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Modeling Volatility Spillover and Role of Volatility Spillover Effect to Improve Forecasting Performance of GARCH Models Based on Varying Distributions

ABSTRACT

The presented study endeavor to examine whether financial returns' volatility spillover effect imparts a role to improve the forecasting accuracy of GARCH family models based on various error distributions. An empirical investigation is conducted by employing standard GARCH, EGARCH, and GJR-GARCH models. Three error distributions, normal, Student t, and General Error Distribution are used in the analysis. Daily data spanning from August 4, 1997, to April 28, 2022, has been analyzed. The strength of the study lies in utilizing the volatility spillover effect along with none normal error distributions to improve the forecasting accuracy of three GARCH family models for stock and currency markets' returns, in the context of Pakistan. In-sample estimation results from all three models validate the existence of significant volatility spillover among the stock and currency markets of Pakistan. Whereas, out-sample forecasting results provide evidence regarding accuracy gain from the perspective of stock and currency markets' returns forecasting. Along with the volatility spillover effect, EGARCH and GJR-GARCH models based on Students t and GED distributions provide better forecasts for stock market and currency market returns. The results of the study hold promise for practical significance for asset allocation and financial risk management applications.

Keywords
Financial Markets, Volatility Spillover, Forecasting, GARCH-type Models, Non-Normal Error Distributions

JEL Classification
C53, D53, F31

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Author's contribution to the article: 1- Conceived and designed the analysis, 2- Reviewed and compiled the literature, 3- Collected the data, 4- Contributed data or analysis tools, 5- Performed the analysis, 6- Wrote the paper, 7- Financial support for the conduct of the study, 8-Other

1. INTRODUCTION

Modeling and forecasting financial markets' returns and their volatility has remained a matter of much attention since the seminal evolution of Autoregressive Conditional Heteroscedasticity (ARCH) family models by Engle (1982); Bollerslev (1986); Nelson (1991) etc. The family of ARCH models was mainly designed to deal with the heteroscedastic nature of financial time series. However, one major drawback embedded in ARCH family models is their assumption of the normally distributed error term. Pragmatic studies on financial econometrics advocate that financial time series often exhibit the feature of leptokurtosis (Baillie & Bollerslev, 2002; Ho et al., 2013). The use of conventional ARCH family models that are based on the normality assumption of error term may lead to underestimation or overestimation of the second moment of financial time series i.e. conditional volatility (Charfi & Mselmi, 2022). To overcome these consequences, clearly identifying appropriate innovation distribution is a matter of the day for accurate estimation and forecasting of financial time series.

Over time, cross markets linkages from the perspective of information flow mainly in terms of volatility spillover render significant implications for investors and policymakers (Ross, 1989). Hence, utilizing this information flow in forecasting financial markets returns will be of paramount significance in managing portfolio diversification, option pricing, and devising hedging strategies (Chang et al., 2018). Since exchange rates and stock prices are key determinants of portfolio risk, therefore cross-market volatility spillover may help investors and policymakers to predict financial markets behavior with greater precision (Mishra et al., 2022). This study does indeed behold such an expectation.

Enriched and efficient analysis always requires a complete and clarified description of the conditional distribution to which the data-generating process belongs (Baillie & Bollersley, 1992). This conclusion has been arrived at by analyzing exchange rate returns through the GARCH model based on non-normal error distribution. Therefore, a good way to extract the benefit from cross-market information is to utilize it in GARCH family models based on varying error distributions. Keeping these things in mind the present study attempts to answer the research question, of do volatility spillover across financial markets, helps to improve the forecasting accuracy of GARCH family models. Another research question analyzed in this study is whether none normal error distributions impart to forecasting gain in GARCH family models. Two none normal error distributions, Students t and General Error Distribution (GED) are used in three GARCH family models. Among financial markets, the Pakistan Stock Exchange (PSX) 100 index and bilateral nominal exchange rate, Pak-rupees in terms of US-Dollar have been selected for analysis. High-frequency daily data spanning from August 4, 1997, to April 28, 2022, has been analyzed by using three financial econometric models; standard GARCH, EGARCH, and GJR-GARCH model. This study holds novelty in terms of utilizing the information on volatility spillover to determine the predictability gain for GARCH family models along with some varying distributions. The results' implications of the study hold paramount importance for investors, policymakers, and researchers. Investors will get help in terms of managing their investment portfolio. Policymakers will be benefited from the perspective of setting financial policies and keeping an eye on the future behavior of financial markets.

The rest of the study constitutes four sections. A literature review is discussed in section 2. Section 3 covers methodology and data. Results and their discussion is provided in section 4 and section 5 concluded the analysis of the study.

2. LITERATURE REVIEW

Substantial evidence of systematic volatility plays an imperative role in volatility spillover across financial markets. A renowned study by Kanas (2000) has reported that significant volatility spillover may induce the nonsystematic risk that reduces gains from portfolio diversification. The first potential theoretical underpinnings regarding interactions among stock prices and the exchange rate are provided by Dornbusch and Fischer (1980) in the name of the flow-oriented model. According to this model exchange rate exert a positive significant impact on stock prices. Whereas, in the stock-oriented model, Branson (1983) demonstrated that stock prices affect the exchange rate in a significant and positive direction. These theoretical explanations establish the existence of some interlinkages between stock markets and currency markets. Owing to these cross markets' interlinkages, any change in returns' volatility of the stock market (currency market) delivers volatility in currency markets (stock market) returns as well.

In literature, an easy and common conventional way adopted to improve the forecasting performance of the GARCH family model is to use the non-normal error distributions. This modification makes the GARCH model more flexible to capture and model a thicker tail, higher kurtosis, and skewness of returns data. Non-normal error distributions have been used in both symmetric and asymmetric GARCH models. Bollerslev (1987) and Hamilton and Susmel (1994) employed Normal, Student t, and GED distributions respectively. Estimation and forecasting results of both studies show that Student's t innovations should be considered because Student's t distribution better captures the leptokurtic behavior of financial returns. Zhang (2009) and Shamiri and Isa (2009) analyzed symmetric and asymmetric GARCH, EGARCH, and NAGARCH models based on Students t, Normal, skewed Students t, Normal Inverse Gaussian and Generalized Error Distribution (GED) for the German stock market and of Malaysian stock market respectively. It has been reported that accurate volatility forecasts depend on the choice of error distribution rather than the type of GARCH model. Analysis suggests that the GARCH model based on heavy-tailed error distributions provides better volatility estimates and volatility forecasts.

Volatility forecasting of the Standard and Poor's 100 stock index data series has been done by Liu and Hung (2010). Analysis has been carried out using six types of symmetric and asymmetric GARCH models based on standard Normal, Student t, and skewed generalized t distributions. Empirical results of the analysis revealed that the asymmetric GARCH model produces better volatility forecasting with non-normal error distributions. The role of Student t and GED distribution to improve the forecasting accuracy of the GARCH model has been explored by Vee et al. (2011). It has been demonstrated in the results that the GARCH model based on GED distribution better performs to improve the forecasting accuracy. The same results have been reported by Kumar and Patil (2016).

