Artículo de investigación

Volatility of pakistan stock market: A comparison of Garch type models with five distribution

Volatilidad del mercado de valores de Pakistán: Una comparación de modelos tipo Garch con cinco distribuciones

Volatilidade do mercado de ações do Paquistão: uma comparação de modelos do tipo Garch com cinco

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Abstract

This study conducts empirical analyses modeling the volatility of Pakistani stock market over the period of 1st January 2008 to 30th June 2018 via different GARCH type Model; Symmetric (GARCH & GARCH-M) and Asymmetric (EGARCH & TGARCH) with five different Distribution Techniques such as Normal Distribution (Norm), Student's t Distribution (Std.), Generalized Error Distribution (GED), Student's t Distribution with fix the degree of freedom (Std. with fix DOF) and Generalized Error Distribution with fix parameters (GED with fix parameters). The results are shown in GARCH (1, 1) lagged conditional variance and squared disturbance which effects conditional variance is significant in all distribution. GARCH-M (1, 1) depicts a positive significant at 1% results in Std. and GED which indicates the existence of risk premium and insignificant in rest of the distribution on. EGARCH and TGARCH both are found to leverage effect significant at 1% level. In determining the accuracy and adequacy of forecasting density and choice of volatility model the results on simulated data indicates choice of conditional distribution appear as a more dominant factor. EGARCH model with Student's t the distribution technique is delivered

Resumen

Este estudio realiza análisis empíricos que modelan la volatilidad del mercado de valores pakistaní durante el período del 1 de enero de 2008 al 30 de junio de 2018 a través de diferentes modelos de tipo GARCH; Simétrico (GARCH & GARCH-M) y Asymmetric (EGARCH & TGARCH) con cinco técnicas de distribución diferentes, como la distribución normal (Norm), la distribución t de Student (Std.), La distribución de errores generalizada (GED), la distribución t de Student con la corrección del grado de libertad (Std. con corrección DOF) y Distribución de errores generalizada con parámetros de corrección (GED con parámetros de corrección). Los resultados se muestran en GARCH (1, 1) varianza condicional retrasada y perturbación al cuadrado, lo que afecta a la varianza condicional es significativo en toda la distribución. GARCH-M (1, 1) muestra un resultado positivo significativo al 1% en la norma. y GED, que indica la existencia de prima de riesgo e insignificante en el resto de la distribución en. Tanto EGARCH como TGARCH tienen un efecto de apalancamiento significativo al nivel del 1%. Al determinar la precisión y la adecuación de la densidad de pronóstico y la elección del modelo de volatilidad, los resultados

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satisfactory results as compare to other models which censored by statistical tools of maximum Log Likelihood, minimum AIC, and SIC. The previous study of Pakistani Stock Market is limited to GARCH family models with one or two distributions. This study covers the limitations and also contributes existing literature in this regard. This research is considered important for investors, policymakers, and researchers.

Keywords: Volatility, stock market, GARCH model, investor, economic

en datos simulados indican que la elección de la distribución condicional aparece como un factor más dominante. El modelo EGARCH con la técnica de distribución de Student se entrega con resultados satisfactorios en comparación con otros modelos que están censurados por las herramientas estadísticas de máxima probabilidad de registro, mínimo AIC y SIC. El estudio anterior de la Bolsa de Valores de Pakistán se limita a los modelos de la familia GARCH con una o dos distribuciones. Este estudio cubre las limitaciones y también aporta la literatura existente en este sentido. Esta investigación se considera importante para los inversores, los responsables políticos y los investigadores.

Palabras claves: Volatilidad, bolsa, modelo GARCH, inversor, económico.

Resumo

Este estudo realiza análises empíricas modelando a volatilidade do mercado de ações paquistanês no período de 1° de janeiro de 2008 a 30 de junho de 2018 através de diferentes modelos do tipo GARCH; Simétrico (GARCH & GARCH-M) e Assimétrico (EGARCH & TGARCH) com cinco diferentes Técnicas de Distribuição, como Distribuição Normal (Norm), Distribuição t de Student (Padrão), Distribuição de Erro Generalizada (GED), Distribuição t de Student com correção do grau de liberdade (Std. com correção de DOF) e distribuição de erros generalizada com parâmetros de correção (GED com parâmetros de correção). Os resultados são apresentados na variância condicional defasada GARCH (1, 1) e na perturbação quadrada que afeta a variância condicional em todas as distribuições. GARCH-M (1, 1) representa um significante positivo com resultados de 1% em Std. e GED que indica a existência de prêmio de risco e insignificante em resto da distribuição em. EGARCH e TGARCH ambos são encontrados para alavancar o efeito significativo ao nível de 1%. Ao determinar a precisão e a adequação da densidade de previsão e a escolha do modelo de volatilidade, os resultados em dados simulados indicam que a escolha da distribuição condicional aparece como um fator mais dominante. O modelo EGARCH com Student t a técnica de distribuição apresenta resultados satisfatórios quando comparado a outros modelos que foram censurados por ferramentas estatísticas de máxima Likelihood, mínima AIC e SIC. O estudo anterior do mercado de ações paquistanês é limitado a modelos de família GARCH com uma ou duas distribuições. Este estudo cobre as limitações e também contribui com a literatura existente a esse respeito. Esta pesquisa é considerada importante para investidores, formuladores de políticas e pesquisadores.

Palavras-chave: Volatilidade, mercado de ações, modelo GARCH, investidor, econômico

Introduction

Volatility forecasting and modeling of financial time series have become a fertile research area because of the volatility effect for many economic and financial applications. Volatility in stock prices is considered as an uncertain and high-risk factor of erosion of capital market due to that developing economies are facing much impairment in their financial market. A high volatile stock is more anxiety-producing for investors; although it's not an inefficiency mark of the market, it stances aftereffect of high volatility as 'market crash' and trivial amount of volatility can actually mean greater profit. Investment behavior[153] of investors in future returns perspective always affected by stock market volatility and they keep in touch with the fluctuation of market for their ventures (Hameed et al, 2006). Shah examined in their study that Pakistan Karachi Stock Exchange (KSE) has not received much attention due to an emerging market. Furthermore, previous researches of Pakistani stock market have based on shorter period of time except Shah's research, took over the period of 2nd November 1991 to 31st December 2013, it is an ever last longest period of data till now. Shah built a comprehensive picture of KSE's volatile nature by applying modern set of volatility model with one error distribution. In 2013 Vesna Bucevska applied Normal, Student and Generalised error distribution with GARCH type models on the Macedonian Stock Exchange (MSE) to measure the volatility and risk premium of Stock market (Bucevska, 2013; Shah et al, 2016). Lim and Sek directed empirical analyses by using the figurative data of Malaysian stock market to measure the volatility by implementing GARCH type models with statistical error measure tool (Lim and Sek, 2013).

