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Abstract

This study compares the performance of autoregressive conditional heteroscedastic (ARCH) model and autoregressive distributed lag (ARDL) model in term of relationship detection. The daily, weekly, and monthly data are used from 2005 to 2019 to explore the dynamic linkages among KSE 100, S&P 500, Nasdaq 100, Dowjones 30, and DFMG indices. The results indicate that the ARDL and ARCH model have same power to detect the relationship among financial series. The results show that due high volatility in daily and weekly data the ARDL model is failed to capture ARCH effect. In case of monthly data, the performance of ARDL model is as good as GARCH model. It concluded that on monthly basis or less frequency data the ARDL model can be used as an alternative method to GARCH model for financial time series modeling.

Key words: *Volatility, Spillover effect, GARCH, ARDL.*

1. Introduction

The viable integration of financial markets has conquered great attention since last few decades. This integration is due to financial globalization. The mian reasons behind this observed globalization are pervasive development in technology, liberalization of capital markets, transnational capital flow, structural transformation of financial markets, and financial linkages among the economies (Buch, 2004). The integration of financial markets causes information transmission among the equity markets. The financial system of current era is immensely more reachable for the individuals, market players, and firms. These financial markets suggest higher risk management tools, mostly for pools of credit risk. Like, mutual funds offer equity funds to their international customers that characterize not only stocks listed on stock markets of advance markets but also equity portfolios in emerging markets. The professional asset management firms manage the mutual funds. The communication among asset management firms at different points is conducted through system of markets transactions because all of this, the globalization of finance has amplified the need of cooperation among the market players, portfolio managers and financial institutions (Knight, 2006).

The financial globalization has increased the integration among the financial markets and contributed to provide high leverages to few industrialized economies, particularly in US economy (Mendoza & Quadrini, 2010). The process of globalization integrated the markets because due to technological advancement it reduces the transaction and transportation costs (Spence, 2011). The financial integration and openness significantly effect economy of any country (Quinn et al., 2011). The global financial integration triggered imbalances in the most of the economies through global financial crisis 2008, which is produced in US economy and hit the economies all over the world (Obstfeld, 2015). In last quarter of 20th century the globalization used to refer to abrupt growth in international economic flows (Perraton, 2019).

The global financialization is a cause of financial flows between economies, particularly from developed countries to emerging economies (Kose, 2007). The global financial integration is a major cause of information transformation among the cross-border equity markets. The shocks in any major economy penetrates all economies that are directly and indirectly interlinked with international financial system (Ghouse et al., 2017, 2019). The significant evidence has been found that private capital flows is a major cause of global financial shocks across economies and also have caused financial crisis (Agénor & Silva, 2018). That is why there is a significant need to explore these spillover effects among the equity markets.

Modern financial econometric tools are being used to inspect the linkages between equity markets. It is well known that financial time series fluctuate and exhibit stochastic trends. Stationarity in such data series has been achieved through (log) differencing but even after achieving stationarity, series demonstrate autoregressive and conditional hetroscedastic behaviour. This violates the basic assumption of independent and identically distributed (IID) observations of sample for regression model and all other procedures which are based on those assumptions (Asteriou and Hall, 2015).

The first of the family of models developed to deal with this specific data series were developed by Engle (1982) for modelling conditional heteroscedasticity, known as autoregressive conditional heteroscedasticity (ARCH) model. He argues conditional variance to be dependent on square of the lagged disturbance terms. Initially, ARCH models were only used to model volatility but later on Engle et al. (1990) introduced meteor shower hypothesis i.e. to inspect intra markets information transmissions using the same technique. Hamao et al. (1990) also introduced his technique to explore the volatility and mean spillover effects among the equity markets.

In this study, we propose an alternative modelling approach to traditional ARCH-type modelling that is based on ordinary least square estimator i.e., the autoregressive distributed lag model (ARDL) model, that has never been used before for exploration of spillover effects. We procced by estimating both conventional ARCH-type model and ARDL model to inspect the spillover effects using daily, weekly, and monthly financial data time series. This inspection is followed by a comparison between the two modelling approaches to see whether ARDL modelling can be a worthy alternative to the conventional ARCH approach.

Two major points make up the grounds for our choice of the ARDL modelling as the alternative: First, to not restrict our estimation process for the requirement of a stationarity treatment. The reason why we do that is the presence of abundant literature on how differencing eliminates the long run dynamics and unique solution from the series. (Asteriou and Hall, 2015). Second, as the model becomes bigger due to inclusion of explanatory variables and lagged values of the ARMA process, convergence starts to become bit of an issue. This study builds on the relationships which have been explored in a previous study by (Ghouse and Khan, 2017).

2. Literature Review

There is a strong integration of global economies through different financial and real channels which are developed due to globalization (Perraton, 2019). The crisis in one economy of the world is much likely to spread to other economies. The global financial markets experienced a huge wave of financial crisis in 2008 due to USA sub-prime mortgage crisis (Amadeo, 2019). It not only impacted domestic economy of USA but also other economies of the world which are integrated directly or indirectly with US economy. The financial shocks are one of the important reasons which have shifted concentration on the dynamic linkages between the financial markets (Ghouse et al., 2019).

The linkages cause information transmission from one financial market to others. Chelley-Steeley (2005) inspected the dynamic linkages among US, UK and European equity markets. The study indicated that the US markets impacted UK and European stock markets. They employed bivariate stock market correlations to identify co-moments among the markets. Angkinand et al. (2009) examined that US financial markets impacted equity markets of seventeen developed economies, also found spillover from the US to other industrial countries. They used structural vector autoregressive (SVAR) and generalized method of moment (GMM). Onour (2010) explored that 2008 global financial crisis initiated in US mortgage market and prompted disparities all those countries which are related to US economy specially, oil producing countries. They used measures of extreme risk expected shortfall (ES) and value at risk (VaR) to measure the impact.