Kosapattarapim et al. (2012) evaluated the performance of GARCH models based on six error distributions for Thailand, Malaysia, and Singapore stock markets. Results of the study suggest that non-Normal error distributions contribute significantly to improving return volatility forecasts. While analyzing Nigerian stock market volatility, Adepoju et al. (2013) and Atoi (2014) argued that the GARCH model based on Student t distribution is best for volatility estimation and forecasting. Because, to cope with risk, volatility prediction using Student t distribution will help to reduce the likelihood of extreme losses by market players in the stock market. The same results have been reported by Aftab et al. (2019). Using symmetric and asymmetric GARCH models based on Normal, Students t, and GED distribution, Mubarik and Javid (2016) estimated and forecasted the volatility of PSE-100 index returns. It has been reported that asymmetric GARCH models based on Student t distribution perform better in terms of forecasting PSX-100 index returns.

Ahmed and Naher (2021) forecasted exchange rate volatility for Bangladesh. GARCH, EGARCH, APARCH, TGARCH and IGARCH models based on Normal and Student t distribution have been analyzed. Results of the study revealed that the GARCH model with Students t distribution performed best on the perspective of out-of-sample exchange rate volatility forecast. Charfi and Mselmi (2022) used GARCH and EGARCH models based on Normal, Students t and Normal Tempered Stable distribution to forecast exchange rate volatility. It has been demonstrated that GARCH and EGARCH models with Normal Tempered Stable distribution outperform on the perspective of out-sample forecasting, relative to other distributions.

Enough literature has been evidenced on the role of none Normal error distributions to improve GARCH model forecasting. However, a little strand of studies has been evidenced in investigating the role of cross markets volatility spillover on the forecasting performance of GARCH-type models. From this perspective, Phan et al. (2016) explored the effect of volatility spillover on the predictability gain of crude oil and stock market volatility of three developed countries. The EGARCH model has been applied to high-frequency data. Results of both in-sample and out-sample analysis demonstrated that cross-market volatility spillover improves price volatility prediction of crude oil and the stock market. The effect of volatility spillover from other assets and stock exchange on forecasting accuracy of oil price volatility has been analyzed by Degiannakis and Filis (2017). Results of the Heteroscedastic Autoregressive (HAR) model suggest that using volatility spillover, as an information channel, plays a significant role in improving forecast accuracy of oil prices realized volatility.

Mubarak and Javid (2017) estimated and forecasted high and low-beta portfolio stock returns' volatility of the PSX-100 index. Analysis has been carried out using a general-to-specific approach in the EGARCH-M model. Results of the study reported that low beta portfolio stock returns' volatility provided better in-sample and out-sample forecast ability. The impact of the volatility spillover effect, from the U.S. stock market, on forecasting the accuracy of other international stock markets' returns has been investigated by Liang et al. (2022). In-sample estimation and out-sample forecasting have been conducted by using the GARCH model. It has been demonstrated in the results that the realization of information on the spillover effect from the U.S.A. credibly improves the forecasting accuracy of other markets' stock prices and their returns. The predictability role of gold and exchange rate volatility in forecasting stock returns' volatility of the Hang Seng Index (HSI) has been investigated by Dai et al. (2020). Results of the AR model suggest that exchange rate volatility imparts significant predictability gain for in-sample and out-sample stock return volatility forecasting.

Chatziantoniou et al. (2021) investigated the predictability usage of volatility spillover from uncertainty indices and the US stock exchange market to oil price volatility prediction. The results of the HAR model advocate that information on volatility spillover does not impart significant predictability gain in oil price volatility. The authors discussed that this result may arise due to the analysis of low-frequency data. To check this assertion, using high-frequency data, Wu et al. (2022) investigated the role of information on volatility spillover in improving oil price volatility forecasting. Results of the study recommend that volatility spillover has significant predictability power in volatility forecasting and can be used in the forecasting field. Ghani et al. (2022) utilized the information on economic variables and uncertainty index to improve the forecasting accuracy of Pakistan stock market volatility. Forecasting results of the GARCH model suggest that using the information on economic variables including exchange rate valuably contributes to the forecasting accuracy of PSX.

A review of historical literature evidenced that a huge volume of studies has been conducted to improve the forecasting performance of GARCH family models. Some studies attempted to do so using non-normal error distributions in GARCH models. Whereas, few other studies used information on economic variables and information on volatility spillover for this purpose. Yet literature encompasses a gap in neglecting the role of information on volatility spillover together with non-normal error distributions to improve the forecasting performance of GARCH models. The intended study has made an effort to address this loophole in existing literature using three econometric models.

3. METHODOLOGY

The main objective of this study is to investigate the role of volatility spillover in financial market returns forecasting using GARCH family models. To meet this endeavor, one way is to split the full sample data into two groups. The first group of data is known as an in-sample data set and the second group of data is known as out-sample data set. The in-sample data set is used for estimating the parameter of the model. Whereas, the out-sample data set is used for returns forecasting.

Financial markets (stock market and currency market) return R_t^x has been calculated as;

$$R_t^x = lnP_t - lnP_{t-1} \tag{1}$$

Whereas, financial markets' returns' volatility has been generated from GARCH/EGARCH/GJR-GARCH models.

3.1. GARCH Model

For the sake of forecasting, GARCH family models are used when there is an ARCH effect in the data. The standard GARCH model developed by Bollerslev (1986) is based on the assumption of symmetric effect[1]. This is due to the reason that the error term in the variance equation of the GARCH model has been taken in square form. GARCH models are based on the concatenation of two main equations; mean equation and variance equation. An important feature of the GARCH model is that variance of the error term in the mean equation is modeled as a linear function of past squared errors and previous conditional variances. Following Enders (2015), the corresponding mean and variance equations used for estimating the volatility spillover through the Standard symmetric ARMA(p, q)-GARCH(p, q) model are as follows:

$$R_t^x = \alpha_0 + \alpha_1 \sum_{i=1}^{p} R_{t-i}^x + \alpha_2 \sum_{j=1}^{q} e_{t-j} + e_t \tag{2}$$

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} + \pi 1_y h_t^y \tag{3}$$

In equation (2) R_t^x is representing returns of variable x at time t. Where x represents stock market returns and currency market returns. R_{t-i}^x is the preceding period returns of variable x. Suitable structure and order of mean equation (2) are determined with the help of Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF). In equation (3) h_t^y is returns' volatility of variable y and $\pi 1_y$ is the volatility spillover parameter for volatility spillover from variable y to variable x i.e. from PSX-100 index returns' volatility (RPSX) to exchange rate returns' volatility (REXR).