Omorogbe (2017) applied the same models and techniques on the Nigerian Bank's Equity in modeling stock market volatility and concluded that variants of GARCH models and alternative error distribution should be considered for robustness of results (Omorogbe et al, 2017). Jyothi and Suresh observed a negative correlation between fluctuating of stock market prices and changing of volatility, financial leverage increase due to a decrease in stock value, this increased volatility and make the stock riskier (Jyothi & Suresh, 2014). Moreover, the results determined GARCH (1, 1) as an appropriate model for time series. After global financial crises of 2008-09, researchers analyzed the volatility on the KSE and worked on volatility's types, risk premium offers of KSE, Pakistani Stock Market to be influenced by good or bad news and better-fitted model which explain market volatility behavior as (Ali Ahmed et al, 2005). In a different era, mathematical and statistical models have been introduced to measure the conditional volatility of financial time series data like as heteroscedasticity models (Ahmed and Suliman, 2011). Literature review supports the application of the GARCH family model on Developed Stock Markets, Emerging Stock Markets and KSE-100 index also.

The primitive purpose of this study is applied to such models and includes Symmetric (GARCH & GARCH-M) and Asymmetric (EGARCH & TGARCH) for measuring the conditional volatility of KSE-100 index. The remaining paper is designed as follow; section 2 consists on overview of the Karachi Stock Exchange. Section 3 elaborates models' overview. Section 4 contains the previous study which conducted in this regard to divergent markets over the world and pakist stock market also. Section 5 describes the methodological description. Section 6 depicted figurative and theoretical description of the results section 7 elaborates the conclusion of this study.

- A Brief Report of the Performance of Pakistan Stock Market (KSE-100 Index); Some Stylized Facts: Karachi Stock Exchange (KSE-100 index) has used multi-indexing to benchmark for evaluating market performance being a most important and protuberant stock market of Pakistan which established after Pakistan's independence on September 18, 1947. KSE has 200 listed members (183 corporate and 17 individual) and 571 companies with 35 different sectors, reflect a market capitalization of US $.72 billion. In 1990, the registered firms were 487 but in 1991 liberalization increased at 542 and capitalization rose from $2850 to $7326 (Khan, 2011). The index was launched with the base of 2000 points in November and in February 2007 it had climbed sharply to 12,285 points. Securities and Exchange Commission of Pakistan (SECP) introduced "Circuit Breakers" protect investor interest and control volatility of the stock market for controlling anxiety selling by tentative trade when the markets drop by assumed levels. It additionally presented and executed the Regimes in various time periods i.e. before 2001 Regime 1 was actualized, after December 2001 Regime 2 was executed and usage of Regime 3 occurred in March 2005 (Hameed et al, 2006). In March 2005, the KSE was expanded by just about 65% with a high index estimation of 10,303 points

[153] When the market predictions show high instability or volatility, it becomes the cause of low rate of investment by speculators, whereas the volatility's low value make a relation between investors and stock market and their confidence about their ventures increase.

from first January 2005 to March 2005. KSE-100 index contacted ever most elevated standard of 14,814 points on 26th December 2007, just one day before the killing of previous Prime Minister Benazir Bhutto. The financial year 2008 showed a downfall in the index due to global crises. Index recover the downfall of 2008 quickly in 2009-10 16,218 points and remain all-time high till now like as 2011-12 (16,905 points), 2013-14 (28,913 points) it was more than 45.2% increased as compared to the previous period, 2015-16[154] (38,777 points) and 2017-till (49,876 points).

- Brief Review of Models: In twentieth-century, prevalently ARCH model displayed by Engle, like as Engle and Bollerslev, Poon and Granger and hundred's diverse authorities used particular approaches that for the most part proficient in a developed nation and to some extant in developing nations has been done by researchers in such manner. In 1982 Engle published time-varying volatility estimating paper. His new model Autoregressive Conditional Heteroskedasticity (ARCH) in light of the common method to refresh a different measurement is to average it with the latest square off deviation of the rate of return from its mean i.e. "surprise/ shocks". The ARCH procedure permit the restrictive fluctuation to change after some time as a component of past error leaving the unequivocal or unconditional variance constant under the presumption of consistent variance (Engle, 1982; Engle and Bollerslev, 1986; Poon and Granger, 2003). Engle and Bollerslev presented Generalized Autoregressive Conditional Heteroskedasticity (GARCH) demonstrates for overpowered the confinements of ARCH with a long lag and conditional variance structure (Engle and Bollerslev, 1986).

ARCH model is a fixed lag structure typically levied, have relatively long lag in the conditional variance equation is repeatedly called for and avoid the problem of negative variance parameters. While the GARCH procedure countenances lagged conditional variance to enter in the model. Nelson protracted the GARCH system for the better portrayal of return instability behavior. Nelson's ARCH system expansions breaking the unbending nature of ARCH particular and provide a new direction. EGARCH is another contribution to test the fluctuation of return theory was partial contrastingly by positive & negative return overabundance (Nelson, 1991). Glosten, Jagannathan, and Runkle acquainted TGARCH in 1993 with receive the confinements of GARCH-M model to positive and negative shocks which depend on the GARCH model implement symmetric reaction of volatility (Goudarzi & Ramanarayanan, 2010).

Literature Review

The Pakistan stock market establishes Karachi, Lahore, and Islamabad Stock Exchange. This examination will focus around Karachi Stock Exchange (KSE-100 Index) or, in other words major trade market of Pakistan. The volatility of stock exchange is an enormously imperative idea in finance for voluminous reasons. The financial specialists of securities exchange including controllers, experts, and every other partaker are consistent about it that dynamic nature of stock price conduct is a key phenomenon however stock price volatility is staying to agitate question in the field of finance. Anyhow, finance specialists in coordinated this inquiry has investigated the stock price volatility from an alternate inclination yet because of the inclusion large number of factors isn't a simple undertaking to settle this inquiry and till now researchers have no consensus about it.