Amjad and Din (2010) explained that Pakistan economy badly impacted by the global financial crisis 2008. It created spillover from US to Pakistan stock exchanges. Draz (2011) explored that Pakistan economy faced 2008 financial crisis. He used Chow break point test to check the structural breaks in financial series and found a significant break in KSE 100 index series. Padhi and Lagesh (2012) investigated that information transmission by using return and volatilities series. They quantified spillover among Indian, Asian and US stock markets by using multivariate GARCH models. Ali and Afzal (2012) inspected that the information of financial crisis transmitted from US stock markets to Pakistan and induna economies and adversely effected the stock returns. They used exponential GARCH model to explain spillover from US to Pakistan and India.

There are some other empirical studies in case of Pakistan explored the spillover from US equity markets to Pakistan stock exchange (Tahir et al., 2013; Attari & Safdar, 2013; Zia-Ur-Rehman et al., 2013). They employed GARCH models, cointegration analysis, and Granger causality testing for the quantification of relationships. Ghouse and Khan (2017) explored that Pakistani stock markets effected directly form the information transmitted from US equity markets and indirectly through Dubai financial market. They used univariate GARCH models. Ghouse et al. (2019) indicated that the spillover from leading foreign stock markets to Pakistan stock market by using multivariate GARCH model.

The whole literature which we reviewed above indicated that there is spillover effect from US economy to emerging economies. That is why the exploration of these co-moments is necessary. Above literature is also indicating that all the studies used univariate and multivariate GARCH models, cointegration, Granger causality testing, correlations, value at risk, expected shortfall, and structural break testing for the detection of spillover effects. We are unable to found any study which used ARDL model for the detection of spillover effects. As we mention above there are some technical complications with the use of ARCH type models that's why there is need to come up with an alternative methodology.

3. Econometric Methodology

Engle (1982) proposed ARCH model for the modeling of time varying conditional variance. Even though ARCH model is a great contribution in financial econometric literature but there are few problems with this model positivity restriction on conditional variance equation parameters and long lag length. In the solution of loss of degree of freedom and convergence Bollerslev (1986) presented generalized autoregressive conditional hetroscedastic (GARCH) model. It reduces the loss of degree of freedom significantly but other restrictions remain existed. Also, these two models consider only symmetric effect when there is leverage and asymmetric effect then these models are no more applicable. There is battery of asymmetric financial econometric model but we use GJR-GARCH model which is proposed by (Glosten et al., 1993). Davidson et al. (1978) presented unrestricted generalized autoregressive distributed lag model, which is started from a general large model and substantially reduced by imposing theoretical restrictions.

Most of the financial series are trendy at level with heavy fluctuations because of this it is implausible to attain valid inferences. It shows that most of the financial series are nonstationary at level with large stochastic variations, to tackle this problem we used log difference. The log reduces the fluctuation at some extent and difference make series stationary or mean reversion. So, the return series are generated with following formula:

$$\mathrm{R_t} = \log(\mathrm{p_t}/\mathrm{p_{t-1}})$$

where $\mathrm{R_t}$ is representing return series, p_t is value of financial time series at the end of time t and p_{t-1} is first lag of financial time series.

3.1 ARCH (q) Model

The ARCH model introduced by Engle (1982) for conditional variance modeling. It has conditional mean and variance equations. The conditional mean equation explains the data generating process of return series and follows ARMA (p, q) process. While conditional variance equation expresses the data generating process of conditional variance in which variance depends upon square lag of residual term.

The general equation structure of ARCH model is following:

Conditional mean equation:

$$R_t = \gamma_0 + \beta' W_t + \varepsilon_t \tag{1.1}$$

where $\varepsilon_t = z_t \sigma_t$, $z_t \sim N\,(0\,,1)$

Conditional variance equation:

$$\sigma_t^2 = \pi_0 + \sum_{i=1}^{q} \varphi_i\, \varepsilon_{t-i}^2 \tag{1.2}$$

where π_0, $\varphi_i > 0$ and i = 1, ……., q

In equation 1.1 the R_t denotes the return series a linear function of X_t the explanatory variables. The β shows the vector of k*1 parameters of explanatory variables. The $\beta' W_t$ is the general form of ARMA (m, n) process. The term ε_{t-i}^2 is square lag of first equation residuals, it also known as ARCH term which parameter φ_i must be positive.

3.2 GARCH (p, q) Model

The ARCH model suffers in some problems like, when the ARMA process specification got lengthy the convergence of ARCH model becomes difficult. Bollerslev (1986) introduced generalized ARCH which is also known as GARCH model. The GARCH model is just a extension of ARCH by just putting lag value of conditional variance in conditional variance equation along with ARCH term.

The general structure of GARCH model equations is:

Conditional mean equation:

$$R_t = \gamma_0 + \beta' W_t + \varepsilon_t \tag{1.3}$$

where $\varepsilon_t = z_t \sigma_t$, $z_t \sim N\,(0\,,1)$

Conditional variance equation:

$$\sigma_t^2 = \pi_0 + \sum_{i=0}^{q} \varphi_i \, \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \omega_j \, \sigma_{t-j}^2 \tag{1.4}$$

where $\pi_0 > 0$, φ_i, ω_j must be positive, j = 1, ………………, p

In GARCH (p, q) model the conditional variance depends upon square of past values of process ε_t and lag of conditional varianceσ_{t-1}^2. The condition of non-negativity of parameter is also applied in this model.

