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Statistical Investigation of Volatility Clustering and Shock Behavior Using Conditional Models

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Abstract—Evaluating businesses and initiatives using the stock market is crucial. Its success or failure is appraised, thereby helping to raise knowledge and comprehension of the realities of companies and projects among investors. Falling stock prices prompt management or policy adjustments aimed at improving their condition. Accordingly, the New York Stock Exchange, the Shanghai Stock Exchange, and the Hong Kong Stock Exchange—three of the most crucial financial hubs in the world—were examined. These exchanges provide a platform for trading equities and exchange-traded funds, thereby enabling investors to have a range of investment options. This study is to investigate the changes and shocks in the stock prices of the New York Stock Exchange, the Shanghai Stock Exchange, and the Hong Kong Stock Exchange. We employed the conditional models GARCH, PARCH, TGARCH, and EGARCH. From 2000 to early 2005, these models drew on weekly historical data for every stock market. The findings show that the conditional models successfully identified stock price shocks and changes. They might also examine these shocks and changes to determine the most significant economic, social, and political ones that had a substantial impact on their performance. This study contributes to the understanding of shocks and volatility in stock values, which can inform wise investment choices.

Keywords—GARCH model; PARCH model; TGARCH model; EGARCH model.

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I. INTRODUCTION

Most of the time, stock markets and stock exchanges do not own the goods and commodities that are traded on them. This is in contrast to conventional markets, which sell a wide range of products and commodities. Stock markets and stock exchanges do not sell the products and commodities that are sold there. The reason for this is that they differ from traditional marketplaces. Unlike dealing in physical goods, they engage in the trading of financial assets, which are often referred to as securities. Other terms for these assets include securities. In comparison to other traders, this provides them with a significant edge. This category of assets comprises two distinct types: stocks and bonds. Both of these forms of assets are stocks.

In the realm of finance, the sector is governed by a wide range of legal and technological regulations. Both of these limitations apply to the situation. Not only do the limits that are now in place specify when and how transactions can take place, but they also specify the kinds of assets that can be selected and the options that can be made for those securities. These regulations are the norms that govern the stock market and serve as the regulatory criteria. If investors make stock purchases or sales on the stock market based on information that is either inaccurate or misleading, or if they do not do a comprehensive analysis of the material themselves, they run the risk of losing a significant amount of money. If they do not conduct a thorough investigation of the material themselves, this danger will be multiplied. Because the stock market is free, an excessive level of speculation has led to the failure of numerous businesses and organizations that have encountered financial difficulties. This has led to the demise of financial institutions and enterprises.

In most cases, the price at which the market closed for the day is used as the foundation for the computation of loss and gain points. This is done to establish profit and loss points. Within the context of the stock market, the level of the market is referred to as a point, and the closing price is frequently utilized to determine whether a point has been achieved [1], [2]. There is no doubt about that; in point of fact, it is. There is a strong connection between the stock market and time series models, which are essential because they help us understand the shifts that occur in financial data over time [3].

This connection is a result of the fact that time series models are significant.

One of the most important reasons for the relevance of time series models is associated with this link. The relationship between the time series models and the stock market is both close and personal. This relationship is very near and personal to the individual. The purpose of this study is to provide individuals with the support they need to make informed decisions about their investments. This will be accomplished through the process of forecasting how the financial markets will act and what prices will be in the future. To analyze price fluctuations and develop more precise predictions, time series data may be utilized in conjunction with techniques such as ARIMA and GARCH [4]. Other approaches that can be used include. Achieving this goal is possible through the utilization of data.

When conducting market research or seeking investment opportunities, it is crucial to have a solid understanding of the concepts of "trend" and "seasonality," as well as how these concepts impact time series. It is crucial to have this understanding, as it enables one to make informed judgments based on accurate information. To be more specific, these components are of utmost importance to the process currently underway [5].

Throughout the research endeavor, the GARCH, TGARCH, EGARCH, and PARCH models were employed, and each was applied to three distinct stock markets. Although the New York Stock Exchange (NYSE) is the largest financial market in the world, the Shanghai Stock Exchange is also considered one of the most important stock exchanges globally [6]. The headquarters of each of these organizations may be found in China. All of these transactions can be traced back to China, the country of origin for each of them. It is estimated that approximately 2,400 firms are listed on the New York Stock Exchange (NYSE), which was established in 1792 and is now managed through the use of computers. The NYSE is home to approximately 2,400 enterprises. There are currently more than 170 million investors registered on the market. This is a direct result of the pandemic caused by the coronavirus, which led to a significant increase in market activity.

On the other hand, the market is facing particular difficulties, such as a decline in the industry. This is one of the obstacles for the market. Real estate and debt capitalization are typically regarded as components of investment within the Chinese stock market (SSE) [7], [8]. The Shanghai Stock Exchange is represented by the acronym SSE. The Hong Kong Stock Exchange (HKSE) is widely regarded as one of the most influential financial institutions in the world, according to a large number of individuals. The Hong Kong Stock Exchange has a total of 2,609 distinct firms and organizations that provide their services to investors. One hundred eighty-one of them have their headquarters located outside of Hong Kong, while the remainder, 2,428, have their corporate headquarters in Hong Kong. It is the third-largest stock market in Asia and the fifth largest in the world [9]. This is because it is the third-largest stock market in Asia.

Many people believe that the Hang Seng Index is one of the most effective metrics for evaluating the market's performance. This is because the Hang Seng index measures the performance of the Hang Seng. Some of the assets that may be acquired on the market are stocks, futures, and real estate investment trusts (REITs). Other assets include futures and futures contracts. You may buy a wide variety of assets from a variety of different sources. The stock market is based on wrong or misleading information, or if they don't carefully look over the material. Because the stock market is free, too much speculation has led to the downfall of many major banks and businesses. A point is the level of the stock market, and the closing price of the market for the day is typically used to figure out loss and gain points [10] . Yes, it is. The stock market is closely linked to time series models, which are essential because they help us understand how financial data changes over time [11]. The stock market is extremely closely linked to time series models.