This section of research paper provides a glimpse of the previous study to readers on this topic by using different techniques of GARCH family models. Nayamongo and Misati explored that the Nairobi stock exchange (NSE) Kenya from 2006 to 2009, by using GARCH family model results indicated a non-normal distribution of return, low value of positive skewness and high value of Kurtosis. Moreover, results are focused on resilient GARCH effect and reflect persistence in the volatility, insignificant leverage parameters of EGARCH & TGARCH and absence of asymmetry effect on volatility. Goudarzi, Ahmed, Cheteni and Hung analyzed Khartoum Stock Exchange (KSE) volatility, Sudan GARCH type models from January 2006 to November 2010 and concluded that asymmetric model is a better-fitted model except symmetric due to the confirmation the manifestation of

[154] http://nation.com.pk/featured/17-Jun-2016/kse-100-index-catapult-to-its-all-time-high-to-close-at-38-777-index-level

leverage effect (Goudarzi & Ramanarayanan, 2010; Ahmed & Suliman, 2011; Cheteni, 2016; Hung, 2018).

The sample period contains high volatility of index return series. Shah also acknowledged that GARCH (1, 1) has a culminating position to measure the volatility of the stock market with a normal distribution model. In August 2016 Hemanth Kumar investigated that volatility forecasting with SP 500 index data by using GARCH model and 9 distribution techniques i.e. Student Distribution (Std), Generalized Error Distribution (GED), Normal Distribution (Norm), Skew Normal Distribution (SNorm), Skew Student Distribution (SSTD), Normal Inverse Gaussian Distribution(NIG), Generalized Hyperbolic Distribution (GHYP), Skewed Generalized Error Distribution (SGED) and Johnson's Reparametrized Su Distribution (JSU) and concluded that GARCH with Generalized Error Distribution (GED) model has outperformed all models for volatility forecasting. The volatility of stock exchange plays a decisive role in the stock market for investors and a variety of models is developed with the prerequisite of time for assessing the volatility to take a money-spinning decision (Shah, 2016). Numerous studies reach a decision on EGARCH model from GARCH family is more excellent and effective model to check the volatility of stock market (Karmakar, 2005; Alberg et al, 2008; Floros 2008; Goudarzi & Ramanarayanan, 2011). For the most appropriate model for volatility measuring used GARCH family models and checks the appropriateness of symmetric or asymmetric effects as well. Amadeus Wennström measured the volatility of Nordic Equity Indices by using simple moving average, exponential weighted moving average, ARCH, GJR-GARCH, EGARCH, and GARCH model and concluded Exponential GARCH (EGARCH) model has better mean square error (MSE) rate as compare to other techniques (Wennström, 2014).

Banumathy, Vijayalakshm and Asemota investigated the volatility of banks equity in Nigeria by applying the asymmetric GARCH model on weekly return of six banks and results are shown the existence of the ARCH effects and EGARCH (1, 1) CGARCH (1, 1) model in student's t distribution are the best volatility model (Banumathy & Azhagaiah, 2015; Vijayalakshmi & Gaur, 2013; Asemota & Ekejiuba, 2017). Previous literature endeavored on the modeling volatility that EGARCH (1, 1) is well-thought-out the best model to capture the symmetric and leverage effect. Consequently, this study will contribute in existing literature by updating the data that were used in previous studies regarding measuring volatility and testing the leverage effect for the Karachi Stock Exchange Index (KSE-100). Earlier researches also support the existence of volatility in Pakistani stock market in respect of other studies directed in developed and emerging markets (Akhtar & khan, 2016). Pakistani economy has been assailed by strife since its commencement, encountering a range of shocks from the gentle to the outrageous and its effect on the fluctuation of instability.

Data Analysis

The analysis of this study based on daily closing prices of KSE-100 index over the period of 1st January 2008 to 30th June 2018 for modeling volatility, resulting in total observation of 2615 except missing values of public holidays etc. This daily data is taken from the Pakistan Stock Exchange and Yahoo Finance. In this research, continuously compounded return calculated of daily returns which calculate the first difference of daily closing prices of Pakistan Stock Exchange (KSE-100 index) of previous days:

$$r_t = log\left[\frac{P_{t}}{P_{t-1}}\right]$$

Where P_t a current daily closing market is index of Pakistan Stock Exchange (KSE-100 index) and P_{t-1} is previous day indexing.

Methodology

Financial Experts, Academic and Policy Makers are keenly concerned the estimation of risk and return especially measuring risk so financial analysts invent satisfactory mathematical models to calculate volatility which is an indicator of risk. Developed countries are espousing lots of studies for modeling conditional volatility to measure the fluctuations of financial market return from last three eras.

In this study we have used mean equation when modeling volatility using GARCH type models for adequacy and accuracy of results. Mean equation eliminate the problem of autocorrelation which could be occurred in the volatility model.

$$Mean\ Equation:\ r_t = \mu + \varepsilon_t$$

In differenced logarithmic stock prices (KSE-100 index) specify the presence of variance equation to volatility model, four different models i.e. GARCH, GARCH-M, EGARCH, & TGARCH from GARCH family with five distributions. The general equation of variance is given below:

$$Variance\ Equation:\ \varepsilon_t = \sqrt{h_t}\,v_t \sim iid\ (0,1)$$

ht is represent several possible models of GARCH family.

Symmetric Measurement

The relationship between Symmetric volatility and return is based on two[155] models GARCH (1, 1) and GARCH-M (1, 1) which we used in this study (Ahmed et al, 2016).

The Generalized ARCH Model

Engle (1982) proposed modeling conditional volatility by utilizing the ARCH process so this avant-grade study is credited to Engle. In simple term ARCH is a function of lagged squared residuals and the general form of this model is given below:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i\, \varepsilon_{t-i}^2$$

Where α_0 represents mean, α_1 is conditional volatility and ε_{t-1} white noise representative residuals of the time series. Engle's ARCH model overcome various weaknesses but at the same time this model unable to the asylum the exhibit volatility clustering (Engle, 1982). Than Engle and Bollerslev presented General Autoregressive Conditional Heteroskedasticity (GARCH) model, modifies ARCH model form which internalize the volatility clustering[156] (past shocks) as well as synchronized variance and both lagged squared residuals (Engle and Bollerslev, 1986). The GARCH (p, q) model is bestowing the following formula:

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \alpha_j\, \varepsilon_{t-j}^2 + \sum_{i=1}^{p} \beta_i\, \sigma_{t-j}^2$$

Where $i = 1,2,3, \ldots .p$ conditional volatility ω, α_j, and β_i are non-negative constant with $\alpha_j + \beta_i < 1$ model accuracy assure if it's value will near to unity, ε_{t-j} is residual and lagged

155 Ahmed directed the symmetric models GARCH & GARCH-M in their study.

156 Volatility clustering isn't consistent after some time yet it displays certain examples. This implies huge developments in returns have a tendency to be trailed by further substantial developments. Along these lines the economy has cycles with high and low volatility periods. High volatility periods for the most part allude to economic crises emergencies and recession.