3.2. GJR-GARCH Model

Symmetric models like ARCH and GARCH models are based on the assumption that positive and negative shocks have a symmetric effect on volatility. Because error terms have been taken in a square form in the model. However, generally, this assumption is frequently violated in practice. It is often observed as well as reported in the literature that bad news has more impact on volatility relative to good news. This phenomenon is called the leverage effect introduced by Black (1976). To capture the leverage effect, Glosten et al. (1993) introduced the GJR-GARCH model. This model uses a dummy variable to capture the leverage effect.

ARMA (p, q)-GJR-GARCH (p, q) model employed in this study is as follows:

$$R_t^x = \alpha_0 + \alpha_1 \sum_{i=1}^{p} R_{t-i}^x + \alpha_2 \sum_{j=1}^{q} e_{t-j} + e_t \tag{4}$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} + \gamma \varepsilon_{t-1}^2 I_t + \pi 2_y h_t^y \tag{5}$$

In equation (5) I_t represent dummy variable, which is equal to one if the preceding period error term is negative and zero otherwise. h_t^y is returns' volatility of variable y and $\pi 2_y$ is the volatility spillover parameter for volatility spillover from variable y to variable x i.e. from PSX-100 index returns' volatility (RPSX) to exchange rate returns' volatility (REXR). The remaining explanation is same as in equation (3).

[1] Effect of good and bad news is different.

3.3. EGARCH Model

In the GJR-GARCH model leverage effect is assumed to be quadratic. The EGARCH model introduced by Nelson (1991) also captures the leverage effect. Where the leverage effect is taken as exponential. Like the standard GARCH model, the GJR-GARCH model imposes non-negativity constraints on estimated parameters. Whereas, in the EGARCH model variance equation is in log form hence negative co-efficient is permissible. Another advantage of the EGARCH model over the GARCH and GJR-GARCH models is that it allows a more natural interpretation of shock persistence letting standardized errors.

The formal, ARMA (p, q)-EGARCH (p, q) model is as follows:

$$R_t^x = \alpha_0 + \alpha_1 \sum_{i=1}^{p} R_{t-i}^x + \alpha_2 \sum_{j=1}^{q} e_{t-j} + e_t \tag{6}$$

$$log(h_t) = \omega_0 + \sum_{i=1}^{p} \gamma_j \, log h_{t-j} + \sum_{j=1}^{q} \rho_j \left| \frac{\mu_{t-j}}{\sqrt{h_{t-j}}} \right| + \sum_{m=1}^{r} \theta_m \frac{\mu_{t-m}}{\sqrt{h_{t-m}}} + \pi 3_y log\left(h_t^y\right) \tag{7}$$

In equation (7) $log(h_t)$ represents the log of variance of the error term in equation (6) which mechanically constrains the variance to be positive. ω_0 represent the constant level of volatility. The logarithm of the conditional variance (h_{t-j}) indicates that the leverage effect is exponential, rather than quadratic. The coefficient ρ_j captures the reaction of volatility in response to changes in the news. Residual modulus measures the response to positive news. θ_m captures the response of volatility to both positive and negative news, as modulus is not being taken here. $\pi 3_y log\left(h_t^y\right)$ is the returns' volatility of variable y and $\pi 3_y$ is the volatility spillover parameter for volatility spillover from variable y to variable x i.e. from PSX-100 index returns (RPSX) volatility to exchange rate returns (REXR).

For the selection of the orders p and q Schwarz Bayesian Information Criteria (SBIC) is used in all the above three models.

3.4. Distribution Assumptions of Residuals

Mandelbrot (1963) has argued that Normal distribution is not feasible for modeling financial returns. Because Normal distribution has characteristics of zero excess kurtosis and skewness. Whereas, probability distributions of financial returns are enriched by skewness, kurtosis greater than three, and heavy tails[2]. Therefore, to model financial returns many none Normal error distributions have been used in literature i.e. Student t distribution, Generalized Error Distribution (GED), Exponential and Gamma distributions, etc. The intended study will make use of Normal distribution and two none Normal distributions i.e. Students t and GED. These none Normal error distributions permit thicker tails relative to Normal distribution and have a property of skewness.

Normal Distribution:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}, \qquad -\infty < x < \infty \tag{8}$$

Student-t Distribution:

$$f(x) = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{v\pi}\,\Gamma\left(\frac{v}{2}\right)} \left(1 + \frac{x^2}{v}\right)^{-\left(\frac{v+1}{2}\right)}, \qquad -\infty < x < \infty \tag{9}$$

v denotes the number of degrees of freedom whereas Γ denotes the gamma function.

[2] These feature are termed as leptokurtic property.

General Error Distribution:

$$f(x;\mu,\sigma,v) = \frac{\sigma^{-1} v e^{\left(-0.5\left|\frac{\left(\frac{x-\mu}{\sigma}\right)}{\lambda}\right|^{v}\right)}}{\lambda 2^{\left(1+\left(\frac{1}{v}\right)\right)}\Gamma\left(\frac{1}{v}\right)}, \qquad 1 < x < \infty \tag{10}$$

$v > 0$ denotes the degree of freedom or tail thickness parameter.

3.5. Error Metrics

To evaluate the forecasting performance of GARCH family models three error metrics have been used i.e. Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percent Error (MAPE). Suppose $Y_1, Y_{2,} \dots, Y_h$ are actual observations whereas $\hat{Y}_1, \hat{Y}_2, \dots, \hat{Y}_h$ are forecasted values then the formula for error metrics being used in the study can be mentioned as:

$$RMSE = \sqrt{\frac{1}{h}\sum_{t=1}^{h}(Y_t - \hat{Y}_t)^2} \tag{11}$$

$$MAE = \frac{1}{h}\sum_{t=1}^{h}\left|Y_t - \hat{Y}_t\right| \tag{12}$$

$$MAPE = \frac{1}{h}\sum_{t=1}^{h}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \tag{13}$$

In the above equation, Y_t represent actual value while $\hat{Y}_t$ represent forecasted value. h indicates the forecast horizon. In this study, we considered dynamic forecasts.

3.6. Data

The intended study has utilized daily data from two financial markets in the context of Pakistan. Closing stock prices of the PSX-100 index as representative of the Pakistan Stock Exchange and bilateral nominal exchange rate (Pak-rupee in term of US-Dollar) representing the Currency market has been analyzed. The data spans almost 25 years. The first observation begins on August 4, 1997, and the last observation is dated April 28, 2022. A total of 6453 daily data observations have been used in the analysis. The main reason for selecting high-frequency data sets is to capture enriched information that we cannot do with low-frequency data sets. Yahoo Finance and the State Bank of Pakistan has been used as data collection source.