The goal of this research is to help individuals make informed investment decisions by predicting future market behavior and future prices. Time series data can be analyzed using methods such as ARIMA and GARCH [12] to examine price changes and improve prediction accuracy. When conducting market research or exploring investment opportunities, it is essential to understand what trends and seasonality are and how they impact time series. This is because these parts are critical to the process. The study employed GARCH, TGARCH, EGARCH, and PARCH models across three different stock markets. The New York Stock Exchange (NYSE) is the biggest financial market in the world, and the Shanghai Stock Exchange is one of the biggest stock exchanges in the world. The New York Stock Exchange (NYSE), founded in 1792 and now operating on computers, has over 2,400 companies listed on it [13].

Due to the coronavirus pandemic, market activity increased significantly, and the number of listed investors now exceeds 170 million. The market, on the other hand, is facing challenges, including a decline in the industry. Real estate and debt capitalization are often part of investment in the Chinese stock market (SSE) [14]. The Hong Kong Stock Exchange (HKSE) is one of the world's most prominent financial organizations. There are 2,609 businesses on the Hong Kong Stock Exchange. Of these, 2,428 are based in Hong Kong and 181 are based outside of Hong Kong. Due to this, it is the third-largest stock market in Asia and the fifth-largest stock market in the world [15], [16]. Many people think that the Hang Seng Index is one of the best ways to measure how well the market is doing. People can buy a lot of different kinds of assets on the market, such as stocks, futures, and REITs.

II. Materials and Methods

A. *Stationary Time Series*

There are two types of models that many believe can be applied to non-stationary time series: autoregressive models and integrated moving averages (ARIMA). These models make the time series stationary on average. The economic analysis makes this assumption, which is sometimes referred to as the assumption of constant variance (Homoscedasticity). It is based on the idea that the variance of the random error factor remains steady over time. This assumption is incorrect in instances where the data is volatile. Heteroscedasticity is a type of variance that isn't consistent. Trying to make it stable makes it less accurate at predicting changes. Therefore, instead of examining the unconditional variance, which represents the long-term variance of the time series and is often assumed to be constant, it is more beneficial to analyze the pattern of variance fluctuation, also known as volatility. The conditional variance test is one example of the previous study [17].

B. Heteroscedasticity Conditional Autoregressive Models

Heteroscedasticity is a common trait in financial time series. People are familiar with the ARCH model through the following sources [18], [19], [20].

$$z_t = \phi x_t + \mu_t \tag{1}$$

$$\begin{aligned}\sigma_t^2 &= \mathrm{E}(\mu_t^2/\mu_{-1}, \mu_{-2} \ldots) \\ &= a_0 + a_1\mu_{t-1}^2 + \cdots\cdots + a_p\mu_{t-p}^2 \\ &= \sum_{i=1}^{p} a_i \mu_{t-i}^2\end{aligned} \tag{2}$$

The variable x_t in the equation that shows the measure of the mean is the independent variable that was measured at time t. The coefficient ϕ, which is a nonzero undefined coefficient, and the random error term μ_t, which is likewise a random error term [21].

C. GARCH model

The GARCH model is a big step forward from the ARCH model. When used on financial time series, it might give a more accurate picture of how likely it is that volatility would cluster. We utilize the following formulae to figure out the conditional variance. We think of this model as a GARCH process in order to figure out the time-varying volatility it includes.

$$z_t = \phi x_t + \mu_t, \mu \sim N(0, \sigma_t^2) \tag{3}$$

$$\sigma_t^2 = \omega + \textstyle\sum_{i=1}^{p} a_i \mu_{t-i}^2 + \sum_{i=1}^{q} B_i \sigma_{t-i}^2 \tag{4}$$

D. PARCH Model

The authors in [22] suggested using the GARCH model to find the standard deviation. This model uses a standard deviation fit instead of the Bollerslev GARCH model to decrease the effect that big shocks have on the conditional variance. The authors [23] used formulas like the one below to add standard deviation to the GARCH model. They called it the PARCH model, which stands for the parametric autoregressive conditional heteroscedasticity model.

$$\sigma_t^\delta = \omega + \textstyle\sum_{j=1}^{q} B_j\, \sigma_{t-j}^\delta + \sum_{i=1}^{p} a_i (|\mu_{t-i}| - \gamma_i \mu_{t-1})^\delta \tag{5}$$

People usually call the power coefficient of the computed standard deviation δ. This coefficient is used to figure out how much the conditional variance varies as the conditions change. The asymmetric coefficient, which is shown by the symbol γ, is a number that shows the asymmetric effect that is higher than or equal to a level of r. For i=1,2,...,r, γ_i is less than 1, and for i>r, γ_i is equal to zero. Also, r is smaller than p. The PARCH model can reach its aims because it gets beyond the GARCH model's restriction on non-negative numerical parameters [24]. Equation 4 shows that the GARCH model can't explain why there is a negative link between the return on financial assets and the volatility of returns. This is because the conditional variance always reacts the same way to changes in both good and bad effects, which is not what truly happens. The ARCH model, which is made up of the part of the equation that was spoken about earlier, shows that the conditional variance model (GARCH (1,1)) is based on the following formula [25]:

$$\sigma_t^2 = \omega + a \times \mu_{t-1}^2 + B \times \sigma_{t-1}^2 \tag{6}$$

$$\sigma_t^2 = \overline{\omega} + a(\mu_{t-1}^2 - \overline{\omega}) + B(\sigma_{t-1}^2 - \overline{\omega}) \tag{7}$$

$$\sigma_t^2 - q_t = a(\mu_{t-1}^2 - q_{t-1}) + B(\sigma_{t-1}^2 - q_{t-1}) \tag{8}$$

$$q_t = \omega + \rho(q_{t-1} - \omega) + \phi(\mu_{t-1}^2 - \sigma_{t-1}^2) \tag{9}$$

$$q_t = \omega + \rho(q_{t-1} - \omega) + \phi(\mu_{t-1}^2 - \sigma_{t-1}^2) + \theta_2 y_{2t} \tag{10}$$

$$\begin{aligned}\sigma_t^2 - q_t = {}& a(\mu_{t-1}^2 - q_{t-1}) + B(\sigma_{t-1}^2 - q_{t-1}) \\ &+ \gamma(\mu_{t-1}^2 - q_{t-1})d_{t-1} + \theta_2 y_{2t}\end{aligned} \tag{11}$$