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conditional volatility. Last part of the formula is based on the main difference of implement of ARCH and GARCH model. Henceforth, α_j and ε_{t-j^2} are components of ARCH and β_i and $\sigma_t - j^2$ are components of GARCH. ARCH and GARCH model is depending on the assumption of that volatility have a symmetric distribution on all of the shock effects.

- The GARCH-In-Mean (GARCH-M) Model: The GARCH in Mean (GARCH-M) model introduced by Engle, Lilien, and Robins (1987) which consists of:

$$y_t = \gamma_0 + \gamma_{1*t} + \gamma_2 g(\sigma_t^2) + \varepsilon_t$$
$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \, \sigma_{t-j}^2$$
$$\varepsilon_t | \emptyset_{t-1} \sim N(0, \sigma_t^2)$$

When $\mathrm{y_t = (r_t - r_f)}$, where $\mathrm{(r_t - r_f)}$ is the risk premium on holding the assest, then the GARCH − M represents a simple way to model the relation between risk premium and its conditional variance The GARCH model used to analyze the possibility of a time-varying risk premium. The equation for turning GARCH − M is given below:

$$y_t | \emptyset_{t-1} \sim N(\gamma_0 + \gamma_{1*t} + \gamma_2 g(\sigma_t^2), (\sigma_t^2)$$
$$in\ applications, g(\sigma_t^2) = \sqrt{\sigma_t^2}\ , g(\sigma_t^2) = \ln(\sigma_t^2)\ and\ g\ (\sigma_t^2) = \sigma_t^2\ have\ been\ used$$

The parameter γ represents the risk premium in mean equation. A positive γ shows a positive relation between risk and volatility i.e. a rise in mean return is caused by an increase in conditional variance as a proxy for increased risk.

- Asymmetric Measurement: The GARCH model have some abatements for different stock market's asymmetric condition introduced by Black so many other models like as Exponential GARCH (EGARCH) by Nelson, GJR GARCH by Glosten, Threshold GARCH by Zakoian and many other models[157] were added to GARCH models family to estimate volatility more efficiently and overcome that declining (Higgins & Bera, 1992; Engle & Ng, 1993; Ding et al,1993; Engle & Bollerslev, 1986; Zakoian, 1994; Taylor, 2008; Schwert, 1990; Ling & McAleer, 2003; Chan et al, 2017; Black, 1976; Nelson, 1991; Glosten et al, 1993; Zakoian, 1994).

- The Exponential GARCH (EGARCH) Model: The EGARCH model has the aptitude to measure the larger impact of volatility by large shocks as well as accurate measurement of asymmetric distribution (Nelson, 1991). The EGARCH formula is given as follows:

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

EGARCH easily figures out due to its advantages that positive parameters since the model uses the log variances and unrestricted parameters included in the formula like as ω, β, γ . But, to make sure the stationary assumptions like as β must be positive and less than 1, γ is used for asymmetric indicator (leverage effect)[158] both

[157] Like as NAGARCH (1, 1) by Higgins & Bera, Engle & Ng, GJRARCH (1,1) model of Glosten, APARCH (1,1) by Ding, SGARCH (1,1) by Bollerslev, IGARCH by Zakoian, AVGARCH (1,1) by Taylor and Schwert, ARMA-GARCH model by Ling and McAleer etc. are available for details of these techniques see Chan.

[158] Leverage effect refers to fluctuation the price negatively correlated with volatility, when the price diminished so the volatility stock increases. Particularly the effect is significantly important for option markets.

should have to negative and significant (Black, 1976; Olbryś, 2013).

- Threshold GARCH (TGARCH) Model: Threshold GARCH by Zakoian generally specified conditional variance (Zakoian, 1994):

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma d_{t-1} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

The γ is identified as asymmetric parameter or leverage, $\varepsilon_{t-1} > 0$ demonstrate good news and $\varepsilon_{t-1} < 0$ use for bad news and both news divergently effected the conditional variance. Good news affected α_i , and bad news has effected $on\ \alpha_i + \gamma_i$. Later positively significant γ is pointed toward negative shocks have a larger effect on σ_t^2 than the positive shocks. Implementation of these models to check stock market volatility of Pakistani Stock Exchange (KSE-100 index), to investigate different properties in Pakistan's stock market concerning the obtainability of volatility clustering, leptokurtosis, long memory and finally leverage effect through EGARCH model.

Model Selection Criteria

The GARCH family model was fitted by the method of Maximum Likelihood. The Akaike information criterion due to Akaike (1974) defined by following formula:

$$AIC = 2k - 2lnL(\hat{\theta})$$

In this equation k symbolizes the number of unidentified parameters; Θ the vector of unknown parameters and Θ estimate their maximum likelihood.

The Bayesian Information Criterion (BIC) or Schwarz Criterion (SIC) due to Schwarz (Schwarz, 1978):

$$BIC = k\ln n - 2\ln L(\hat{\theta})$$

The Akaike Information Criterion (AIC) by Hurvich and Tsai (1989) is defined by the following equation:

$$AICc = AIC + \frac{2k(k+1)}{n-k-1}$$

The better-fitted model must be shown the smallest value of the Schwarz Criterion (SIC) and The Akaike Information Criterion (AIC) [159] Koima (Bozdogan, 1987; Hannan and Quinn, 1979; Chan et al, 2017; Koima et al, 2015).

Distributional Assumption

In modeling the conditional variance of Pakistan Stock Exchange (KSE-100 index), five conditional distributions would be measured for the standardized residuals of returns innovations: Student's t, the Gaussian (Normal distribution) and the Generalized Error Distribution (GED).