Figure 1a: Log of PSX 100 Index

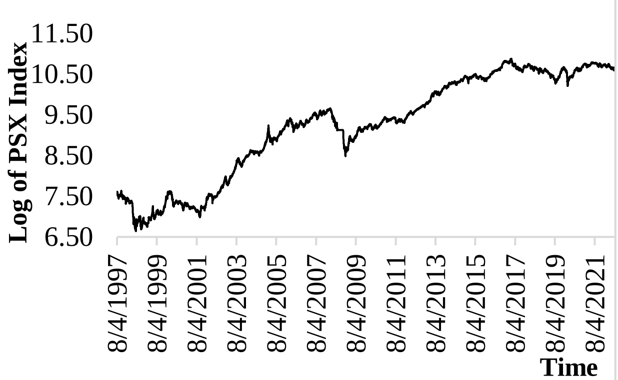
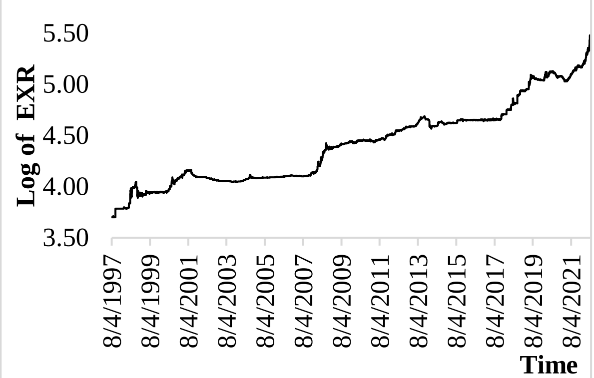


Figure 1d: Log of Exchange Rate



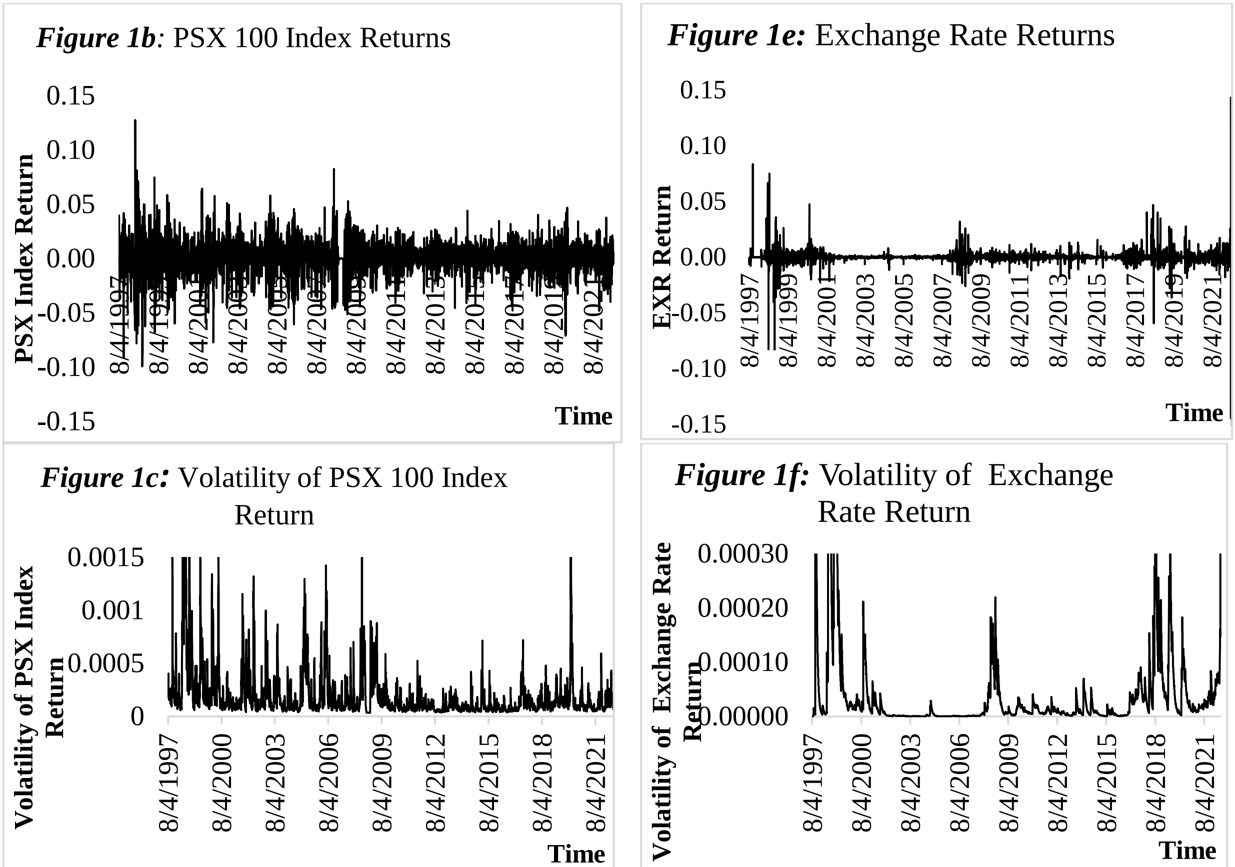


Figure 1: Graphical Analysis
Source: Authors' work.

In the above figure graph 1a and 1d, $LEXR$ and $LPSX$ portray trendy behavior with some instabilities. In the 1990s $LPSX$ it depicted plunge behavior due to a bearish trend in PSX for quite a few months. This behavior of PSX appears mainly because of economic sanctions due to a nuclear test in 1998. $LEXR$ in figure 1d is depicting a constantly rising trend due to currency depreciation in Pakistan. The figure 1b and 1c show the Pakistan Stock Exchange return $(RPSX)$ and their volatility respectively. RPSX and REXR are showing high fluctuations and volatility clustering from 1999 to 2001, 2007 to 2008, and 2019 to 2020. In Figures 1d and 1f Exchange rate return $(REXR)$ and its volatility is being graphed. The exchange rate also shows the same fluctuations in returns and their volatility during the same period, as shown by PSX. High fluctuations and evidence of volatility clustering show that the ARCH effect is present and hence analysis can be carried out using ARCH family models.

4. RESULTS AND DISCUSSION

Table 1 presents descriptive statistics of the logarithm and returns of the PSX-100 index and bilateral nominal exchange rate. The mean of the logarithm and growth rate of both variables is positive and not significantly different from zero. Statistics of kurtosis show that the empirical distribution of PSX and EXR return is leptokurtic. Whereas, the RPSX index is negatively skewed and REXR is positively skewed. The significance of Jarque-Bera statistics rejects the normality of both variables used in the study. Therefore, various none normal error distributions can be used for the analysis of RPSX and REXR. ARCH tests advocate the presence of heteroscedasticity in the underlying variables. Therefore, empirical analysis can be carried out using GARCH family models.