E. TGARCH Model

Authors in [26], [27] came up with the TGARCH model to learn more about volatility asymmetry. Adding default variables to the original model gives us the following equation:

$$d_t = \begin{cases} 1, & \mu_{t-1} < 0 \\ 0, & \mu_{t-1} \geq 0 \end{cases} \tag{12}$$

The TGARCH variance equation is defined by the following formula [28]:

$$\begin{aligned}\sigma_t^2 = {}& \omega + \sum_{i=1}^{p} a_i\, \mu_{t-i}^2 + \sum_{j=1}^{q} B_j \sigma_{t-j}^2 \\ &+ \sum_{k=1}^{r} \gamma_k \mu_{t-k}^2\, d_{t-k}\end{aligned} \tag{13}$$

Equation (13) shows financial market fluctuations for less stable whenever γ is greater than zero. On the other hand, when γ is smaller than zero, the asymmetric effect makes the financial market far less volatile [29], [30].

F. EGARCH model

In 1991, Nelson proposed the EGARCH model and demonstrated a logarithmic variant of the variance equation. He came up with the idea. In comparison to other models, the EGARCH model is superior when it comes to estimating the parameters of σ_t^2 since it does not impose any limitations on the parameters of the model. This is demonstrated by the computation that is presented below [31].

$$\begin{aligned}\ln(\sigma_t^2) = {}& \omega \sum_{i=1}^{p} a_i \left|\frac{\mu_{t-i}}{\sigma_{t-i}} - E\left(\frac{\mu_{t-i}}{\sigma_{t-i}}\right)\right| \\ &+ \sum_{j=1}^{q} B_j ln\left(\sigma_{t-j}^2\right) + \sum_{k=1}^{r} \gamma_k \frac{\mu_{t-k}}{\sigma_{t-k}}\end{aligned} \tag{14}$$

III. Results and Discussion

A. Analysis and Interpretation of Results

In this part of the research, conditional models will be applied to actual data to predict and evaluate their performance. Weekly historical data from 2000 to 2005 will be used for stock prices on the New York, Shanghai, and Hong Kong Stock Exchanges. The data will be analyzed using conditional models, GARCH, PARCH, TGARCH, and EGARCH to identify the most significant fluctuations and shocks in the stock market.

B. *Summary of Series*

The first thing we talk about is the descriptive statistics of the time series in Table 1. Before looking at the time series of the stock markets in New York, Shanghai, and Hong Kong, this is done.

TABLE I
DESCRIPTIVE STATISTICS FOR WEEKLY TIME SERIES

Statistics	NYSE	SSE	HKSE
Mean	10.22031	1.323844	0.255445
Median	24.95000	0.730000	0.000000
Maximum	1256.000	463.0800	67.60000
Minimum	-1718.800	-687.9900	-93.80000
Std.Dev.	237.5877	90.85163	9.661146
Skewness	-0.878997	-0.723161	0.020134
Kurtosis	10.36754	10.90945	17.42196
Jarque-Bera	31310511	3531.570	10902.39
Probability	0.000000	0.000000	0.000000

The average price of a stock on the New York Stock Exchange is 10, but the median price is 24. The weekly high (1256) and low (1718) reveal that the market has been very volatile in the recent week, with a standard deviation of 237. To get the profits you want without taking on too much danger, though, you need to come up with more careful investment strategies. The Shanghai Stock Exchange is one of the most significant stock exchanges in Asia and plays a pivotal role in the Chinese economy. It is one of the biggest stock markets in the world. Descriptive statistics for the stock exchange indicate a significant variation in values, suggesting that prices fluctuate substantially. The distribution is also not symmetrical and is skewed to the left, which means that some big numbers on the negative side are not connected. Because of this, investors should be careful when putting money into the Shanghai Stock Exchange. There are significant price changes on the Hong Kong Stock Exchange because valuations differ significantly from one another. Also, the distribution is unequal and favors one side over the other. Because of this, it is crucial to keep a close eye on the economy to detect any changes in distribution or variation.

C. *Stationary Test*

For time series analysis to work, the mean and variance must stay the same throughout time. This is especially significant in the domains of statistics . Most models require non-stationary variables, which differ from those that employ constant variables. A distinguishing feature of time series is that they encompass a large amount of data, which can be collected on a monthly, weekly, or daily basis. On the other hand, financial series are often not stationary. Both Figure 1 and Table 2 illustrate that the time series of global stock markets (NYSE, SSE, and HKSE) exhibit instability, as they fluctuate significantly due to various events and factors.