3.3 GJR-GARCH (p, q) Model

The GARCH model has also some limitations, it only considers symmetric effect when the effect is asymmetric then GARCH model cannot captures it. Glosten et al. (1993) introduce another extension of GARCH model which includes a dummy variable to identify special effects. The GJR is also capture the leverage effect which cannot be measured with simple GARCH models.
The general structure of GJR-GARCH model equations is:

Conditional mean equation:

$$R_t = \gamma_0 + \beta' W_t + \varepsilon_t \tag{1.5}$$

where $\varepsilon_t = z_t \sigma_t$, $z_t \sim N\,(0\,,1)$

Conditional variance equation:

$$\sigma_t^2 = \pi_0 + \sum_{i=0}^{q} \varphi_i \, \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \delta_i \, \varepsilon_{t-i}^2 G_t + \sum_{i=1}^{p} \omega_j \, \sigma_{t-j}^2 \tag{1.6}$$

where $\pi_0 > 0$, φ_i, ω_j must be positive, j = 1, ………………, p

where the $0 \leq \delta_i \geq 1$ is the Range of parameter of leverage effect. The dummy variable is G_t = 1 when the residual is $\varepsilon_{t-1} < 0$ and G_t = 0 when the residual is $\varepsilon_{t-1} \geq 0$. When G_t =1 means news is bad and G_t = 0 means news is good.

3.4 GARCH (p, q) Model (for Exploring Spillover Effect)

The general structure of GARCH model equations is:

For mean spillover effect:

$$R_{At} = \gamma_0 + \beta' W_t + \pi_1 R_{Bt} + \varepsilon_t \tag{1.7}$$

where $\varepsilon_t = z_t \sigma_t$, $z_t \sim N\ (0\ ,1)$

For volatility spillover effect:

$$\sigma^2_{At} = \pi_0 + \sum_{i=0}^{q} \varphi_i\, \varepsilon^2_{t-i} + \sum_{i=1}^{p} \omega_j\, \sigma^2_{t-j} + \pi_2 R^2_{Bt} \qquad (1.8)$$

The mean and volatility spillover effect explore by following Hamao et al. (1990) technique. Suppose we have 2 markets A and B. The R_{At} and R_{Bt} are the return series of market A and B. To check mean spillover effect simply put R_{Bt} in conditional mean equation of A like equation 1.7. if it is significant it means there is mean spillover effect from market B to market A. Same is the case with volatility spillover effect. By following Efficient Market Hypothesis (EMH) we can say that the square return series is mimic of variance. That is why the square return series are used instead of variances (Ghouse & Khan, 2017).

3.5 ARDL Model

The ARDL is an unrestricted generalized model presented by Davidson et al. (1978) for the modeling of UK consumption function. In ARDL model the dependent variable is explained by its own lag values and current and lag values of independent variable. Usually starts from general model and gets reduction by the imposition of theoretical restrictions. According to Charemza and Deadman (1997) simplest form of ARDL is ARDL (1, 1) which can make lot of model through restriction. The ARDL model is also known as a solution of misspecification which causes spurious regression (Ghouse et al., 2018). The general form of ARDL model is following:

$$y_t = a + \sum_{i=0}^{q} \beta x_{t-i} + \sum_{i=1}^{p} \delta y_{t-i} + \varepsilon_{yt} \qquad (1.9)$$

where β and δ are the vectors of parameters. The current and lag values of x and lag values of y are the explanatory variables.

Data is taken from the official websites of the stock markets and investing. Daily, weekly, and monthly data are collected from these websites and synchronized with respect to day, week, and month. We took data on the US, Dubai and Pakistan stock exchanges. The data are taken from 2005 to 2019. We choose this data span on two major reason one is that this data set contain global financial crisis 2008 period which effect had been transmitted all over the world. Second, a major portion this data is used in (Ghouse et al., 2017) and the results of that study can be used for comparison.

4. Results and Discussion

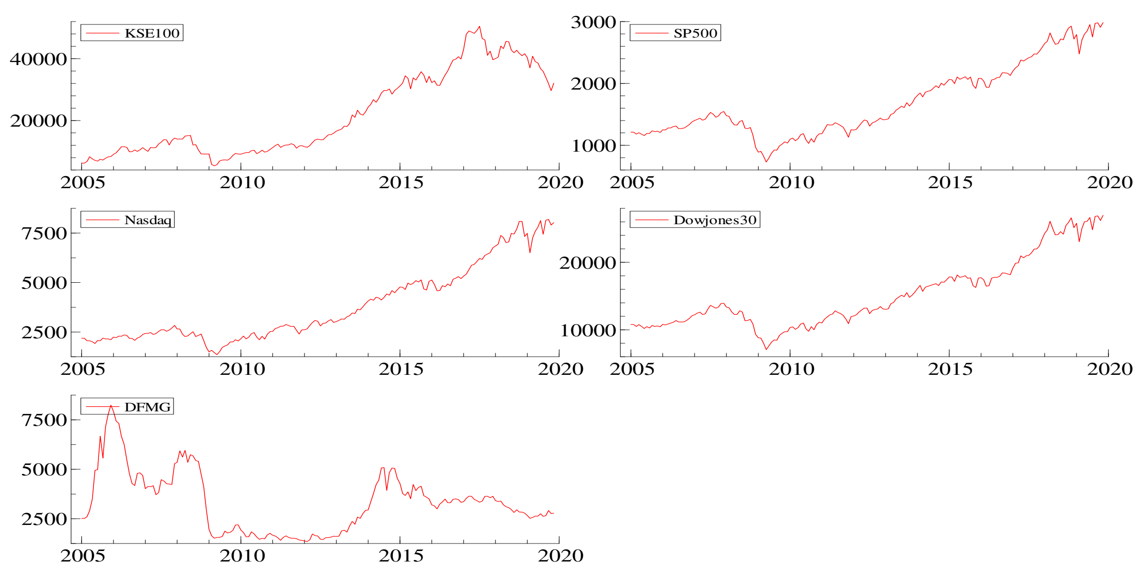
This section consists on graphical, descriptive, and regression analysis. We employed the GRACH and ARDL models to measure the spillover effect between Pakistani and leading foreign markets. The results show that the GARCH model perform well in all cases but ARDL only performed in case of monthly data. It indicates that the ARDL model could not work in high volatility cases and as we reduce the data frequency from weekly to monthly it worked as good as GARCH model. The ARDL model results with daily and weekly are given in table 8 and 12 respectively and the residual analysis of these models are given in table 9 and 13 in appendix. The results show that ARDL model residual are not getting IID in case of daily and weekly data. While the table 6 and 10 show the results of GARCH model and the post estimation analysis results of these models are given in table 7 and 11 in appendix. In all the cases the GARCH model produces

That is why in this section we only discuss monthly data results, while the daily and weekly data results are given in appendix.