Table 1: Descriptive Statistics

Statistics	RPSX	REXR
Mean	0.00049	0.00026
Median	0.0009	0.000
Maximum	0.128	0.143
Minimum	-0.099	-0.145
Std. Dev.	0.014	0.005
Skewness	-0.413	0.437
Kurtosis	8.662	261.55
Jarque-Bera	8806.190	17977997
	(0.000)	(0.000)
ARCH-LM(50)	1170.762	1159.063
	(0.000)	(0.000)

Source: Authors' Calculations.

To determine the unit root in the data, Augmented Dickey and Fuller (1979), Phillips and Perron (1988) and KPSS unit root tests have been applied to each variable's data series involved in the analysis.

Table 2: Results of Unit Root Tests

Variables	ADF-test	PP-test	KPSS-test	Order of Integration
DLPSX	-51.069***	-73.043***	0.111	I(0)
DLEXR	-90.554***	-90.562***	0.277	I(0)

Source: Authors' calculations.

Note: Critical values for ADF and PP test at 1%, 5%, and 10% significance levels are -3.431482, -2.861925, and -2.567018 respectively. Whereas, Critical values for the KPSS test at 1%, 5%, and 10% significance levels are 0.73900, 0.46300, and 0.34700, respectively. ***, ***, ** and * indicate level of significance at 1%, 5% and 10%, respectively.

The results of the ADF, PP, and KPSS test in table 2 shows that the first differenced log of the Pakistan Stock Exchange (DLPSX) and the first differenced log of the Exchange Rate (DLEXR) are stationary. Stationarity of both variables at first difference implies that DLPSX and DLEXR are integrated of order zero I(0). After detecting evidence of a possible ARCH effect, cross-market volatility spillover is analyzed as below:

Table 3 presents results from the variance equation of the nGRACH, nEGARCH, and nGJR-GARCH models. Results from all three models advocate the existence of significant bidirectional volatility spillover between the stock market and currency markets of Pakistan. Similar results are reported by Jebran and Iqbal (2016) and Iqbal et al. (2020) for Pakistan and some Asian countries.

Table 3: Volatility Spillover across Stock Market and Currency Market based on Normal Error Distribution

Models / Coefficients	nGARCH		nEGARCH		nGJR-GARCH	
	RPSX → REXR	REXR → RPSX	RPSX → REXR	REXR → RPSX	RPSX → REXR	REXR → RPSX
$\boldsymbol{\alpha_0}$	2.53E-05*** (29.37)	4.19E-06*** (3.77)			2.31E-05*** (19.62)	2.03E-06** (1.85)
$\boldsymbol{\alpha_1}$	0.260*** (21.88)	0.174*** (23.38)			0.125*** (23.10)	0.101*** (15.03)
$\boldsymbol{\beta_1}$	0.508*** (37.64)	0.796*** (114.11)			0.042*** (3.347)	
$\boldsymbol{\beta_2}$	0.039*** (17.21)				0.468*** (17.66)	0.792*** (111.89)
$\boldsymbol{\pi 1}$	-0.008*** (-30.48)	-2.01E-07** (-1.95)			0.029*** (6.977)	
$\boldsymbol{\gamma_T}$					0.008 (0.329)	0.145*** (11.40)
$\boldsymbol{\pi 2}$					-0.008*** (-28.17)	-4.2E-07*** (-4.103)
ω			-0.093*** (-13.58)	-0.844*** (-20.12)		
$\boldsymbol{\gamma}$			0.966*** (1476.04)	0.927*** (239.30)		
$\boldsymbol{\rho}$			0.179*** (75.44)	0.314*** (27.69)		
$\boldsymbol{\theta}$			0.048*** (26.93)	-0.088*** (-13.39)		
$\boldsymbol{\pi 3}$			0.042*** (49.14)	0.004*** (2.02)		
SBIC	-7.61	-6.09	-8.63	-6.09	-7.74	-6.109
nGARCH(p, q)	nGARCH(1,2)	nGARCH(2,2)	nEGARCH(1,1)	nEGARCH (1,1)	nGJR-GARCH(2,2)	nGJR-GARCH(1,1)
Standardized Residual Analysis						
Jarque-Bera	4969834 (0.000)	2445.47 (0.000)	60465479 (0.000)	5553.059 (0.000)	6025826 (0.000)	2684.100 (0.000)
$\boldsymbol{Q}$- stat (10)	55.317 (0.255)	43.429 (0.179)	39.590 (0.093)	47.423 (0.166)	56.322 (0.132)	38.817 (0.412)
ARCH-LM (10)	0.0112 (0.325)	0.0162 (0.199)	-0.00043 (0.907)	0.0110 (0.376)	0.0155 (0.215)	0.0022 (0.859)

Source: Authors' calculations.

Note: Values in parenthesis are z-Statistics. Whereas, ***, **, and * indicate the level of significance at 1%, 5%, and 10%, respectively.

In Table 4, the results of the tGARCH model advocate only unidirectional volatility spillover from $REXR \rightarrow RPSX$. However, in the case of $RPSX \rightarrow REXR$ volatility spillover disappears. A similar result was documented by Sevinç (2022) for South Korean markets. Results from tEGARCH and tGJR-GARCH models suggest bidirectional volatility spillover across both markets. Analogous results have been reported by Aftab et al. (2019) and Musa et al. (2020). The significance of the degree of freedom parameter validates the choice of Students' t distribution over normal distribution.

Table 4: Volatility Spillover across Stock Market and Currency Market based on Students t Error Distribution

Models / Coefficients	tGARCH		tEGARCH		tGJR-GARCH	
	RPSX → REXR	REXR → RPSX	RPSX → REXR	REXR → RPSX	RPSX → REXR	REXR → RPSX
$\boldsymbol{\alpha_0}$	3.53E-05*** (7.39)	-1.34E-06*** (-3.02)			2.53E-05*** (7.57)	-9.04E-06*** (-8.29)
$\boldsymbol{\alpha}$	0.150*** (6.09)	0.211*** (13.43)			0.150*** (5.60)	0.123*** (8.54)
$\boldsymbol{\beta}$	0.543*** (12.95)	0.812*** (79.19)			0.600*** (13.34)	0.804*** (85.31)
$\boldsymbol{\pi 1}$	-0.002 (-0.04)	-6.36E-07*** (-5.94)				
$\boldsymbol{\gamma_T}$					0.050 (0.83)	0.201*** (8.02)
$\boldsymbol{\pi 2}$					-0.028*** (-0.76)	-1.03E-06*** (-8.23)
ω			-0.269*** (-11.092)	-0.712*** (-13.29)		
$\boldsymbol{\gamma}$			0.994*** (1086.51)	0.953*** (185.63)		
$\boldsymbol{\rho}$			2.385*** (2.00)	0.356*** (18.41)		
$\boldsymbol{\theta}$			0.192** (1.74)	-0.098*** (-18.195)		
$\boldsymbol{\pi 3}$			-0.010*** (-4.74)	-0.004*** (-2.36)		
Degree of Freedom	20.000 (15.26)	4.778 (15.41)	2.000 (714.5)	4.889 (16.89)	20.000 (14.39)	4.959 (15.33)
SBIC	-10.157	-6.180	-10.055	-6.198	-7.61	-6.196
tGARCH(p, q)	tGARCH(1,1)	tGARCH(1,1)	tEGARCH(1,1)	tEGARCH(1,1)	tGJR-GARCH(1,1)	tGJR-GARCH(1,1)
Standardized Residual Analysis						
Jarque-Bera	5810910 (0.000)	4240.46 (0.000)	26194317 (0.000)	818953.2 (0.000)	6025826 (0.000)	3827.52 (0.000)
$\boldsymbol{Q}$- stat (10)	55.317 (0.293)	47.712 (0.199)	15.478 (0.083)	39.027 (0.161)	56.322 (0.219)	42.233 (0.186)
ARCH-LM (10)	0.0168 (2.35)	-0.006 (-2.51)	-0.002 (-2.17)	-0.003 (-2.21)	0.015 (2.26)	-0.006 (-2.48)