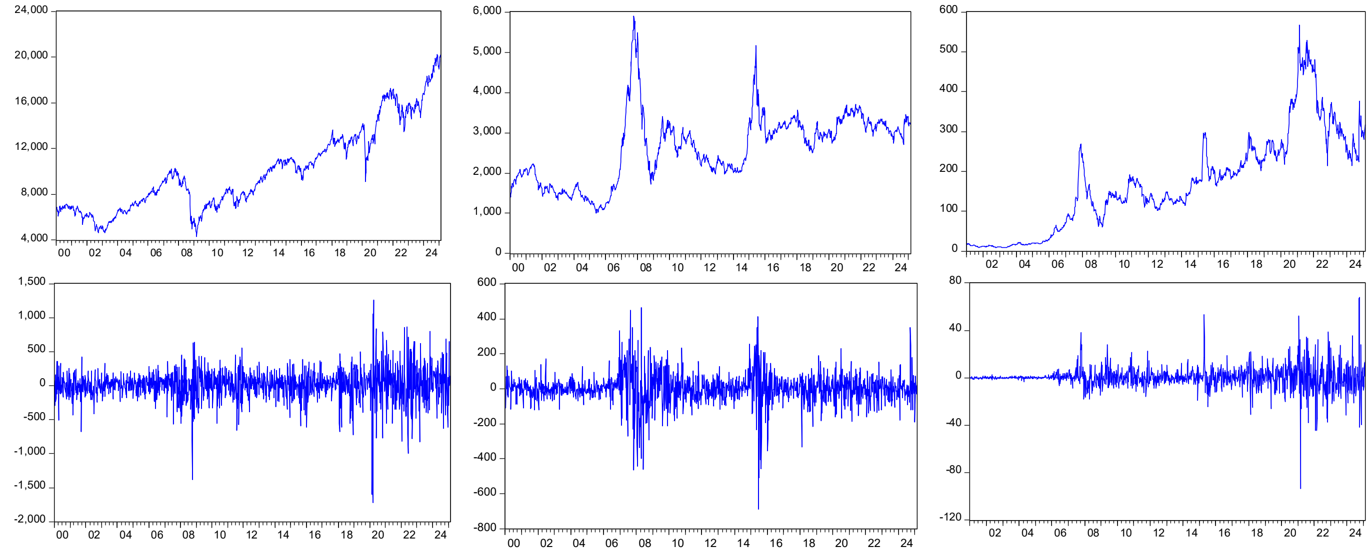

Fig. 1 Distribution of Open Price (the first row), and Volatility Clustering of weekly NYSE, SSE, and HKSE Composite Index.

TABLE II
AUGMENTED DICKEY –FULLER TEST

Series	Augmented Dickey –Fuller					
	Constant		Constant Linear Trend		First Derivative	
	t-Statistic	Probability	t-Statistic	Probability	t-Statistic	Probability
NYSE	0.278961	0.9772	2.309350	0.4280	37.77681	0.0000
SSE	2.269424	0.1822	2.630791	0.2665	33.41090	0.0000
HKSE	1.448994	0.5593	3.337083	0.0608	32.50085	0.0000

The fact that these time series are unstable shows that this instability is fundamental. The fact that the ADF statistic value was higher than 0.05 confirmed that the three-time series were unstable. The first difference of the time series was taken to obtain a stable time series that could display all the positive and negative changes and their impact on the rise or fall of stock prices on the world's largest stock exchanges, based on the market capitalization of the companies listed on them.

D. *Estimation Model with Normal Distribution*

Four separate models were used to determine the value of the stock models. According to Table 3, a model called

GARCH (1,1) suggests that the conditional variance of the New. Even if prior shocks do not have much of an effect on conditional variance, a high conditional variance means that prices are somewhat volatile. All of this suggests that past shocks have little impact on the market.

TABLE III
GARCH (1,1) MODELS WITH NORMAL DISTRIBUTION

	Variance Equation	NYSE	SSE	HKSE
ω	Coefficient	1929.857	178.1236	0.011099
	Std. Error	389.8180	32.01263	0.003416
	Z- Statistic	4.950662	5.564165	3.249097
	Prob.	0.0000	0.0000	0.0012
α	Coefficient	0.229643	0.165633	0.0168013
	Std. Error	0.020984	0.016613	0.009284
	Z- Statistic	10.94380	9.970164	18.09789
	Prob.	0.0000	0.0000	0.0000
β	Coefficient	0.757451	0.814664	0.859533
	Std. Error	0.022103	0.017102	0.005560
	Z- Statistic	34.26855	47.63513	132.5446
	Prob.	0.0000	0.0000	0.0000

Normal distribution of the PARCH (1,1) models is shown in Table 4. The results of the estimation, as shown in Table 4, indicate that the PARCH (1,1) model suggests a large permanent conditional variance. This indicates that the New York Stock Exchange experiences significant price fluctuations and that the market does not rely solely on stocks, but instead on the conditional variance that has been present in the past.

TABLE IV
PARCH (1,1) MODELS WITH NORMAL DISTRIBUTION

Parameter	Variance Equation	NYSE	SSE	HKSE
ω	Coefficient	190.9480	22.88716	0.009895
	Std. Error	235.0108	26.29058	0.003158
	Z- Statistic	0.812507	0.870546	3.133299
	Prob.	0.4165	0.3840	0.0017
α	Coefficient	0.203047	0.157584	0.132215
	Std. Error	0.018167	0.016281	0.013428
	Z- Statistic	11.17657	9.678800	9.845847
	Prob.	0.0000	0.0000	0.0000
β	Coefficient	0.340777	-0.170293	-0.336142
	Std. Error	0.067428	0.051727	0.061481
	Z- Statistic	5.053913	-3.292163	-5.467404
	Prob.	0.0000	0.0010	0.0000
γ	Coefficient	0.775555	0.838395	0.896198
	Std. Error	0.019508	0.018330	0.006996
	Z- Statistic	39.75669	45.73930	128.1101
	Prob.	0.0000	0.0000	0.0000
θ	Coefficient	1.522795	1.521458	1.608705
	Std. Error	0.236010	0.262935	0.141288
	Z- Statistic	6.452258	5.786448	11.38597
	Prob.	0.0000	0.0000	0.0000

The Shanghai Stock Exchange's prices can move a lot, but it is crucial to remember that the market does not depend on previous shocks as much as it does on the conditional variation that happened in the past. The Hong Kong Stock Exchange has trouble with small price changes, and the fact that the market does not depend on past shocks as much as it relies on the previous conditional variance makes things worse.