- The Normal (Gaussian) Distribution: The equation form of the Normal (Gaussian) by Azzalini distribution log likelihood contributions are given below (Azzalini, 1985):

$$logL(\theta_t) = \sum_{t=1}^{T} L(\theta_t) = -\frac{1}{2}Log[2\pi] - \frac{1}{2}\sum_{t=1}^{T} Log(\sigma_t^2) - \frac{1}{2}\sum_{t=1}^{T} \frac{\mu_t^2}{\sigma_t^2}$$

$$where\ \mu_t^2 = [y_t - \gamma y_{t-1}]^2$$

[159] Further criterions are also help out to measure the better fitted model like as the the consistent akaike information criterion (CAIC) by Bozdogan and the Hannan-Quinn criterion by Hannan and Quinn, which explained in the study of Chan.

- The Student's t Distribution: The assumed form of the student's t distribution likelihood contributions is:

$$L(\theta)_t = -\frac{1}{2}log\left[\frac{\pi[v-2]\Gamma\left[\frac{v}{2}\right]^2}{\Gamma\left[\frac{v+1}{2}\right]^2}\right] - \frac{1}{2}log\sigma_t^2 - \frac{[v+1]}{2}log\left[1+\frac{[y_t-x_t]^2}{\sigma_t^2[v-2]}\right]$$

Where σt^2 is the variance at the time, and the degree of freedom $v > 2$ control the tail behavior (Gosset, 1908).

- The Generalized Error Distribution (GED): The likelihood contributions of Generalized Error Distribution (GED) are assumed to be a form of:

$$L(\theta)_t = -\frac{1}{2}log\left[\frac{\Gamma\left[\frac{1}{r}\right]^3}{\Gamma\left[\frac{3}{r}\right]\left[\frac{r}{2}\right]^2}\right] - \frac{1}{2}log\sigma_t^2 - \left[1+\frac{\Gamma\left[\frac{3}{r}\right][y_t-x_t]^2}{\sigma_t^2\Gamma\left[\frac{1}{r}\right]}\right]^{r/2}$$

In the Generalized Error Distribution (GED) $r > 0$ is a shaping parameter which accounts for the skewness of the returns. The higher the value of r, the greater the weight of tail and the GED is a normal distribution if $r = 0$ and fat-tailed if $r < 2$ (Theodossiou, 1998).

Last two error distributions Student's t Distribution with Fix DF (Fernandez and Steel, 1998) and Generalized Error Distribution with Fix Parameters give a flexible condition for the user to use Degree Of Freedom (DOF) and different parameters. Stoyanov investigated in his study that Student's t distribution can be closed to a normal distribution when the value of DOF of Student's Distribution has a value of about 30 or above (Stoyanov et al, 2011). Student's t distribution with 10 degrees of freedom and generalized error distribution with fix parameter 1.5 estimates the GARCH set model under Gaussian. In this study, we also consider 1.5 fix parameters distribution and check the impact of fix parameter on the improvement of estimation efficiency for the sample.

Descriptive statistics of daily stock prices of Pakistan Stock Exchange (KSE-100 index) is presented in table-1. Mean of daily stock exchange is positive, its indication toward the increasing price over the period. The result shows that stock prices are positively skewed[160], indicating a low probability of earning which is less than mean (Kanasro et al, 2009). The kurtosis of series is slim tailed and not normally distributed, Jarque and Bera test also reject the null hypothesis and support the non-normality of data distribution. ADF shows that data is not stationary (Jarque & Bera, 1987).

Table 1. Descriptive Statistics and ADF test of Daily stock prices

Mean	23402.14	Minimum	4815.34	Jarque-Bera	242.4722
Median	18613.44	Std. Dev.	13381.61	Probability	0.0000
Maximum	52876.46	Skewness	0.442989	ADF	0.023128
Observations	2615	Kurtosis	1.799829	Probability	0.9595

[160] Kanasro examined the significant positive mean and positive skewness by using the data of KSE-100 index over the period of 1st January 2003 to 31st December 2008.

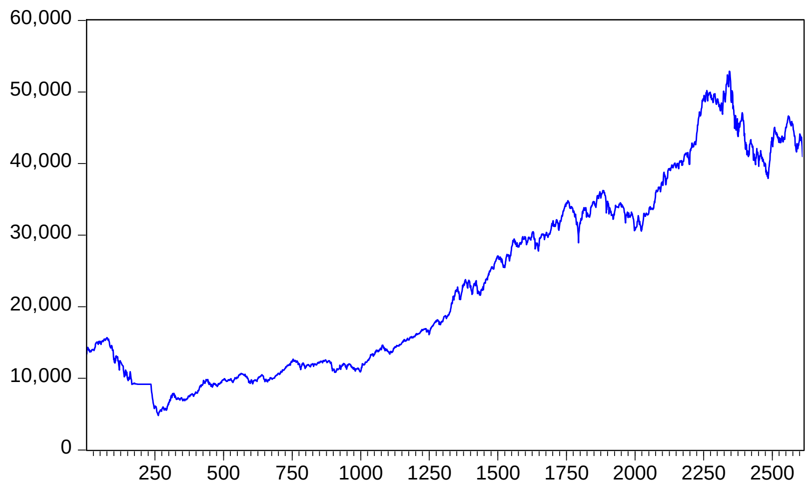

Figure 1. Graphically representation of Daily stock prices

Table 2. Descriptive Statistics and ADF test of Daily stock Return

Mean	0.000195	Minimum	-0.0223	Jarque-Bera	1946.991
Median	0.000185	Std. Dev.	0.004906	Probability	0.0000
Maximum	0.03585	Skewness	-0.267496	ADF	-42.0041
Observations	2615	Kurtosis	7.193199	Probability	0.0000

Descriptive statistics of daily stock returns of Pakistan Stock Exchange (KSE-100 index) is presented in table-2. Mean of daily stock exchange is positive, its indication toward the increasing price period. The outcome demonstrates stock prices are contrarily negatively skewed, showing that there is a high probability of earning which is not as much as mean. The kurtosis of the series is fat-tailed and not normally dispersed and is additionally affirmed by Jarque and Bera test measurements, or, in other words 1% level of Jarque and Bera shows the null hypothesis of normality is rejected. The noteworthiness significance of 1% level of ADF demonstrates that data information is stationary (Banumathy and Azhagaiah, 2015; Jarque & Bera, 1987).