Source: Authors' calculations.

Note: Values in parenthesis are z-Statistics. Whereas, ***, **, and * indicate the level of significance at 1%, 5%, and 10%, respectively.

Analysis of volatility spillover across the stock market and currency market based on GED distribution is presented in Table 5. Outcomes of the analysis suggest the existence of significant bidirectional volatility spillover, using gedGARCH. Similar results are reported by Iqbal et al. (2020). However, according to gedEGARCH and gedGJR-GARCH models there exist a unidirectional volatility spillover from $RPSX \rightarrow REXR$. The empirical results of the study are supported by theoretical justifications provided by flow-oriented and stock-oriented models. Appropriate lag order for the above three models is determined according to Schwarz Bayesian Information Criterion (SBIC).

Table 5: Volatility Spillover across Stock Market and Currency Market based on GED Error Distribution

Coefficients \ Models	gedGARCH		gedEGARCH		gedGJR-GARCH	
	RPSX → REXR	REXR → RPSX	RPSX → REXR	REXR → RPSX	RPSX → REXR	REXR → RPSX
$\boldsymbol{\alpha_0}$	2.46E-05*** (4.555)	-1.67E-06*** (-4.029)			2.34E-08*** (3.70)	-1.06E-05*** (-14.27)
$\boldsymbol{\alpha_1}$	0.489*** (3.35)	0.189*** (13.91)			5.90*** (7.16)	0.123*** (11.47)
$\boldsymbol{\alpha_2}$					-1.84*** (-3.25)	
$\boldsymbol{\beta}$	0.589*** (8.31)	0.818*** (78.19)			0.598*** (29.46)	0.797*** (344.84)
$\boldsymbol{\pi 1}$	-0.007*** (-5.198)	-7.87E-07*** (-8.47)				
$\boldsymbol{\gamma_T}$					-0.241 (-0.42)	0.203*** (8.57)
$\boldsymbol{\pi 2}$					-1.42E-05 (-0.51)	-1.21E-06*** (-14.27)
ω			-10.054 (-1.366)	-0.813*** (14.10)		
$\boldsymbol{\gamma}$			-0.014 (-0.21)	0.941*** (172.36)		
$\boldsymbol{\rho}$			0.109 (1.39)	0.346*** (17.06)		
$\boldsymbol{\theta}$			-0.047 (-0.06)	-0.102*** (-8.37)		
$\boldsymbol{\pi 3}$			-0.043 (-0.66)	-0.005*** (-2.51)		
Degree of Freedom	2.000 (74.81)	1.215 (48.10)	0.198 (57.45)	1.192 (50.99)	2.000 (73.39)	1.217 (47.89)
SBIC	-10.106	-6.179	-10.102	-6.189	-10.22	-6.190
gedGARCH(p, q)	gedGARCH(1,1)	gedGARCH(1,1)	gedEGARCH (1,1)	gedEGARCH(1,1)	gedGJR-GARCH(2,1)	gedGJR-GARCH(1,1)
Standardized Residual Analysis						
Jarque-Bera	5810910 (0.000)	3484.48 (0.000)	9570211 (0.000)	39622.73 (0.000)	6025826 (0.000)	3257.88 (0.000)
$\boldsymbol{Q}$- stat (10)	55.317 (0.193)	46.464 (0.201)	34.070 (0.532)	43.990 (0.091)	56.322 (0.360)	46.233 (0.173)
ARCH-LM (50)	0.017 (2.35)	-0.004 (-2.50)	0.112 (2.93	-0.0003 (-2.25)	0.015 (2.24)	-0.004 (-2.33)

Source: Authors' calculations.

Note: Values in parenthesis are z-Statistics. Whereas, ***, **, and * indicate the level of significance at 1%, 5%, and 10%, respectively.

The robustness of results in Tables 3, 4, and 5, is being checked by carrying out diagnostic analysis on the standardized residuals of the models. Q-statistics and ARCH test statistics are insignificant, showing that there is no ARCH effect and no autocorrelation till the 10th lag of standardized residuals. Results of Jarque-Bera test statistics confirm that residuals are non-normally distributed.

After identifying the evidence of volatility spillover across the stock market and currency markets of Pakistan, the role of returns' volatility spillover in achieving forecasting gain is analyzed. For this purpose, we utilize the information on volatility spillover to improve the forecasting performance of standard GARCH, EGARCH, and GJR-GARCH models based on Normal, Student t, and GED distributions. Forecasting results are presented in the following tables.

Table 6: Forecast Evaluation of GARCH Family Models Based on Normal Distribution for RPSX with and without Volatility Spillover Effect

RPSX						
Multi-Step Ahead Forecast	Without Volatility Spillover			With Volatility Spillover		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE
nGARCH						
1 Day Ahead	0.00648	0.00648	144.839	0.00631	0.00631	144.008
2 Days Ahead	0.00524	0.00519	106.713	0.00521	0.00513	106.279
3 Day Ahead	0.00593	0.00571	124.594	0.00587	0.00562	124.374
4 Days Ahead	0.00869	0.00755	103.539	0.00859	0.00748	103.255
5 Days Ahead	0.01058	0.00914	102.701	0.01044	0.00903	100.489
nEGARCH						
1 Day Ahead	0.00652	0.00652	145.907	0.00623	0.00623	138.528
2 Days Ahead	0.00534	0.00529	109.321	0.00506	0.00504	102.803
3 Day Ahead	0.00589	0.00579	125.765	0.00570	0.00571	125.143
4 Days Ahead	0.00865	0.00748	102.936	0.00854	0.00739	101.820
5 Days Ahead	0.01037	0.00909	102.999	0.01022	0.00893	101.601
nGJR-GARCH						
1 Day Ahead	0.00689	0.00689	142.431	0.00659	0.00659	142.081
2 Days Ahead	0.00529	0.00565	107.964	0.00523	0.00539	106.614
3 Day Ahead	0.00598	0.00583	124.624	0.00592	0.00579	123.966
4 Days Ahead	0.00876	0.00757	106.337	0.00868	0.00754	104.041
5 Days Ahead	0.01079	0.00938	102.182	0.01057	0.00919	101.877

Source: Authors' calculations.

