Section 4 Conclusions.

2. Data and Methodology

2.1 Using GARCH models to measure stock risk

Models that describe the changes that accompany the curve representing time series are divided into two types. The first includes linear models, which are constructed using regression analysis models. They reflect the interrelationships between variables with the aim of achieving the most accurate estimation and prediction of the values of a single variable, based on the values of other explanatory variables. These, in turn, include a set of methods, perhaps the most important of which is autoregressive (AR(P)) models, which rely on studying the current value of the time series based on the sum of previous values and the error of the current value (Xu, 2024).

These models rely on the fact that current experience is explained by the weighted average of the values of previous periods up to period P, which represents the degree of the model. What distinguishes autoregressive models is the state of stability that accompanies the autocorrelation function of the time series. The moving average (MA(q)) model relies on error values to represent the time series under study. That is, each observation in the series is explained by a weighted average of random errors up to period q, which represents the degree of the model (Obeng, 2021).

The ARCH and GARCH models primarily aim to address the statistical problem of homoskedasticity. The absence of homoskedasticity in time series values across time limits makes many statistical tests inapplicable, as well as the insignificance of regression function coefficients, due to the lack of independence. The variance of the random term is assumed to be constant over time, or what is known as the constant variance assumption. However, this condition is often not met in financial and economic data, as different variances and fluctuations appear across the periods that comprise the series (Singh & Alruwaili, 2024).

2.2 ARCH models

These models are based on the assumption that the variance of the time series over time is a variable dependent on the available information about the phenomenon. The analysis of this model depends on both the mean and variance equations, as the model consists of two parts, the first of which represents the mean equation, which is a function of the explanatory variable x, and the random error ε_t (Dong & Ren, 2023):

$$Y_t = \beta_0 + \beta_1 x_t + \varepsilon_t \quad (1)$$

Where β_0 represents the fixed part, the second part of the model depends on the conditional variance equation with the information available during the period t, and this equation takes the following form- :

$$H_t = \sigma_t^2 = V\left(\frac{\varepsilon_t}{\varepsilon_{t-1}}\right) = \alpha_0 + \alpha_1\, \varepsilon_{t-1}^2 \quad (2)$$

The conditional variance function can also take into account errors of several previous periods, and then it becomes as follows (Ming & Jiang, 2023)

$$H_t = \sigma_t^2 = h(\varepsilon_{t-1}, \varepsilon_{t-2}, \dots\dots\dots, \varepsilon_p, \alpha) \quad (3)$$

Where p represents the degree of the ARCH model and α represents the vector of unknown parameters, the general shape of the residual function is what makes it more likely to use one ARCH model than another. When we find that fluctuations take a sequential form, meaning that positive fluctuations are followed by positive fluctuations during the following periods, and negative fluctuations are followed by negative fluctuations as well, this is a strong indicator of the possibility of relying on ARCH models (Cong & Kang, 2025).

2.3 Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Models

These models can be denoted by the form GARCH(p, q), where (p) reflects the number of parameters of the ARCH model used, while (q) represents the number of parameters of the GARCH model. The larger the number of parameters, the more accurate the model is in describing the heterogeneity process in the series. The function representing this model depends on the values of the squares of the residual series for the previous periods in addition to the constant term α_0. The function takes the following form (Osho & Oloyede, 2024)

$$\sigma_t^2 = \alpha_0 + \alpha_1\, x_{t-1}^2 + \dots\dots + \alpha_p\, x_{t-p}^2 + \beta_1\, \sigma_{t-1}^2 + \cdots . + \beta_q\, \sigma_{t-q}^2 \quad (4)$$

Where

$$x_t = \sigma_t\, \varepsilon_t$$

Therefore, the GARCH(1,1) model can be formulated as follow:

$$\sigma_t^2 = \alpha_0 + \alpha_1\, x_{t-1}^2 + \beta_1\, \sigma_{t-1}^2 \quad (5)$$

The GARCH (2,2) model can also be formulated as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1\, x_{t-1}^2 + \alpha_2\, x_{t-2}^2 + \beta_1\, \sigma_{t-1}^2 + \beta_2\, \sigma_{t-2}^2. \quad (6)$$