The results of the TGARCH (1,1) estimate in Table 5 show that the New York Stock Exchange has a lot of price volatility and that the market is not very dependent on past shocks or the previous conditional variance. The market is significantly affected by past shocks, but the last conditional variance has a limited impact. The Shanghai Stock Exchange has low price volatility. The Hong Kong Stock Exchange has an unfavorable prior conditional variance and, therefore, exhibits significant fluctuations. Previous shocks have had a considerable effect on the Hong Kong Stock Exchange.

TABLE V
TGARCH (1,1) MODELS WITH NORMAL DISTRIBUTION

	Variance Equation	NYSE	SSE	HKSE
ω	Coefficient	2156.362	0.033549	-0.204462
	Std. Error	357.0522	0.039335	0.011286
	Z- Statistic	6.039347	0.852887	-18.11631
	Prob.	0.0000	0.3937	0.0000
α	Coefficient	0.105902	0.273834	0.329181
	Std. Error	0.025728	0.023895	0.015843
	Z- Statistic	4.116176	11.45971	20.77831
	Prob.	0.0000	0.0000	0.0000
β	Coefficient	0.217947	0.048347	0.109567
	Std. Error	0.037206	0.011628	0.012743
	Z- Statistic	5.857812	4.157815	8.598481
	Prob.	0.0000	0.0000	0.0000
γ	Coefficient	0.760089	0.971910	0.989566
	Std. Error	0.020419	0.004837	0.001853
	Z- Statistic	37.22471	200.9126	533.9587
	Prob.	0.0000	0.0000	0.0000

The EGARCH (1,1) estimate in Table 6 indicates that the New York Stock Exchange exhibits significant price volatility. The market also relies heavily on past shocks and has a negative connection with the previous conditional variance. On the other hand, the stock markets in Shanghai and Hong Kong are highly volatile in terms of prices. Additionally, the market is primarily based on the preceding conditional variance, rather than on shocks or changes that have already occurred.

TABLE VI
EGARCH (1,1) MODELS WITH NORMAL DISTRIBUTION

Parameter	Variance Equation	NYSE	SSE	HKSE
ω	Coefficient	0.466887	185.2339	0.009541
	Std. Error	0.099103	3210051	0.003064
	Z- Statistic	4.711106	5.770433	3.114239
	Prob.	0.0000	0.0000	0.0018
α	Coefficient	0.350769	0.205752	0.201488
	Std. Error	0.024837	0.024545	0.011900
	Z- Statistic	14.12285	8.382697	16.93127
	Prob.	0.0000	0.0000	0.0000
β	Coefficient	-0.132208	-0.09128	-0.136080
	Std. Error	0.018286	0.025575	0.016785
	Z- Statistic	-7.230222	-3.569120	-8.107360
	Prob.	0.0000	0.0004	0.0000
γ	Coefficient	0.930540	0.818181	0.890277
	Std. Error	0.009599	0.018107	0.007304
	Z- Statistic	96.94587	45.18538	121.8839
	Prob.	0.0000	0.0000	0.0000

E. Sensitivity of the Risk Function

The findings of the estimate of the ARCH (1,1) model in Figure 2 reveal that the permanent conditional variance is significant. This illustrates that the New York Stock Exchange experiences considerable price changes and that the market does not rely heavily on stocks, but instead on the conditional variance that has been present in the past.

The Shanghai Stock Exchange uses the risk function shown in Figures 3 and 4.