Graphically representation of the Daily stock return

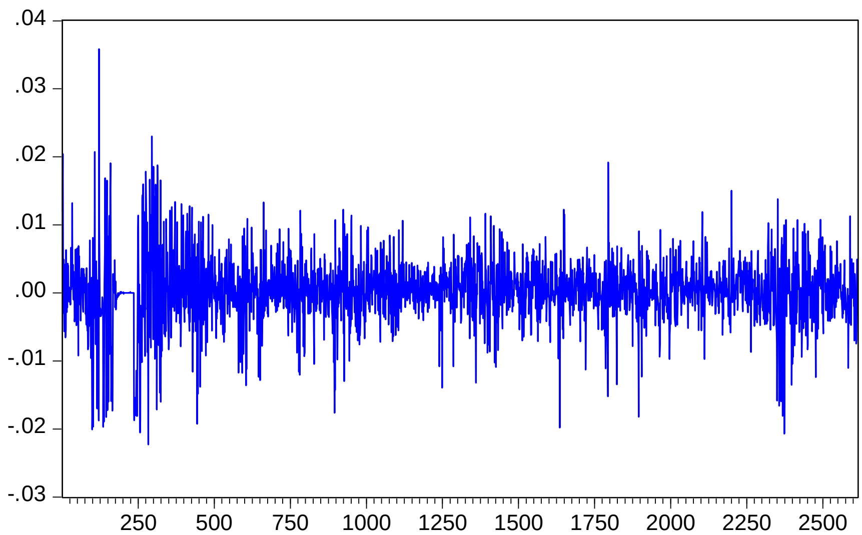

Figure 2. Graphically representation of the Daily stock return

In table 3 the evaluated consequence of the restrictive mean models at the logarithmic stock prices utilizing Ordinary Least Squares (OLS) strategy. OLS connected to assess relapse when the arrangement saw to be mean reverting which appeared in above graphically portrayal. Literature supported the different conditional mean equations estimated like as Abdullah Saeed but in this study, one conditional mean equation was estimated with constant only (Saeed et al, 2017). The results are depicted that significance of constant term at 5% level as well as F-Statistics testing the null hypothesis about ARCH effect is statistically significant at 1% level.

Table 3. OLS estimation for testing ARCH effect

Variable	**Coefficient**	**Probability**
μ	0.000195** (0.0000959)	0.0427
	: No ARCH EffectH_0	
F- Statistic	281.1229*	0.000

Standard errors are in parentheses.
*1% level of significance
** 5% level of significance
*** 10% level of significance

The outcomes of ARCH test introduced in table-3 which demonstrates the presence of heteroskedasticity in the series data[161] information (Ahmad & Suliman, 2011). The existence of heteroskedasticity is very noteworthy for clustering volatility. This research is mainly focused on exploring GARCH techniques with five (5) different distribution models to measure the volatility of KSE -100 index returns[162] (Hassan et al, 2009; Kumar and Patil, 2016).

Table 4. Estimated result of GARCH (1, 1) Model under five distribution techniques

GARCH (1, 1) Model					
Mean	**Norm**	**Std**	**GED**	**Std with fix DF**	**GED with fix parameter**
μ (Constant)	0.0004878* (7.89E-05)	0.000362* (6.19E-05)	0.000281* (6.01E-05)	0.00044* (6.79E-05)	0.000386* (7.02E-05)
Variance					
ω (Constant)	1.05E-06* (7.29E-08)	3.92E-07* (9.83E-08)	7.49E-07* (1.20E-07)	5.62E-07* (9.07E-08)	8.49E-07* (8.98E-08)
α (ARCH effect)	0.151253* (0.011831)	0.196917* (0.024818)	0.176952* (0.02317)	0.807903* (0.016832)	0.158927* (0.016541)

[161] Ahmad & Suliman's results are shown that after examined the heteroskedasticity, ARCH test directed strong evidence of ARCH in residual series.

[162] Hassan, Kumar and Patil are also used different distribution models with GARCH family models to measure the volatility.

β (GARCH effect)	0.803246*	0.811634*	0.802946*	0.169478*	0.802388*
	(0.011836)	(0.024818)	(0.020017)	(0.015443)	(0.016113)
α+β	0.954499	1.008551	0.979898	0.977381	0.961315
Log likelihood	10602.87	10710.88	10710.08	10692.31	10688.37
Akaike info criterion	-8.106211	-8.18805	-8.18744	-8.17462	-8.1716
Schwarz criterion	-8.097234	-8.176829	-8.176218	-8.16564	-8.16263
ARCH test	0.938477	0.222609	0.293621	0.333203	0.481732
Prob.	0.3328	0.6371	0.588	0.5638	0.4877
Jarque-Bera	1016.39	11217.59	2164.18	3180.71	1462.22
Prob.	0.00	0.00	0.00	0.00	0.00

Standard errors are in parentheses.
*1% level of significance
** 5% level of significance
*** 10% level of significance

First three equation of GARCH model ω (constant) α (ARCH effect) and β (GARCH effect) is highly significant at 1% level in all distribution by using the variance equation. Its mean the significance of α (ARCH effect) and β (GARCH effect) has affected the conditional variance or preceding period on current volatility with lagged conditional variance and squared disturbance. The sum of coefficients $(\alpha \,\&\, \beta)$ is less than one $(\alpha + \beta < 1)$ in all models except Student's t model is mean reverting whereas Student's t model shows $\alpha + \beta = 1$ which depicted a high persistence in stock return and $\mathcal{E}t - 1$ is stationary. The highest value of Log likelihood[163] (10710.88), the lowest value of Akaike info criterion (AIC) [164] -8.18805 and Schwarz criterion (SIC) -8.176829 indicated that Student's t distribution is superlative fitted distribution technique for GARCH (1, 1) model. No ARCH effect is observed it's assure the suitability of selected models for series and Jarque and Bera test is significant pointed out the non-normality of error distribution (Akaike, 1974; Fang et al, 2011; Burnham & Anderson, 2004; Jarque & Bera, 1987).

Table 5. Estimated result of GARCH- M (1, 1) Model under five distribution techniques

GARCH-M (1, 1) Model					
Mean	**Norm**	**Std**	**GED**	**Std with fix DF**	**GED with fix parameter**
μ (Constant)	0.000217	-5.45E-06	-0.00018	0.000171	3.70E-05
	(0.000262)	(3.52E-05)	(0.000176)	(0.0002)	(0.000224)
λ (Risk Premium)	0.072109	0.113108*	0.126351*	0.079912	0.097449***
	(0.066301)	(0.019409)	(0.047662)	(0.056529)	(0.060185)
Variance					

[163] Maximum value of Log Likelihood is shown the better fitting of ARCH family model and adequate distribution model Akaike.