The formula for the unconditional variance function of the model takes the following form:

$$E(x_t^2) = \frac{\alpha_0}{1-(\alpha_1+\beta_1)}. \quad (7)$$

To estimate the model parameters, the maximum likelihood function (MLM) method is used, under the assumption of random error distribution, which assumes that the random error depends on the normal distribution. Therefore, the likelihood function will take the following form (Gbolagade & Okegbade, 2022):

$$L(r_t \,/\, \Theta) = -\frac{N}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{N}\log\sigma_t^2 - \frac{1}{2}\sum_{t=1}^{N}\varepsilon_t^2 \,/\sigma_t^2 \quad (8)$$

Where

$$r_t = \mu + a_t \quad (9)$$

$$a_t = \sigma_t\,\varepsilon_t\,,\ \varepsilon_t \sim iidN(0,1) \quad (10)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1\,\sigma_{t-1}^2 \quad (11)$$

The GARCH model is based on a vector of parameters denoted in the previous function by the symbol Θ, where the model parameters include $(\mu, \alpha_0, \alpha_1, \beta_1)$, and these parameters are estimated using the location function method (Jeribi & Ghorbel, 2022).

3. Empirical Findings & Results

3.1 Regression modeling that describes the time series of stock prices

Describing the regression relationship for stock prices represents the first step in the proposed model, with the goal of arriving at the general form of the residuals, which will be subjected to study and analysis (Farahani & Hajiagha, 2021). Table (1) illustrates the significance of the regression relationship. This results in the possibility of relying on the values of the residuals derived from it in constructing GARCH models (Md & Tee, 2023).

Table.1 Characteristics of the regression model describing the change in stock prices relative to changes in time

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.0055	0.0013	4.9009	0.0000
$S.E.$ of regression	0.0120	Akalke info criterion		-7.69701
Sum squared resid	0.0114			
Log likelihood	315.6911	Schwarz criterion		-7.66272
Durbin-Watson stat	1.9094	Hannan-Quinn criter.		-7.68319

Examining the time series graph reveals an increase in the pattern of fluctuations and volatility observed in the residual values of the stock price time series. This pattern of fluctuations represents one of the most important justifications for applying the ARCH and GARCH models (Tan & Webb, 2021).

3.2 GARCH(1,1) model

Since the effect of prior information derived from the time series of stock prices is not significant, which we call the ARCH effect, to show the effect of prior fluctuations, which we refer to as the GRACH effect, we need a model that combines both the effect of prior information and prior fluctuations on modeling the series of residuals of the regression relationship of stock prices, and we call that model the GARCH(p,q) model, and this model depends on the fact that the variance function of the residuals takes the following form (Mustafa, S., Bajwa & Iqbal,2022):

$$H_t = \alpha_1 + \alpha_2 H_{t-1} + \alpha_3 e_{t-1}^2 + \alpha_4 x_1 + \alpha_5 x_2 \quad (12)$$

Where H_t (the error value) represents the variance of the residuals, which was estimated using the mean equation for the variable under study. It refers to the current volatility in the time series of stock prices, while α_1 represents the fixed part of the equation. The current volatility depends on a set of factors, including the variance function of the residuals during the previous period H_{t-1}, which we call the GARCH effect. It indicates the expected effect of past volatility on current volatility H_t, as well as the amount of volatility in stock prices during previous periods e_{t-1}^2, which is the square of the residual values, and it reflects the previous information derived from volatility in stock prices, and we refer to it as the ARCH effect. The previous function represents the basic formula for the GARCH(1,1) model. It includes a part that reflects the first-order ARCH effect e_{t-1}^2, as well as the first-order GARCH effect H_{t-1}. By applying the model, the following results were obtained (Grach & Demekhov, 2025):

Table. 2 Applied results of the (GARCH(1,1)) model for the time series of residuals