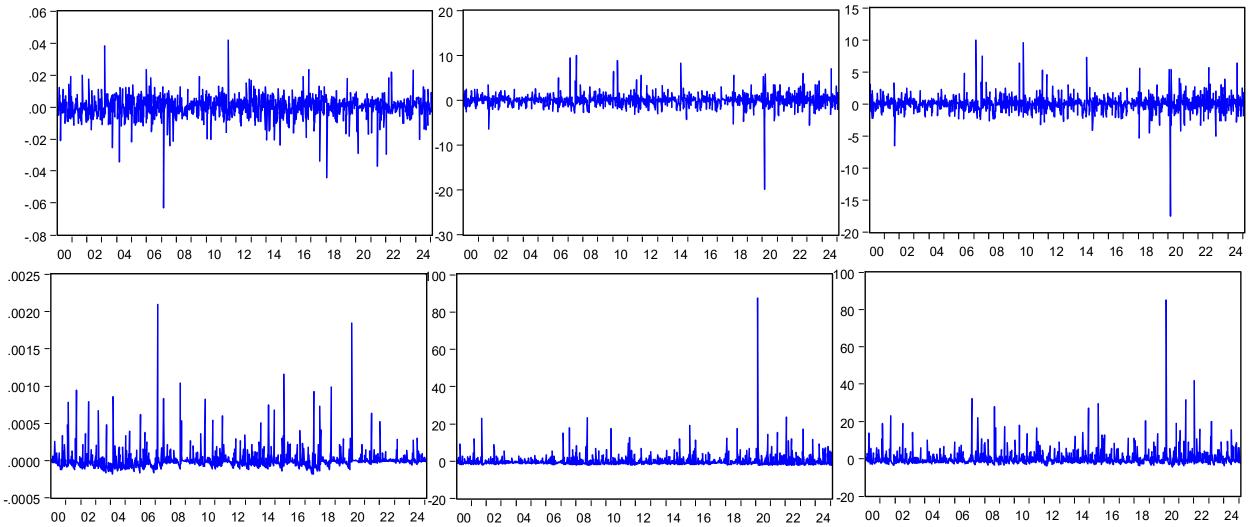

Fig. 2 Risk function of the parameters in the model for New York Stock Exchange

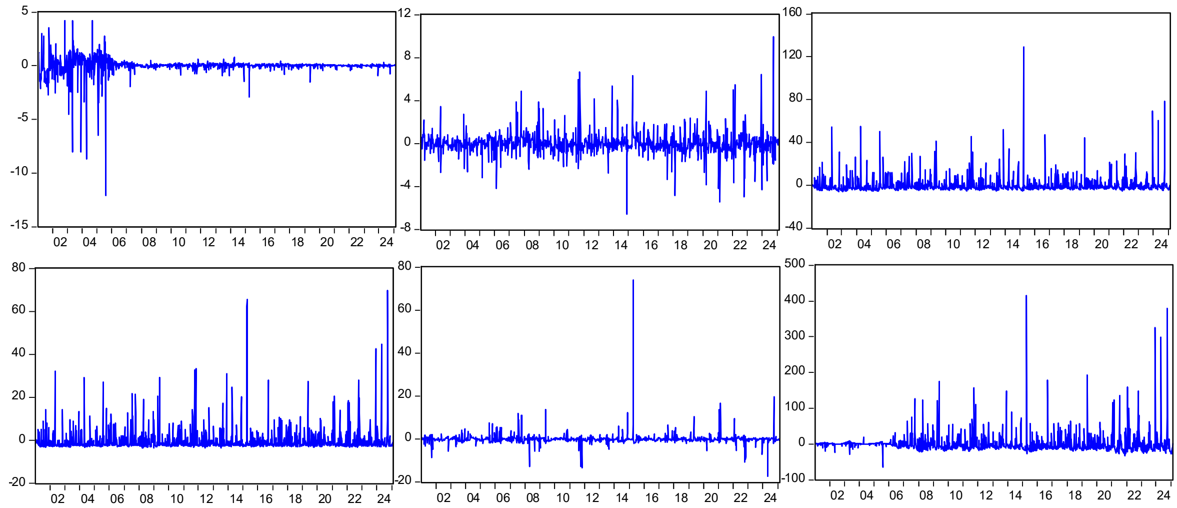

Fig. 3 Risk function of the parameters in the model for Hong Kong Exchange

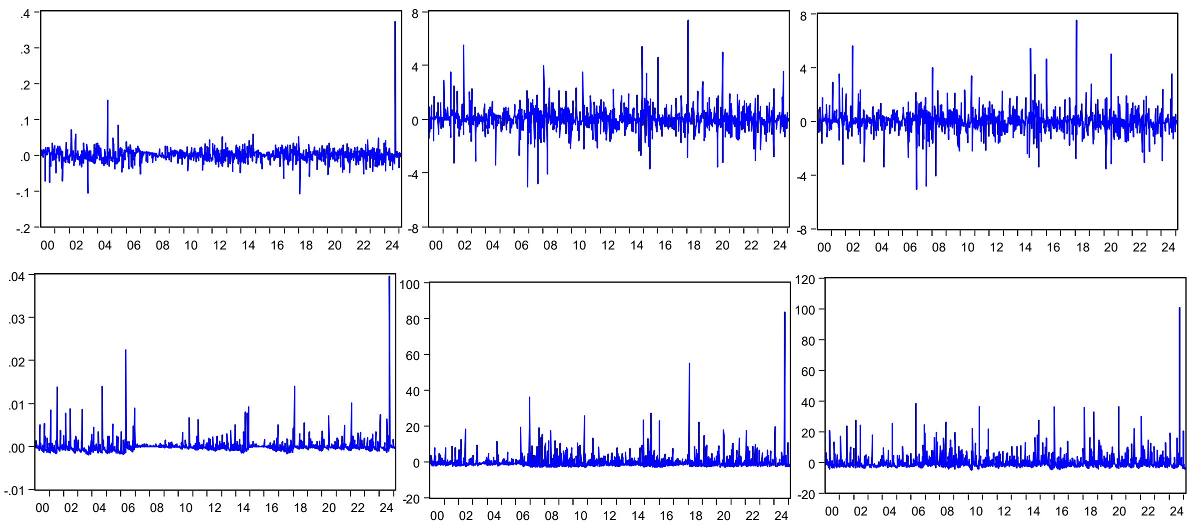

Fig. 4 Risk function of the parameters in the model for the Shanghai Exchange

F. *Estimation with t-Student*

The outcomes of the estimate of the PARCH (1,1) model in Table 3 reveal that the permanent conditional variance is significant. This illustrates that the New York Stock Exchange experiences considerable price changes and that the market does not rely heavily on stocks, but instead on the conditional variance that has been present in the past.

TABLE VII
GARCH (1,1) MODELS WITH T-DISTRIBUTION

Parameter	Variance Equation	NYSE	SSE	HKSE
ω	Coefficient	1312.417	85.24757	0.050332
	Std. Error	424.1265	32.86006	0.023559
	Z- Statistic	3.094400	2.594261	2.136442
	Prob.	0.0020	0.0095	0.0326
α	Coefficient	0.164939	0.115270	0.599783
	Std. Error	0.027737	0.020254	0.092836
	Z- Statistic	5.946434	5.691087	6.460642
	Prob.	0.0000	0.0000	0.0000
β	Coefficient	0.820966	0.877763	0.695309
	Std. Error	0.027582	0.020217	0.021465
	Z- Statistic	29.76481	43.41654	32.39301
	Prob.	0.0000	0.0000	0.0000