[164] These criterions' lowest values are a positive gesture toward the better fitting model, Fang, Burnham and Anderson.

ω (Constant)	1.06E-06*[165]	1.84E-12*	6.90E-07*	5.44E-07*	8.54E-07*
	(7.39E-08)	(1.68E-10)	(1.08E-07)	(8.72E-08)	(8.91E-08)
α (ARCH effect)	0.153331*	0.246001*	0.194211*	0.174544*	0.160114*
	(0.012063)	(0.01828)	(0.024697)	(0.01704)	(0.016927)
β (GARCH effect)	0.800688*	0.817287*	0.795513*	0.805152*	0.801058*
	(0.012054)	(0.007822)	(0.019871)	(0.015377)	(0.016294)
α+β	0.953998	1.063288	0.989724	0.979696	0.961172
Log likelihood	10603.44	10757.46	10714	10692.4	10689.8
Akaike info criterion	-8.105878	-8.222918	-8.189674	-8.1748	-8.171934
Schwarz criterion	-8.094656	-8.209451	-8.176208	-8.163578	-8.160712
ARCH test	0.943887	0.000365	0.193528	0.337465	0.440121
Prob.	0.3314	0.9848	0.66	0.5613	0.5071
Jarque-Bera	1019.839	7.22E-08	2880.203	3720.08	1510.067
Prob.	0.00	0.00	0.00	0.00	0.00

Standard errors are in parentheses.
*1% level of significance
** 5% level of significance
*** 10% level of significance

The results of GARCH-M models are shown in table-5 exposes significantly behavior of GARCH-M parameters at 1% level of significance. Positive results of λ (Risk Premium) indicating volatility impact on the expected return, pointed out diminishing lack of risk-return trade-off overtime period. The sum of $\alpha + \beta \leq 1$ which depict shock will persist in future periods. Risk returns parameter show a positive risk and return relationship. The conditional variance functions of mean equation of the return series by GARCH-M[166] model (Banumathy & Azhagaiah, 2013).

Application of ARCH-LM test on residuals not observed the further ARCH effect for complete study period demonstrating the well specified variance equation, the highest value of LL (10757.46) and lowest AIC (-8.222918) & SIC (-8.209451) are described that the Student's t distribution model is accurate instead of remaining others. ARCH effect is not found, series free from the heteroskedasticity. Jarque and Bera test is significant pointed out the non-normality of error distribution (Jarque & Bera, 1987).

Table 6. Estimated result of EGARCH (1, 1) Model under five distribution techniques

EGARCH (1, 1) Model					
Mean	**Norm**	**Std.**	**GED**	**Std. with fix DF**	**GED with fix parameter**
μ (Constant)	0.000484*	0.000188*	0.000187*	0.000236*	0.00033*

[165] Exponent is a mathematical operation which is having either positive or negative exponent integer. bn shows n integer is positive and 1/bn is depict negative expression. b represents the base and n represents exponent integer. Here E stands for exponent of 10.
[166] Banumathy and Azhagaiah examined a positive value of λ (Risk Premium) and sum of coefficients near to one.

	(5.61E-05)	(5.23E-05)	(. 5.14E-05)	(5.21E-05)	(5.60E-05)
Variance					
ω (Constant)	-0.986743*	-0.727926*	-0.94727*	-0.73839*	-0.96308*
	(0.075544)	(0.092811)	(0.115985)	(0.078121)	(0.09624)
α (ARCH effect)	0.358724*	0.112905*	0.106842*	0.090851*	0.280474*
	(0.019552)	(0.028563)	(0.035602)	(0.024218)	(0.026854)
β (GARCH effect)	0.550903*	0.91454*	0.834087*	0.853472*	0.932042*
	(0.00611)	(0.007561)	(0.009134)	(0.006296)	(0.007572)
γ (leverage effect)	-0.150903*	-0.11046*	-0.141628*	-0.1147*	-0.14353*
	(0.01197)	(0.017159)	(0.020642)	(0.014229)	(0.016037)
α+β	0.909627	1.027445	0.940929	0.944323	1.212516
Log likelihood	10652.75	10764.57	10751.89	10749.92	10732.79
Akaike info criterion	-8.143598	-8.22835	-8.218654	-8.14791	-8.15481
Schwarz criterion	-8.132376	-8.214884	-8.205188	-8.19669	-8.12359
ARCH test	0.005818	0.083303	0.267771	0.135581	0.250322
Prob.	0.9392	0.7729	0.6049	0.7127	0.6169
Jarque-Bera	1598.594	308869.5	29885.51	106793.9	5511.344
Prob.	0.00	0.00	0.00	0.00	0.00

Standard errors are in parentheses.
*1% level of significance
** 5% level of significance
*** 10% level of significance

The asymmetric results of exponential GARCH (1,1) [167] capture leverage effect (γ) of KSE-100 index, γ is significant and negative in all distribution models which show a correlation between past and future return of volatility over the study period in table 6 (Najjar et al, 2016). The ARCH effect test statistic disclosures acceptance of the null hypothesis that no heteroskedasticity in the residuals. Coefficients are also significant at 1% level. The sum of coefficients $\alpha + \beta > 1$, the LL's highest value (10764.57) and lowest AIC (-8.22835) & SIC (-8.214884) are described that the Student's t distribution model is accurate instead of remaining others. The other studies are also supported by results of this study over different periods (Karmakar, 2005; Alberg et al, 2008; Floros, 2008; Goudarzi & Ramanarayanan, 2011). No ARCH effect observed and Jarque and Bera test is significant pointed out the non-normality of error distribution. (Jarque & Bera, 1987).

Table 7. Estimated result of TGARCH (1, 1) Model under five distribution techniques

TARCH (1, 1) Model					
Mean	**Norm**	**Std**	**GED**	**Std with fix DF**	**GED with fix parameter**

[167] Najjar described that expected outcomes of EGARCH (1, 1) for check asymmetric effect presence effect in the data is related to having negative significant gamma (γ) otherwise there will be unavailability of existence support to leverage effects.