Table 7: Forecast Evaluation of GARCH Family Models Based on Students t Distribution for RPSX with and without Volatility Spillover Effect

RPSX						
Multi-Step Ahead Forecast	Without Volatility Spillover			With Volatility Spillover		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE
tGARCH						
1 Day Ahead	0.00646	0.00646	143.703	0.00588	0.00588	130.573
2 Days Ahead	0.00525	0.00519	106.419	0.00509	0.00510	103.000
3 Day Ahead	0.00596	0.00573	125.214	0.00567	0.00553	119.827
4 Days Ahead	0.00898	0.00756	103.797	0.00876	0.00746	98.3398
5 Days Ahead	0.01070	0.00929	103.009	0.01078	0.00921	99.1100
tEGARCH						
1 Day Ahead	0.00687	0.00687	140.981	0.00591	0.00591	137.032
2 Days Ahead	0.00536	0.00568	104.664	0.00518	0.00515	103.091
3 Day Ahead	0.00578	0.00594	124.346	0.00575	0.00569	123.511
4 Days Ahead	0.00879	0.00781	103.451	0.00868	0.00772	101.991
5 Days Ahead	0.01098	0.00915	108.938	0.01053	0.00878	101.205
tGJR-GARCH						
1 Day Ahead	0.00647	0.00647	143.751	0.00641	0.00641	142.114
2 Days Ahead	0.00582	0.00517	105.818	0.00531	0.00515	105.671
3 Day Ahead	0.00597	0.00573	135.200	0.00592	0.00558	126.830
4 Days Ahead	0.00879	0.00751	102.981	0.00875	0.00749	102.409
5 Days Ahead	0.01093	0.00923	104.005	0.01066	0.00918	102.463

Source: Authors' calculations.

Table 8: Forecast Evaluation of GARCH Family Models Based on GED Distribution for RPSX with and without Volatility Spillover Effect

RPSX						
Multi-Step Ahead Forecast	Without Volatility Spillover			With Volatility Spillover		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE
gedGARCH						
1 Day Ahead	0.00625	0.00625	138.881	0.00624	0.00624	138.603
2 Days Ahead	0.00522	0.00516	105.186	0.00515	0.00511	104.507
3 Day Ahead	0.00575	0.00565	123.086	0.00578	0.00559	121.836
4 Days Ahead	0.00753	0.00753	101.976	0.00877	0.00755	101.807
5 Days Ahead	0.01058	0.00913	101.763	0.01058	0.00911	100.539
gedEGARCH						
1 Day Ahead	0.00659	0.00659	138.522	0.00625	0.00625	137.809
2 Days Ahead	0.00535	0.00546	109.311	0.00512	0.00509	103.973
3 Day Ahead	0.00538	0.00557	123.039	0.00522	0.00555	122.725
4 Days Ahead	0.00889	0.00790	107.352	0.00869	0.00747	100.392
5 Days Ahead	0.01099	0.00929	103.794	0.01079	0.00920	100.276
gedGJR-GARCH						
1 Day Ahead	0.00671	0.00671	140.251	0.00623	0.00623	138.526
2 Days Ahead	0.00516	0.00512	104.669	0.00512	0.00510	103.999
3 Day Ahead	0.00581	0.00561	122.287	0.00579	0.00559	121.983
4 Days Ahead	0.00873	0.00792	101.452	0.00846	0.00775	100.731
5 Days Ahead	0.01088	0.00937	101.098	0.01077	0.00928	100.473

Source: Authors' calculations.

In one of the papers, Lopez (2001) demonstrated that numerous forecast evaluation criteria can be used to evaluate the forecast performance of financial econometric models. In this study, we have used three loss functions; Root Mean Squared Error (RMSE) Mean Absolute Error (MAE), and Mean Absolute Percent Error (MAPE). While taking care of information on volatility spillover across the stock market and currency market, for RPSX, forecasting accuracy of standard GARCH, EGARCH, and GJR-GARCH models is being compared in Table 6, Table 7, and Table 8 respectively. Outcomes from the above three models indicate that information on volatility spillover remains effective in improving the forecasting accuracy of stock market returns (RPSX). This comparison is made within tables 6, 7, and 8 by comparing forecasting results of RPSX with and without volatility spillover effect and highlighted in bold. These results are supported by the findings of Chatziantoniou et al. (2021) and Wu et al. (2022).

After that, we compared forecasting results of GARCH, EGARCH, and GJR-GARCH models based on Normal, Students t, and GED distribution respectively. This comparison is across tables 6, 7, and 8 with volatility spillover effect and based on distinct error distributions. According to RMSE, MAE, and MAPE, among nGARCH, tGARCH, and gedGARCH models, the tGARCH model stands out in terms of better forecasting accuracy for RPSX. Whereas, nEGARCH and gedEGARCH models performed better relative to the tEGARCH model, according to all error metrics. Among nGJR-GARCH, tGJR-GARCH, and gedGJR-GARCH models gedGJR-GARCH provides relatively more accurate forecast results for RPSX. Similar results are provided by Aftab et al. (2019) and Charfi and Mselmi (2022). Therefore, this study suggests a thoughtful implication. After considering the role of information on volatility spillover in forecasting, the family of GARCH models based on Students t and GED distributions should be considered to obtain an accurate forecast for RPSX.

Table 9: Forecast Evaluation of GARCH Family Models Based on Normal Distribution for REXR with and without Volatility Spillover Effect

REXR						
Multi-Step Ahead Forecast	Without Volatility Spillover			With Volatility Spillover		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE
nGARCH						
1 Day Ahead	0.00186	0.00186	620.667	0.00136	0.00136	260.769
2 Days Ahead	0.00349	0.00271	187.398	0.00281	0.00245	151.750
3 Day Ahead	0.00504	0.00438	373.850	0.00365	0.00283	149.437
4 Days Ahead	0.01231	0.00766	115.152	0.01160	0.00737	107.799
5 Days Ahead	0.01188	0.00731	119.034	0.01146	0.00689	102.631
nEGARCH						
1 Day Ahead	0.00076	0.00076	251.982	0.00048	0.00048	159.979
2 Days Ahead	0.00316	0.00258	166.15	0.00243	0.00197	105.043
3 Day Ahead	0.00322	0.00268	198.631	0.00291	0.00217	187.307
4 Days Ahead	0.01302	0.00799	123.04	0.01289	0.00777	121.174
5 Days Ahead	0.01159	0.00792	148.293	0.01146	0.00758	131.672
nGJR-GARCH						
1 Day Ahead	0.00185	0.00185	616.781	0.00069	0.00069	233.124
2 Days Ahead	0.00349	0.00271	189.103	0.00314	0.00246	163.905
3 Day Ahead	0.00496	0.00433	374.742	0.00366	0.00282	247.164
4 Days Ahead	0.01231	0.00766	115.152	0.01164	0.00738	107.947
5 Days Ahead	0.01291	0.00731	119.034	0.01176	0.00698	102.684

Source: Authors' calculations.