TABLE VIII
PARCH (1,1) MODELS WITH T-DISTRIBUTION

Parameter	Variance Equation	NYSE	SSE	HKSE
ω	Coefficient	162.7578	12.29211	0.003613
	Std. Error	266.9755	19.91740	0.003377
	Z- Statistic	0.609635	0.617154	1.069738
	Prob.	0.5421	0.5371	0.2847
α	Coefficient	0.161079	0.106653	0.093690
	Std. Error	0.031391	0.021552	0.018305
	Z- Statistic	5.131380	4.948598	5.118226
	Prob.	0.0000	0.0000	0.0000
β	Coefficient	0.379018	-0.214860	-0.379596
	Std. Error	0.115960	0.085742	0.131744
	Z- Statistic	3.268514	-2.505884	-2.881309
	Prob.	0.0011	0.0122	0.0040
γ	Coefficient	0.813202	0.897232	0.934967
	Std. Error	0.026942	0.018405	0.011011
	Z- Statistic	30.18325	48.74869	84.90836
	Prob.	0.0000	0.0000	0.0000
θ	Coefficient	1.539420	1.567894	1.156105
	Std. Error	0.314920	0.394152	0.264968
	Z- Statistic	4.888288	3.977889	4.363181
	Prob.	0.0000	0.0001	0.0000

TABLE IX
TGARCH (1,1) MODELS WITH T-DISTRIBUTION

Parameter	Variance Equation	NYSE	SSE	HKSE
ω	Coefficient	1751.674	77.27296	0.047914
	Std. Error	445.1646	30.32246	0.022474
	Z- Statistic	3.934890	2.548374	2.132039
	Prob.	0.0001	0.0108	0.0330
α	Coefficient	0.075487	0.139338	0.655333
	Std. Error	0.035620	0.025872	0.105769
	Z- Statistic	2.119206	5.385640	6.195899
	Prob.	0.0341	0.0000	0.0000
β	Coefficient	0.184005	-0.071796	-0.163234
	Std. Error	0.047268	0.027324	0.118436
	Z- Statistic	3.892817	-2.627602	-1.378237
	Prob.	0.0001	0.0086	0.1681
γ	Coefficient	0.799599	0.890040	0.699678
	Std. Error	0.028763	0.019875	0.021355
	Z- Statistic	27.80003	44.78224	32.76381
	Prob.	0.0000	0.0000	0.0000

TABLE X
EGARCH (1,1) MODELS WITH T-DISTRIBUTION

Parameter	Variance Equation	NYSE	SSE	HKSE
ω	Coefficient	0.285731	-0.042483	-0.074409
	Std. Error	0.112259	0.041234	0.016805
	Z- Statistic	2.545273	-1.030295	-4.427905
	Prob.	0.0109	0.3029	0.0000
α	Coefficient	0.284274	0.197579	0.372231
	Std. Error	0.039809	0.030363	0.065150
	Z- Statistic	7.140975	6.507215	5.713427
	Prob.	0.0000	0.0000	0.0000
β	Coefficient	-0.124954	0.048908	-0.259329
	Std. Error	0.024410	0.015385	0.051553
	Z- Statistic	-5.119052	3.178946	-5.030323
	Prob.	0.0000	0.0015	0.0000
γ	Coefficient	0.951859	0.987638	0.976610
	Std. Error	0.011319	0.005107	0.003786
	Z- Statistic	84.09239	193.3719	257.9621
	Prob.	0.0000	0.0000	0.0000

G. Comparison of Conditional Models

To evaluate conditional models for each stock exchange in isolation, we made use of the AIC, the log-likelihood criteria, and the Schwartz criterion. The three stock exchanges in question were the New York Stock Exchange, the Shanghai Stock Exchange, and the Hong Kong Stock Exchange. Having a low AIC value indicates that the model is the most accurate; however, a high log-likelihood value suggests that the model is more likely to be accurate. Since the Schwartz criteria take into consideration the total number of parameters in the model, they are superior for evaluating models that contain a variety of parameter values. The results of this research showed that the EGARCH model was the one that displayed the highest level of success in achieving the conditions for comparability set out by the New York Stock Exchange. In terms of performance, the Shanghai Stock Exchange model TGARCH and the Hong Kong Stock Exchange model GARCH were the most successful compared to one another.

TABLE XI
COMPARISON CRITERIA

Series	The Model	AIC		Schwarz		Likelihood	
		Normal distribution	t- distribution	Normal-distribution	t- distribution	Normal-distribution	t- distribution
	GARCH	13.41939	13.35809	13.43916	13.38182	-8777.988	-8736,870
NYSE	PARCH	13.40389	13.34869	13.43158	13.38033	-8765.847	-8728.721
	TGARCH	13.40414	13.34841	13.42787	13.37610	-8767.013	-8729.536
	EGARCH	13.40250	13.34859	13.42623	13.37628	-8765.939	-8729.653
SSE	GARCH	11.33192	11.27480	11.35168	11.29851	-7417.408	-7378.991
	PARCH	11.32687	11.27138	11.35454	11.30300	-7412.099	-7374.753
	TGARCH	11.32672	11.27073	11.35043	11.29840	-7412.999	-7375.329
	EGARCH	11.33218	11.27300	11.35590	11.30066	-7416.581	-7376.813
HKSE	GARCH	6.102889	6.119734	6.123321	6.144251	-3830.666	-3840.253
	PARCH	6.083221	5.963124	6.111825	5.995815	-3816.304	-3739.824
	TGARCH	6.080970	6.119651	6.105488	6.148255	-3815.890	-3839.200
	EGARCH	6.073678	6.254905	6.098195	6.283509	-3811.306	-3924.208

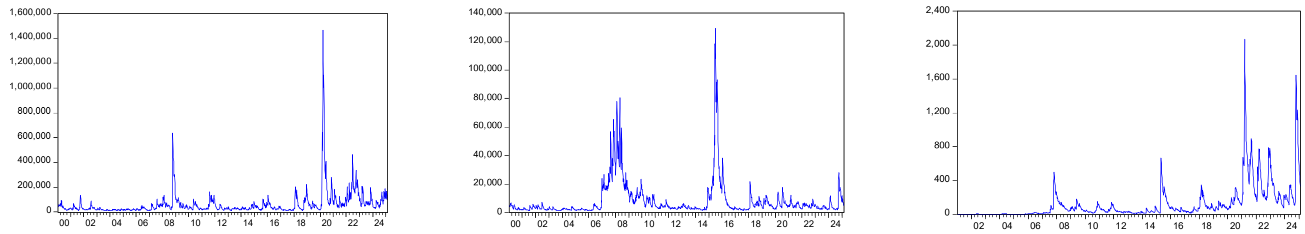

Fig. 5 Conditional Variance for NYSE, SSE, and HKSE, respectively.