4.1 Graphical Analysis

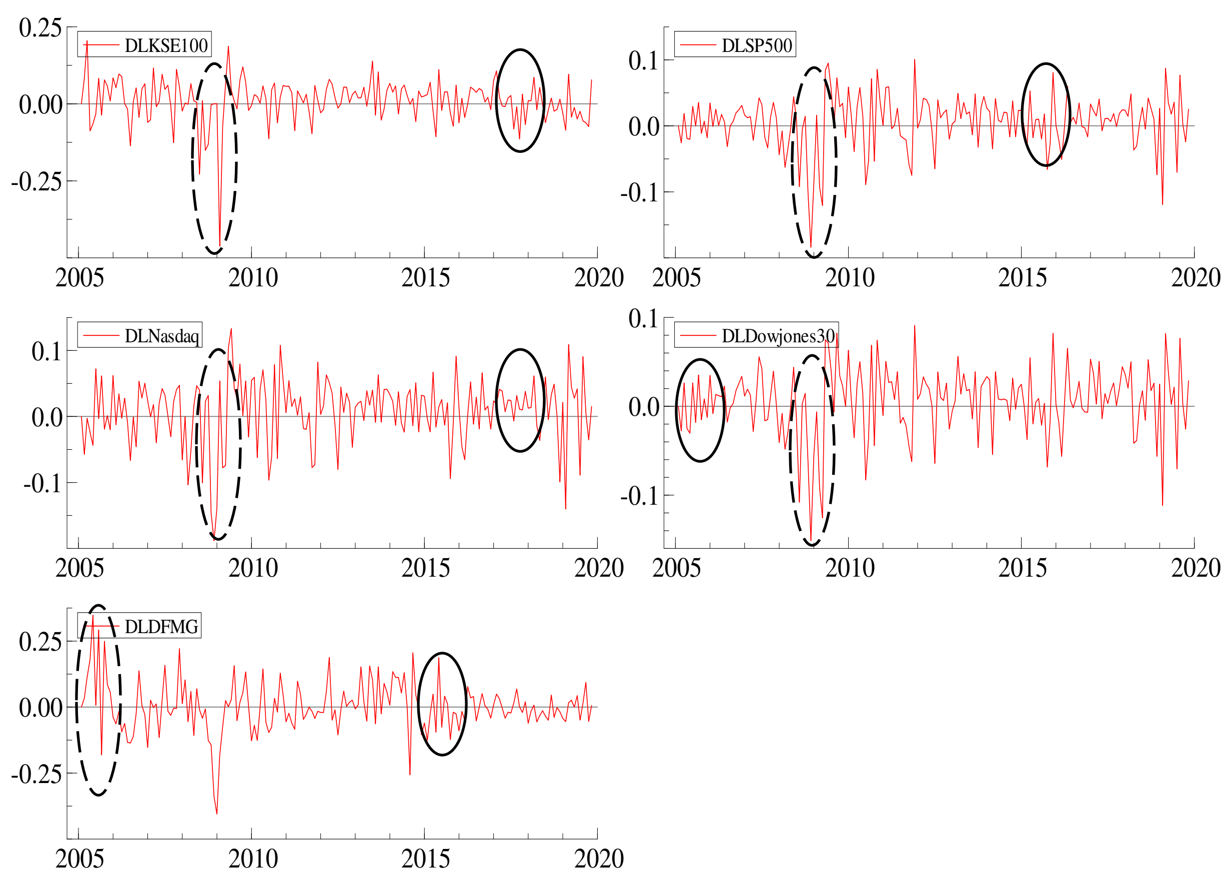
Figure 1, shows that in beginning all series have upward trend than sharp decline and then again there is an upward trend continuously.

Figure 1: Raw Data Series



This sharp decline is due to global financial crises 2008. It also shows that series are overall upward trendy but with huge stochastic fluctuation which indicates that the series are nonstationary at level that is we make them stationary before analysis for GARCH modeling. The return series are given in figure 2 given below. The figure 2 represents return series which are attained by log differencing. The series are moving around the constant value which indicates that the series are stationary at first difference. The dash line circle indicates that the high volatility generates again high volatility and make a bunch of high volatility which is also known as volatility clustering.

Figure 2: Return Data Series



Similarly, case is with solid line circles which are indicting about low volatility clustering. The volatility clustering is termed as ARCH effect. It means all the return series are having ARCH effect.

The figure 3 given below shows the autocorrelation function (ACF) and partial autocorrelation function (PACF) of return series. The ACF is indicating about the lags of moving average (MA) and PACF is representing the autoregressive lags (AR). Any bar outside the green line band is indicating that that lag is significant. The ACF and PACF helps to determine the specification of ARMA process.