μ (Constant)	0.000391*	0.000354*	0.000265*	0.000386*	0.00033*
	(7.77E-05)	(6.42E-05)	(6.14E-05)	(6.80E-05)	(6.90E-05)
Variance					
ω (Constant)	1.10E-06*	7.72E-07*	9.47E-07*	7.65E-07*	9.73E-07*
	(7.95E-08)	(1.37E-07)	(1.34E-07)	(1.08E-07)	(1.02E-07)
α (ARCH effect)	0.052613*	0.096405*	0.078975*	0.077452*	0.065527*
	(0.010794)	(0.02223)	(0.020963)	(0.016161)	(0.015331)
β (GARCH effect)	0.204163*	0.780559*	0.781732*	0.786558*	0.787154*
	(0.01299)	(0.01978)	(0.021418)	(0.017131)	(0.017626)
γ (leverage effect)	0.204163*	0.233641*	0.229734*	0.210245*	0.213042*
	(0.021962)	(0.039458)	(0.040628)	(0.030071)	(0.03083)
$\alpha + \beta$	0.256776	0.876964	0.860707	0.86401	0.852681
Log likelihood	10645.46	10735.59	**10735.85**	10723.28	10720.87
Akaike info criterion	-8.13802	-8.206186	**-8.206389**	-8.19754	-8.19569
Schwarz criterion	-8.126798	-8.19272	**-8.192923**	-8.18631	-8.18447
ARCH test	0.015663	0.348822	0.3622	0.251703	0.198231
Prob.	0.9004	0.5548	0.5473	0.6159	0.6562
Jarque-Bera	837.3753	2299.703	1399.145	1774.276	1124,929
Prob.	0.00	0.00	0.00	0.00	0.00

Standard errors are in parentheses.
*1% level of significance
** 5% level of significance
*** 10% level of significance

In TGARCH leverage effect coefficient is positively significant at 1% level. The results of TGARCH are revealed the greater effect of bad news on conditional variance as compared to a positive one. To check the normality of residuals distribution the diagnostic test is performed. The ARCH test statistics explore the good quantification of variance equation by presenting no additional ARCH effect exists in the residuals. TGARCH results are supported to Generalized Error Distribution (GED) model as a best-fitted model via the greater value of LL and lower value of AIC & SIC (10735.85), (-8.206389) and (-8.192923) respectively. ARCH effect shows that no further ARCH effect. Jarque and Bera test statistics is significant at 1% level which shows the non-normality of errors distribution (Jarque & Bera, 1987).

According to a comparison of five distribution models and ARCH family model, the best-fitted model is EGARCH with Student's t Distribution Model.

In EGARCH (1, 1) model, the coefficients sum $\alpha + \beta$ is 1.02 which implies high persistency of volatility.

- In EGARCH (1, 1) demonstrate the parameters γ are caught asymmetric impacts is(- 0.11046) adversely significant at 1% which gives leverage effect presence and announced that positive shocks are not more effective when contrasted with negative shock though the coefficients of leverage effect are significant and positive at 1% level. Significantly positive of coefficients is demonstrated leverage effect existence over study period frame.
- The superlative fitted models in symmetric and asymmetric impact are

chosen on the base of most elevated Log likelihood (LL) value and least estimated value of Akaike information Criterion (AIC) and Schwarz Criterion (SIC). As indicated by the Student's t Distribution show EGARCH have the most highest estimated value of Log likelihood (10764.57) and least values of Akaike information Criterion (AIC) and Schwarz Criterion (SIC) (- 8.22835, - 8.214884) separately when contrasted with it exchange symmetric models and asymmetric model TGARCH too.

Conclusion

This investigation has analyzed the relative execution of symmetric and asymmetric GARCH family models which dependent on five residual distributions in term of their ability to appraise KSE-100 index volatility. Utilizing the KSE-100's every day returns through the time of first January 2008 to 30th June 2018, this investigation has analyzed the relative execution of each GARCH model demonstrate with five different distributions. Descriptive statistics measurements delineate skewness and kurtosis exists for the KSE-100 index. The consequences of the conducted study ARCH impact test point out the significant presence of ARCH impact in the residual. We have demonstrated the econometric volatility estimation can be identified with selected GARCH type models and distribution. The parameters estimate of the symmetric GARCH (1, 1) model $(\alpha \, and \, \beta)$ shows high constancy in all error distribution models in contingent instability of stock profits for KSE-100 record. The block term (α) is in contingent difference positive and factually significant in all cases, demonstrates that there is a significant time-invariant part in the return generation process.

The uppermost value of LL and lowermost values of AIC and SIC are pointed toward Student's t distribution as an accurate model for measuring clustering volatility.

The parameters observed the conditional variance in the mean equation, the risk premium effect measuring for the symmetric GARCH-M (1, 1) is positively significant in Generalized Error distribution and Student's t model and insignificant but positive in rest of distributions; a sign of positivity pointing out the existence of risk premium. Maximum LL and minimum AIC & SIC have also supported Student's t Distribution. Asymmetric EGARCH (1, 1) and TGARCH (1, 1) are applied in this study so that the effect measures of news nature on future volatility in the KSE-100 index. EGARCH (negative & significant) and TGARCH (positive & significant) coefficients have expected in both models which revealed the presence of leverage effect in KSE-100 index, which found that good news has less effect on conditional variance as compared to bad news. Student's t distribution model is best fitted for EGARCH (1, 1) and Generalized Error Distribution model is better fitted for TGARCH (1, 1), it's concluded that on the base of LL, AIC and SIC criterions. Comparison of the adequate distribution models results (GARCH (1, 1), EGARCH (1,1) and GARCH-M (1,1) with Student's t Distribution and TGARCH (1, 1) with GED are shown. The EGARCH from GARCH family model with Student's t Distribution model is more accurate than the rest of error distribution models according to comparison of the individual best better-fitted models. This study, in particular, is consistency with few studies such as Wilhelmsson, Banumathy and Peters, with analysis of different countries (Wilhelmsson, 2006; Banumathy & Azhagaiah, 2015, Peters, 2017). To condense, the outcomes from all GARCH type models with various error distribution techniques appropriation determined in this paper clarify that unstable and explosive volatility process is observed in KSE-100 index returns over the sample time frame. Also, the findings of this paper give critical data particularly to speculators and policymakers in assessing the volatility of the share trading system, occurrence of risk, risk estimating, and management strategies, at last policymakers in designed money related strategies. Policymakers having knowledge the nature of volatility impact on stock market returns could provide useful information to portfolio management purpose both broadly and globally. Financial specialists ought to pursue the more closely the money related strategy to take a decision on their venture and policymakers should take the condition of indexing system into account when they precede fiscal strategies. This is essential since the role of stock returns in the KSE-100 index in financial development. Economic growth significance and fiscal strategies help to build up a sound and stable stock market.

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