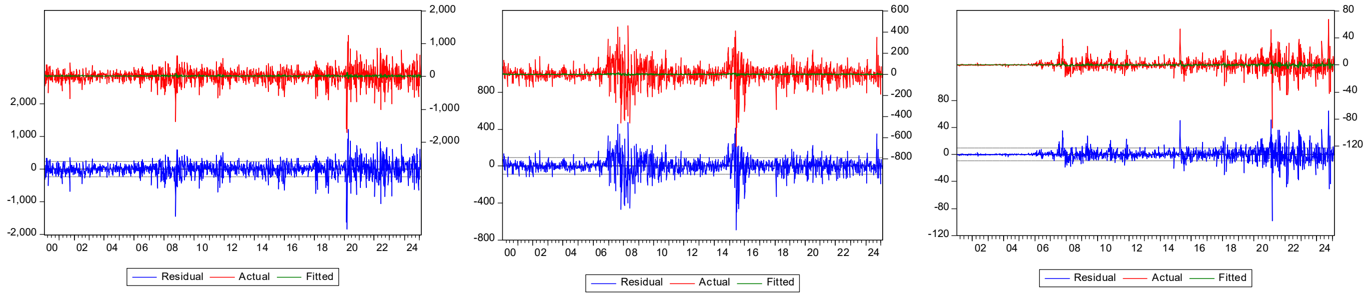

Fig. 6 The Actual(Red) and Residual(Blue) for NYSE, SSE, and HKSE, respectively.

H. Conditional Variance

Take note of the fact that the conditional variance corresponds to the initial period of the time series that is being investigated. There are some slight changes in the stock price in the years 2000 and 2002, after which it enters a condition of near-stabilization. Subsequently, the stock price undergoes substantial fluctuations in 2008, and it also experiences considerable oscillations in the stock price throughout the periods of 2020 and 2022. The New York Stock Exchange is the recipient of this. Regarding the Shanghai Stock Exchange, we observe the variations that occurred from 2006 to 2009, the fluctuations in 2016, and the relatively modest fluctuations that took place from 2018 to 2021. Despite the Hong Kong Stock Exchange's greater stability compared to its predecessors, it has experienced some minor fluctuations from 2007 to 2009 and 2015, in addition to significant swings from 2020 to 2024. This is something that we have observed.

I. Model Suitability

Suppose a model can continue to work well even when the data or parameters change, and the conclusions obtained from the model don't vary significantly. In that case, it is considered very good. Figure 6 illustrates the model's ability to effectively display time series data for the stock markets in New York, Shanghai, and Hong Kong. There are clear ups and downs in the graph from 2000 to 2024. This is because each stock market underwent a variety of political and economic changes, as well as global crises, which affected the prices of significant assets.

IV. Conclusion

The New York Stock Exchange, the Shanghai Stock Exchange, and the Hong Kong Stock Exchange are among the world's largest stock exchanges, with their influence extending globally. Therefore, these stock exchanges were modeled as a time series of weekly data from 2000 to 2025, by studying, plotting, and estimating the models GARCH (1,1), PARCH (1,1), TGARCH (1,1), and EGARCH (1,1). We conclude that these stock exchanges have been exposed to numerous fluctuations and political and social crises that have impacted global stock markets. Estimating the model parameters and examining the risk function revealed significant volatility from October 2007 to March 2009. This was due to the impact of the subprime mortgage crisis, as the markets experienced substantial fluctuations in stock prices.

Some companies listed on the New York Stock Exchange experienced significant declines in their stock prices. The major indices of the Shanghai and Hong Kong stock exchanges also declined, as evidenced by the estimated model parameters and the rest of the model, as well as by the conditional variance and risk function, where we see the peak of the graph rise during this period. It also shows that between 2010 and 2012, there was significant volatility in both the conditional variance and risk function. This is due to the euro crisis that began in 2010, one of the most critical financial crises in the history of the European Union, which led to increased volatility in stock prices on the New York, Shanghai, and Hong Kong stock exchanges. We also see notable changes in the risk function and conditional variance for 2008.

As some nations experienced notable declines in GDP, stock prices underwent significant fluctuations, and their impact on the global economy drove these variations. The conditional variance and risk function for the Shanghai Stock Exchange for the period 2015-2016 likewise showed rather noticeable variations. The Chinese economic crisis (2015-2016), which significantly impacted the Hong Kong Stock Exchange, is a contributing factor. Especially on the Hong Kong Stock Exchange, the conditional variance models show unambiguously how the COVID-19 situation affects stock market volatility. From the foregoing, we infer that conditional models are appropriate for examining the world's most significant stock exchanges—the New York, Shanghai, and Hong Kong—each of which has a considerable influence on all nations across the globe. When comparing stock exchanges in terms of volatility, the New York and Hong Kong stock markets show considerable volatility, whereas the Shanghai stock exchange shows moderate fluctuations. Moreover, the New York and Hong Kong stock markets react quickly to fluctuations in the global economy, whereas the Shanghai stock exchange does so slowly.

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