Figure 3: The ACF and PACF of Return Series

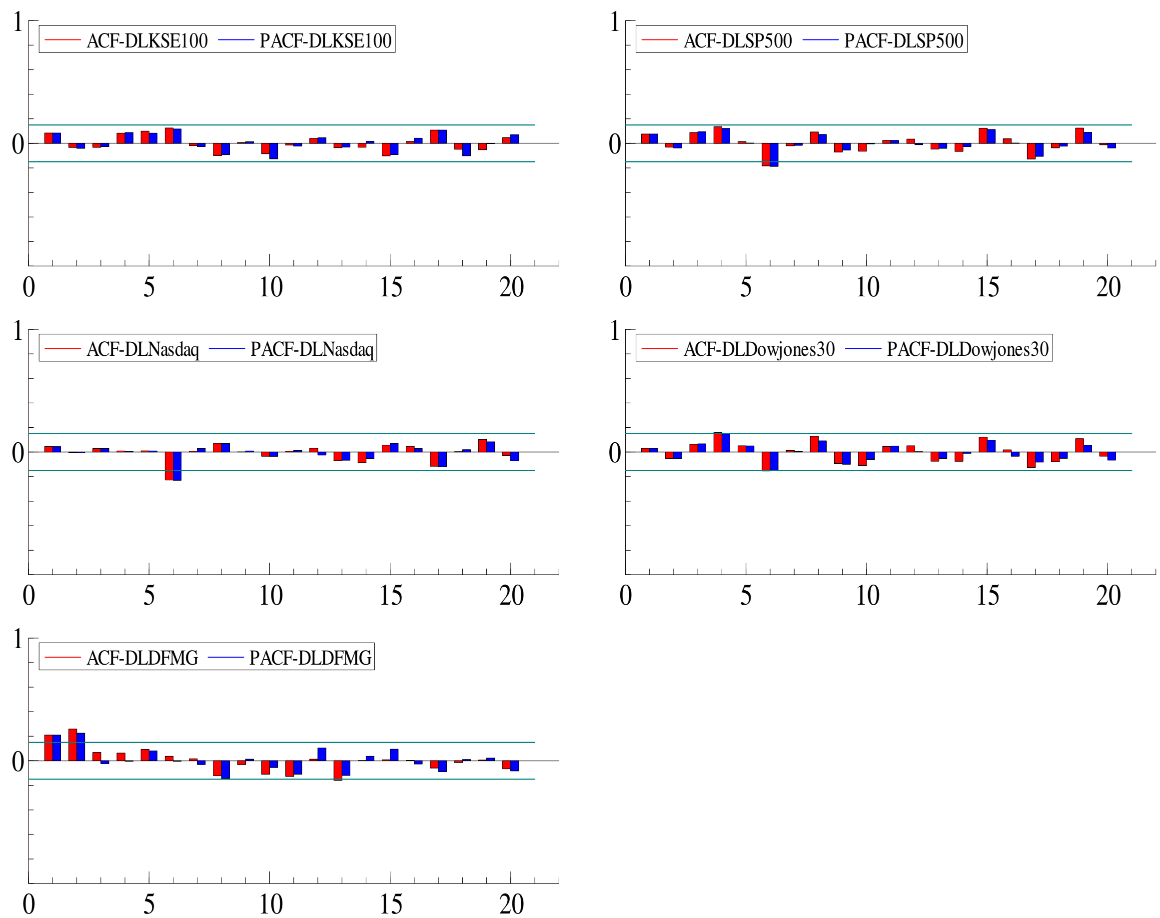
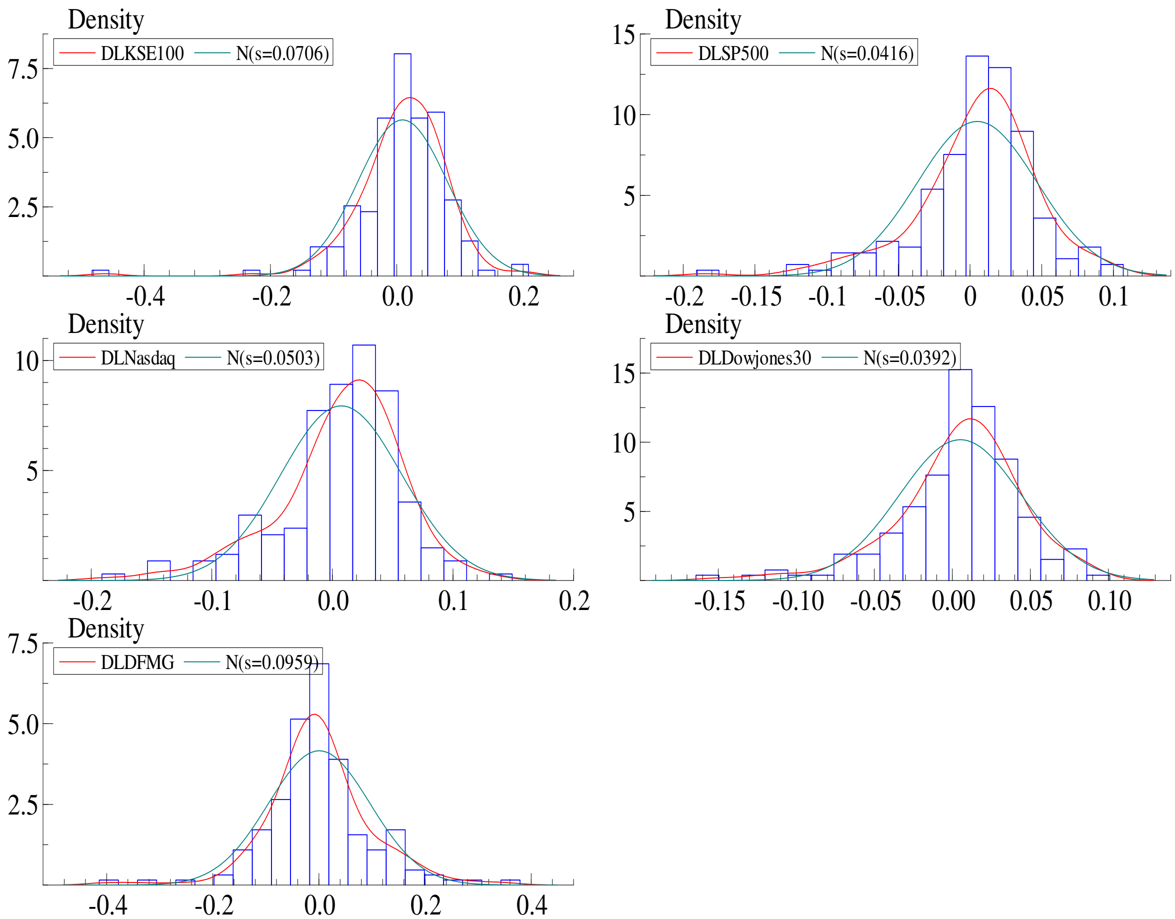


Figure 4 shows the distributions of return series, which is seemingly not normal. The reference normal distribution is also given in graph with green line which is quite different form actual distribution. The distribution of return series high peaks as compare to normal distribution which means the distributions are leptokurtic. Also, the left tail of all the distributions are larger than the normal size which means that the distributions are negatively skewed.