Dependent Variable		GARCH(1,1)	**GARCH(1,1) MODEL**	
Method: ML ARCH – Normal distribution				
Date: 02/08/25		Time: 21:32		
Sample: 2015M01 2025M04				
GARCH = C(2) + C(3) * RESID(-1)^2 + GARCH(-1)				
Variable	**Coefficient**	**Std. Error**	**Z-Statistic**	**Prob.**
C	0.00426	0.00031	3.94258	0.0000
Variance Equation				
C	4.93E-05	8.93E-06	4.93837	0.0000
RESID(-1)^2	0.83635	0.261528	7.03645	0.0004
GARCH(-1)	-0.00752	0.003625	-3.74647	0.02615
R-Squared	0.6374	**Akaike info criterion**		-7.93847
Adjusted R-squared	0.6192	**Schwarz criterion**		-7.64736

Table. 2 shows the significance of each of the parameters of the mean and variance function of the model. Therefore, both ARCH(RESID(-1)^2) and GARCH(-1) have a significant impact in explaining the fluctuations in the stock prices of the company under study. The function expressing the previous model takes the following form (Grach & Demekhov, 2023):

GARCH(1,1) = $4.93E-05 + 0.83635$*RESID(-1)^2 -0.00752*GARCH(-1)

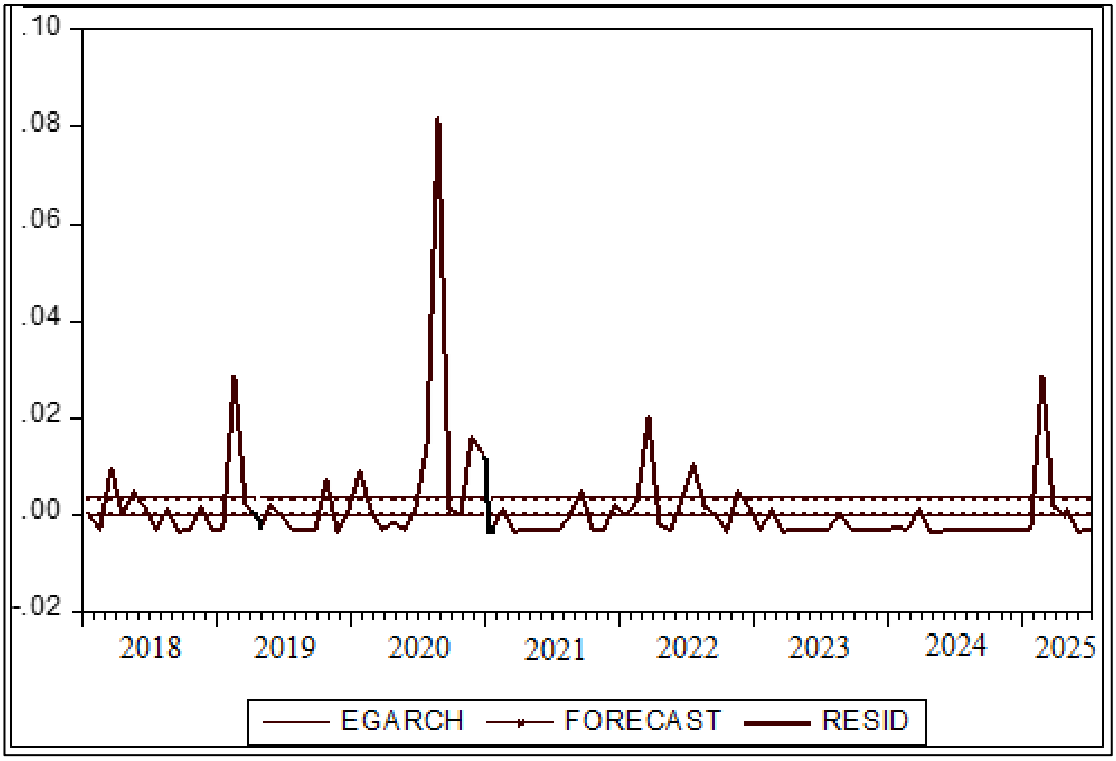
Where RESID(-1)^2 represents the ARCH effect and GARCH(-1) represents the GARCH effect, it is also clear from the previous table that the value of the test statistic for the selection criterion AIC reached -7.93847, and it reached -7.64736 for the SIC criterion. For the model to be applicable, there should be no autocorrelation between the values of the residuals of the time series. Table.3 shows the autocorrelation of the time series of residuals, which is used to test the extent of the presence of autocorrelation between the residuals (Babu & Shrestha, 2023).