Table 10: Forecast Evaluation of GARCH Family Models Based on Student t Distribution for REXR with and without Volatility Spillover Effect

REXR						
Multi-Step Ahead Forecast	Without Volatility Spillover			With Volatility Spillover		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE
tGARCH						
1 Day Ahead	0.00073	0.00073	149.861	0.00051	0.00051	148.147
2 Days Ahead	0.00312	0.00277	109.464	0.00297	0.00271	107.194
3 Day Ahead	0.00414	0.00239	119.977	0.00367	0.00229	118.570
4 Days Ahead	0.02885	0.00799	104.653	0.01231	0.00767	102.802
5 Days Ahead	0.01147	0.00725	107.079	0.01106	0.00716	111.464
tEGARCH						
1 Day Ahead	0.00094	0.00094	204.774	0.00052	0.00052	173.269
2 Days Ahead	0.00649	0.00371	125.755	0.00350	0.00271	121.703
3 Day Ahead	0.00349	0.00269	141.035	0.00356	0.00197	134.569
4 Days Ahead	0.01478	0.00765	111.369	0.01274	0.00741	101.777
5 Days Ahead	0.01181	0.00696	122.724	0.01071	0.00546	109.835
tGJR-GARCH						
1 Day Ahead	0.00051	0.00051	156.117	0.00039	0.00039	141.653
2 Days Ahead	0.00377	0.00483	113.716	0.00350	0.00371	105.149
3 Day Ahead	0.00326	0.00244	117.588	0.00285	0.00241	113.798
4 Days Ahead	0.01179	0.00786	112.268	0.01161	0.00766	109.743
5 Days Ahead	0.01083	0.00797	119.085	0.01049	0.00731	112.415

Source: Authors' calculations.

Table 11: Forecast Evaluation of GARCH Family Models Based on GED Distribution for REXR with and without Volatility Spillover Effect

REXR						
Multi-Step Ahead Forecast	Without Volatility Spillover			With Volatility Spillover		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE
gedGARCH						
1 Day Ahead	0.00100	0.00100	133.333	0.00081	0.00081	131.742
2 Days Ahead	0.00396	0.00395	105.000	0.00379	0.00295	103.661
3 Day Ahead	0.00323	0.00227	105.183	0.00303	0.00211	101.134
4 Days Ahead	0.02387	0.00766	100.453	0.01279	0.00758	100.003
5 Days Ahead	0.01098	0.00696	101.912	0.01079	0.00678	100.992
gedEGARCH						
1 Day Ahead	0.00050	0.00050	100.999	0.00042	0.00042	100.032
2 Days Ahead	0.00497	0.00395	100.524	0.00413	0.00315	100.135
3 Day Ahead	0.00799	0.00530	100.000	0.00714	0.00486	102.145
4 Days Ahead	0.01226	0.00745	101.544	0.01180	0.00688	101.006
5 Days Ahead	0.01183	0.00698	101.797	0.01064	0.00652	101.233
gedGJR-GARCH						
1 Day Ahead	0.00150	0.00150	133.333	0.00093	0.00093	119.331
2 Days Ahead	0.00396	0.00295	100.000	0.00363	0.00298	99.6554
3 Day Ahead	0.00363	0.00277	107.183	0.00346	0.00255	105.434
4 Days Ahead	0.01183	0.00757	107.496	0.01150	0.00750	100.030
5 Days Ahead	0.01183	0.00698	109.797	0.01041	0.00642	104.173

Source: Authors' calculations.

The role of information on volatility spillover in improving the forecasting performance of GARCH, EGARCH, and GJR-GARCH models, for REXR, is being compared in Table 9, Table 10, and Table 11 respectively. For REXR, outcomes of comparison within the tables indicate that information on volatility spillover imparts remarkable predictability gain to GARCH, EGARCH, and GJR-GARCH models. This result is drawn by comparing with and without volatility spillover results for REXR forecasting. After achieving forecasting accuracy by utilizing information on volatility spillover, the role of error distributions, in forecasting REXR, is being analyzed by comparing results across tables 9, 10, and 11. Analysis shows that tGARCH and gedGARCH models provide better REXR forecasts relative to the nGARCH model. However, gedEGARCH and gedGJR-GARCH models provide better forecasts as compared to rival EGARCH models. Analogous outcomes are evidenced in Vee et al., (2011) and Kumar and Patil (2016). Hence, from the overall results of the research question we have analyzed in this section, a meaningful implication can be drawn. To improve the forecasting performance of GARCH family models, after tracing the role of information on volatility spillover in forecasting REXR, Students t, and GED distribution should be considered.

5. CONCLUSION

This study examined the returns' volatility spillover and the role of returns' volatility spillover in forecasting financial markets returns. From this perspective, this study contributed to the existing literature by analyzing the effect of information on volatility spillover along with none Normal error distributions on forecasting accuracy of standard GARCH, EGARCH, and GJR-GARCH models.

Analysis of the study from all three models indicates that there exists significant bidirectional volatility spillover across both financial markets of Pakistan. According to forecasts error metrics, information on volatility spillover effect imparts an effective role in improving the forecasting accuracy of GARCH family models based on Normal, Students t, and GED distributions, for PSX-100 index returns ($RPSX$) and bilateral nominal exchange rate returns (REXR). Moreover, we analyzed a second research question on the role of various error distributions in improving forecasting accuracy. From this viewpoint, our analysis suggests that Student t and GED error distributions should be considered to attain a relatively accurate forecast for RPSX and REXR. Therefore, it can be established from the results of the study that not only does the information on volatility spillover impart a remarkable role in improving the forecasting performance of GARCH family models but various error distributions also support forecasting accuracy gain. The outcomes of this study will provide more accurate future insight regarding financial markets to researchers, policymakers, and investors. Further research can be conducted by incorporating volatility spillover from the commodity market and bond market of Pakistan and by using multivariate financial econometric models. Furthermore, the role of some other none Normal error distributions can be examined for achieving forecasting accuracy in financial econometric models.

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