Figure 4: Distribution of Return Series of KSE 100



4.2 Descriptive Statistics

The descriptive statistics offers an understanding about the nature of data series. Table 1 shows the descriptive statistics of US, Dubai and Pakistani stock markets indices. The mean of all the series is very close to zero, which is according to efficient market hypothesis. The skewness and kurtosis test statistics are significant, shows that the distributions of all the return series are approximately non normal. The distribution according to kurtosis and skewness statistics are negatively skewed and leptokurtic as we see in graphical analysis.

Table 1: Summary of Statistics of Stock returns

Series	Mean	Standard deviation	Skewness	Jarque Bera	Excess Kurtosis	Q-stat (5)	Q^2-stat (5)	ARCH 1-2	KPSS
KSE 100	-0.4622	0.0707	-1.8396 (0.000)	923.19 (0.000)	10.533 (0.000)	16.165 (0.000)	1041.01 (0.000)	12.912 (0.000)	0.1408
S&P 500	-0.1838	0.0416	-0.9858 (0.000)	75.732 (0.000)	2.5147 (0.000)	14.106 (0.000)	64.695 (0.000)	12.667 (0.000)	0.1819
NASDAQ 100	-0.1883	0.0503	-0.8766 (0.000)	39.233 (0.000)	1.4886 (0.000)	9.54855 (0.000)	65.024 (0.000)	19.810 (0.000)	0.1631
Dowjones 30	-0.1511	0.0392	-0.8349 (0.077)	43.657 (0.000)	1.7600 (0.000)	9.64737 (0.000)	48.0858 (0.000)	3.7129 (0.026)	0.1888
DFMGI	-0.4048	0.0959	-0.0403 (0.000)	67.562 (0.000)	3.0171 (0.000)	23.451 (0.000)	36.798 (0.000)	15.462 (0.000)	0.0998

Null Hypotheses

"KPSS H_0: Return series is level stationary, Asymptotic significant values 1% (0.739), 5% (0.463), 10% (0.347). Q-stat (return series) there is no serial autocorrelation. Q^2-stat (square return series) H0: there is no serial autocorrelation. Jarque-Bera H0: distribution of series is normal. LM-ARCH H_0: there is no ARCH effect. Use these Asymptotic Significance values of t-stat 1% (0.01), 5% (0.05), 10% (0.1) and compare these critical values with P-values (Probability values). P-values are in the parenthesis".

The Q-stat statistics are significant which means that the observations are having autoregressive behaviour. Q-square statistics are also significant which shows that the variance of observation is depending upon past history. The LM ARCH test is used to identify ARCH effect, the statistics of test are indicating that all the series are having ARCH effect. The KPSS test is used to check the stationarity of variables, the statistics are indicating that all the return series are stationary.

4.3 Tracing Spillover Effect with GARCH and ARDL models

In section 4.3 we explore the direct and indirect linkages between KSE 100 and leading foreign stock markets indices S&P 500, NASDAQ 100, DOWJONES, and DFMGI. The procedure to find out the spillover effect with GARCH model stated above in section 2. In ARDL models, we introduced the raw series of one stock market into the ARDL equation of other stock market without making them stationary. If it is significant, it means there is a spillover effect from one series to other series. In ARDL models we are using series without making them stationary because according to Ghouse et al. (2018), there is no need of unit root testing for ARDL modeling. But for GARCH modeling we used return series because the basic assumption for GARCH model is that the series must be stationary otherwise the results are the misleading.

Table 2: Spillover Effect by using GARCH Models A Bidirectional Analysis

Parameters / Spillover direction	Mean spillover effect R_t (π_1)	Volatility Spillover effect R_t^2 (π_2)
KSE 100 to S&P 500 ARMA(1,1) GARCH (1,2)	0.1213 (0.1989)	0.03146 (0.1992)
S&P 500 to KSE 100 ARMA(1,2) GJR (1,1)	0.02013*** (0.0012)	-0.01132*** (0.0023)
KSE 100 to NASDAQ 100 ARMA(1,1) GARCH (1,1)	0.01567 (0.5673)	0.0029* (0.09212)
NASDAQ 100 to KSE 100 ARMA(1,1) GJR (1,1)	0.01871*** (0.0012)	-0.1214*** (0.0003)
KSE 100 to DJI ARMA(1,1) GARCH (1,1)	0.0134 (0.3723)	0.0023 (0.1734)
DJI to KSE 100 ARMA(1,1) GARCH (1,1)	0.3675 (0.1234)	0.5456 (0.07134) *
KSE 100 to DFMGI ARMA(1,1) GJR (1,1)	0.0561** (0.0312)	0.0451* (0.0751)
DFMGI to KSE 100 ARMA(1,1) GARCH (1,1)	0.0181*** (0.0007)	-0.0015*** (0.0015)
S&P 500 to DFMGI ARMA(1,1) GARCH (1,2)	0.0613*** (0.0014)	0.00134 (0.5541)
DFMGI to S&P 500 ARMA(1,1) GARCH (2,1)	0.0321** (0.05431)	-0.0031 (0.5871)
NASDAQ 100 to DFMGI ARMA(1,1) GARCH (1,1)	0.0631** (0.0176)	0.0179 (0.5988)
DFMGI to NASDAQ 100 ARMA(1,1) GARCH (1,1)	0.02010** (0.0356)	-0.0002 (0.9081)
DJI to DFMGI ARMA(1,1) GARCH (1,1)	0.05614*** (0.0023)	0.0041 (0.5671)
DFMGI to DJI ARMA(1,1) GARCH (1,1)	0.0324** (0.0189)	-0.0028 (0.6541)

Null Hypotheses

"Mean spillover H0:π_1= 0 No mean spillover, volatility spillover H0: π_2= 0 No volatility spillover. P-values are in the parenthesis".