Table. 3 Results of the autocorrelation test for the time series residuals of GARCH(1,1) model

Correlogram of Standardized Residuals Squared						
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.1572	0.1572	2.2716	0.0690
		2	-0.0058	-0.0318	2.2767	0.1980
		3	0.1142	0.1242	3.5010	0.2380
		4	0.0682	0.0312	3.9361	0.2920
		5	-0.0528	-0.0638	4.2156	0.3960
		6	0.0142	0.0252	4.2331	0.5220
		7	-0.0138	-0.0368	4.2570	0.6270
		8	-0.0298	-0.0098	4.3525	0.7010
		9	0.0262	0.0362	4.4175	0.7590
		10	0.0242	0.0132	4.4743	0.8000

Table. 3 shows that all P-values are greater than the 5% significance level used, thus ensuring the absence of autocorrelation between the residuals. Forecasting represents the next step in selecting the appropriate model to model the variance of the time series of stock prices for the company under study. By developing a model that accommodates all fluctuations and oscillations that accompany the time series of stock prices, in addition to achieving stability for the conditional variance of the time series using the GARCH model, highly accurate results can be achieved when analyzing the time series. This is achieved by estimating the conditional standard deviation value during the study period, which is estimated based on the variance equation after applying the model. Therefore, the values derived from the function can be compared with their actual counterparts for the conditional standard deviations of the time series of residuals, taking into account that the average values represented by the average equation are constant values for the time series. Figure. 1 shows the graphical representation of both the time series of values predicted using the GARCH model, the values predicted from the mean equation, and the time series of residual values (Hong & Chan,2023):

Figure.1 Comparative graph of the time series of values predicted using the GARCH model and the values predicted from the mean equation and the time series of residuals



The values in tables (2&3) demonstrate that the proposed model was able to achieve stability for the time series and eliminate the effect of heteroscedasticity, as the predicted values of the conditional standard deviations were close to the unconditional standard deviation. Therefore, the model successfully modeled the volatility of the stock price time series (Han & Awwad, 2024). Therefore, it can be said that the use of nonlinear GARCH models to model the volatility of the stock price time series has succeeded in making the time series a linear series in the case of achieving stationarity, as a result of the convergence of the predicted values from the proposed model and the unconditional variance of the series values. In other words, these models were able to accurately describe the variance associated with the stock price time series, which is characterized by heteroscedasticity (Dadhich & Doshi, 2021).

4. Conclusion

The study concludes the importance of modeling stock price volatility in insurance companies, as these volatility factors represent a key measure of the risks associated with equity investment. By using the GARCH(1,1) model, the study was able to provide an accurate description of stock price variability, enhancing understanding of the financial risks faced by insurance companies. The results showed that irregular volatility significantly impacts investor confidence, leading to a decline in the market value of these companies, a significant challenge to their success. The study also demonstrated that the GARCH(1,1) model is most appropriate for modeling these volatility factors, demonstrating its effectiveness in stabilizing the time series of stock prices. Statistical tests demonstrated the absence of significant autocorrelation coefficients, indicating the stability of the time series. This stability is a prerequisite for using nonlinear models, enhancing the credibility of the results. The study recommends that insurance companies adopt the proposed model, as it will enable them to accurately predict stock price movements, helping to reduce the irregular risks associated with this type of asset. Understanding the relationship between changes in volatility and price heterogeneity will have a positive impact on the decision-making strategies of these companies. In conclusion, the findings of this research highlight the urgent need for further research in the field of financial risk modeling for insurance companies, which will contribute to improving financial performance and increasing investor confidence. Adopting advanced analytical methods such as the GARCH model will help achieve greater sustainability in this vital sector.

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