The ****, **, and * asterisks indicate the level of significance at 1%, 5%, and 10% respectively.

In table 2, the parameter of return series π_1 and parameter of squared return series π_2 of S&P 500 are statistically significant in conditional mean and variance equations of KSE 100 but there is no reverse effect from KSE 100 to S&P 500. It shows there is unidirectional mean and volatility spillover effect from S&P 500 to KSE 100. Similarly, the parameter of return series π_1 and parameter of squared return series π_2 of NASADQ 100, DJI, and DFMGI in conditional mean and variance equations of KSE 100 are statistically significant. It means there is also mean and volatility spillover effect from NASADQ 100, DJI, and DFMGI to KSE 100. This clearly indicates that the disturbance in returns and volatility of return in NASADQ 100, DJI, and DFMGI affect the return and volatility of KSE 100 but there is no reverse effect from KSE 100 to these markets.

The parameter of return series $\pi_1$of S&P 500, NASADQ 100, DJI are significant in conditional mean equations of DFMGI, which means there is mean spillover effect from S&P 500, NASADQ 100, and DJI to DFMGI. While the parameter of squared return series π_2 of S&P 500, NASADQ 100, and DJI in conditional variance equations of DFMGI are statistically insignificant. It means there is volatility spillover effect from these markets to DFMGI. The parameter of return series $\pi_1$of DFMGI is significant in conditional mean equations of S&P 500, NASADQ 100, and DJI, which means there is mean spillover effect from DFMGI to S&P 500, NASADQ 100, and DJI. While the parameter of squared return series π_2 of DFMGI in conditional variance equations of S&P 500, NASADQ 100, DJI are statistically insignificant. It means there is volatility spillover effect from DFMGI to S&P 500, NASADQ 100, and DJI.

There are bidirectional mean and volatility spillover effects between KSE 100 and DFMGI. Because the parameter of return series π_1 and parameter of squared return series π_2 of DFMGI are statistically significant in conditional mean and variance equations of KSE 100 but there is also reverse mean and volatility spillover effect from KSE 100 to DFMGI. It shows there is bidirectional mean and volatility spillover effect between DFMGI and KSE 100. The evident shows that DFMGI, S&P 500, NASADQ 100, and DJI have direct mean and volatility effect on KSE 100 but also there is indirect effect from S&P 500, NASADQ 100, and DJI to KSE 100 through DFMGI. For the validations of results, we employed residual analysis given below in table 3.

Table 3: Residual Analysis of GARCH Model

Parameter / Series	Jarque Bera	Q-Stat (5)	Q-Stat (10)	Q^2-Stat (5)	Q^2-Stat (10)	LM -ARCH (1-2)	LM-ARCH (1-5)
KSE 100 to S&P 500	756.50*** (0.0007)	6.8451 (0.1987)	10.1981 (0.5129)	3.4321 (0.6215)	10.1012 (0.1980)	0.3195 (0.5126)	0.5632 (0.9651)
S&P 500 to KSE 100	4345.3*** (0.0002)	1.189 (0.5671)	10.731 (0.3289)	1.9815 (0.9651)	4.6751 (0.91352)	1.5621 (0.5631)	0.2319 (0.4532)
KSE 100 to NASDAQ 100	113.78*** (0.0010)	1.5891 (0.6918)	7.7451 (0.3701)	4.6731 (0.2231)	12.861 (0.1781)	3.6114* (0.09867)	0.16771 (0.19751)
NASDAQ 100 to KSE 100	7018.1*** (0.0002)	5.6541 (0.1312)	18.331 (0.5631)	0.7451 (0.4651)	4.7861* (0.08719)	0.32341 (0.7640)	0.2401 (0.8731)
KSE 100 to DJI	209.55*** (0.0003)	9.7681 (0.2138)	10.981 (0.1243)	6.2981 (0.2930)	12.1342 (0.2541)	4.4237 (0.1561)	1.4421 (0.1423)

DJI to KSE 100	1314.3***	6.4531	12.5531	2.4181	5.2316	0.2751	0.2871
	(0.0003)	(0.1431)	(0.1231)	(0.1761)	(0.9812)	(0.8861)	(0.4131)
KSE 100 to DFMGI	231.87***	5.8871	30.5641	7.1871	6.6751	0.1781	0.5641
	(0.0000)	(0.4531)	(0.5641)	(0.5671)	(0.4561)	(0.7541)	(0.7541)
DFMGI to KSE 100	3564.4***	13.134	24.8741	2.2453	6.4321	0.2423	0.1431
	(0.0002)	(0.3781)	(0.5641)	(0.9534)	(0.4234)	(0.3665)	(0.4531)
S&P 500 to DFMGI	1314***	8.6751	11.8231*	6.2345	6.2341	0.3451	0.7656
	(0.0001)	(0.08761)	(0.04321)	(0.1231)	(0.1431)	(0.1531)	(0.6751)
DFMGI to S&P 500	567.2***	6.7331	8.6751	5.7781*	11.841*	3.1451*	1.3454
	(0.0000)	(0.5431)	(0.8231)	(0.08713)	(0.130)	(0.0800)	(0.9013)
NASDAQ 100 to DFMGI	11764***	7.4531	14.823*	4.0231	10.0107	0.1871	0.4871
	(0.0002)	(0.1654)	(0.0790)	(0.1871)	(0.3341)	(0.8561)	(0.4431)
DFMGI to NASDAQ 100	187.43***	8.1821	9.1312	7.7030	12.823*	3.6743*	2.5541
	(0.0002)	(0.1431)	(0.6321)	(0.1762)	(0.1238)	(0.1786)	(0.1564)
DJI to DFMGI	10561***	7.7081	13.341	5.1321	9.4531	0.3861	0.5978
	(0.0000)	(0.0765)	(0.49700)	(0.6561)	(0.5231)	(0.9898)	(0.3413)
DFMGI to DJI	476.76***	7.8141	3.8715	3.8145	8.14	3.8816	0.7891
	(0.0002)	(0.3987)	(0.5134)	(0.5143)	(0.14)	(0.7851)	(0.6451)

Null Hypotheses

"Q-stat (return series) there is no serial autocorrelation. Q^2-stat (square return series) H0: there is no serial autocorrelation. Jarque-Bera H0: distribution of series is normal. LM-ARCH H_0: there is no ARCH effect. P-values are in the parenthesis".

The ****, **, and * asterisks indicate the level of significance at 1%, 5%, and 10% respectively.

The results in table 3 are indicating that all the test statistics are insignificant except Jarque-Bera which is test of normality. Normality is not necessary for validation of results but the residual of model must be independent identically distributed (IID). This condition is fulfilled according to the results of Q stat, Q square. Also, the ARCH effect is also insignificant. We employed F-test to test the joint significance of the lag values of independent variable. The results of ARDL model are following:

Table 4: Spillover Effect by using ARDL Models A Bidirectional Analysis

Spillover direction	F-stat	Spillover direction	F-stat
S&P 500 to KSE 100	6.6423*** (0.0041)	**KSE 100 to S&P 500**	10.6423*** (0.0021)
NASDAQ 100 to KSE 100	11.753*** (0.0021)	**KSE 100 to NASDAQ 100**	3.9408* (0.0526)
DJI to KSE 100	7.0973*** (0.0001)	**KSE 100 to DJI**	2.9811* (0.0821)
DFMGI to KSE 100	4.6432*** (0.0000)	**KSE 100 to DFMGI**	4.0341** (0.0420)
S&P 500 to DFMGI	7.7401*** (0.0000)	**DFMGI to S&P 500**	4.8537*** (0.0001)

NASDAQ 100 to DFMGI	5.0071*** (0.0010)	**DFMGI to NASDAQ 100**	6.7201*** (0.0013)
DJI to DFMGI	9.0234*** (0.0000)	**DFMGI to DJI**	7.9472*** (0.0000)

The ****, **, and * asterisks indicate the level of significance at 1%, 5%, and 10% respectively.

Table 4 shows that the S&P 500, NASADQ 100, and DJI series coefficients are significant in the equation of KSE 100. It means there is spillover effect from S&P 500, NASADQ 100, and DJI to KSE 100. But there is no spillover effect found from KSE 100 to S&P 500, NASADQ 100, and DJI because their coefficients are insignificant in the equation of KSE 100. It shows that there is unidirectional spillover effect from S&P 500, NASADQ 100, and DJI to KSE 100. The DFMGI series coefficients are significant in the equation of KSE 100 and KSE 100 series coefficients are significant in the equation of DFMGI. It means there is bidirectional spillover effect between DFMGI and KSE 100.

The results in table 4 also show that the S&P 500, NASADQ 100, and DJI series coefficients are significant in the equation of DFMGI and DFMGI series coefficients are also significant in the equation of S&P 500, NASADQ 100, and DJI. It means there is bidirectional spillover effect between S&P 500, NASADQ 100, DJI and DFMGI. These results support the results of GARCH models because the directions of spillover remain same. This shows that DFMGI, S&P 500, NASADQ 100, and DJI have direct spillover effect on KSE 100 and also there is indirect effect from S&P 500, NASADQ 100, and DJI to KSE 100 through DFMGI. For the validation of ARDL results we employed the residual analysis.

Table 5: Residual Analysis of ARDL Model

Series	AR 1-7 test	ARCH 1-7 test	Hetero test
S&P 500 to KSE 100	0.7423 (0.1932)	1.3822 (0.2111)	0.4024 (0.6492)
KSE 100 to S&P 500	2.0071 (0.8341)	1.3481 (0.7532)	1.3642 (0.1932)
NASDAQ 100 to KSE 100	0.0927 (0.3731)	1.8130 (0.7321)	1.7926 (0.8913)
KSE 100 to NASDAQ 100	2.3824 (0.7342)	0.7429 (0.1022)	1.6482 (0.1841)
DJI to KSE 100	0.9284 (0.6420)	2.7322* (0.0926)	1.7410 (0.4821)
KSE 100 to DJI	0.6024 (0.3546)	0.8444 (0.1037)	0.8201 (0.1834)

DFMGI to KSE 100	0.8742 (0.1784)	2.0331 (0.1068)	1.8322 (0.8945)
KSE 100 to DFMGI	1.3872 (0.7423)	1.6381 (0.1842)	0.8231 (0.2940)
S&P 500 to DFMGI	1.5482 (0.1013)	0.7206 (0.4611)	1.8492 (0.2932)
DFMGI to S&P 500	1.9201 (0.3096)	1.9432 (0.1201)	0.8942 (0.8432)
NASDAQ 100 to DFMGI	1.3011 (0.7501)	0.6231 (0.1842)	0.9734 (0.8931)
DFMGI to NASDAQ 100	1.8503 (0.3042)	0.8072 (0.9115)	1.8470 (0.2515)
DJI to DFMGI	2.9321 (0.0946)	0.6911 (0.8521)	1.7834 (0.1904)
DFMGI to DJI	2.1038* (0.0703)	1.0372 (0.3592)	0.9444 (0.6492)

Null Hypotheses
"LM-ARCH H0: there is no ARCH effect. P-values are in the parenthesis. AR H0: there is no autocorrelation in residuals. P-values are in the parenthesis. Hetero test H0: there is no Heteroscedasticity in residuals. P-values are in the parenthesis".

The ****, **, and * asterisks indicate the level of significance at 1%, 5%, and 10% respectively.

All the statistics in table 5 are insignificant at 5% level of significance. It shows that the results of table 4 are valid.

5. Conclusion and Policy Implications

This study investigates the direct and indirect dynamic linkages between Pakistani and leading global stock markets. Daily data are used from 2005 to 2019. The appropriate univariate GARCH type models and ARDL models are employed to examine information transmission between stock markets and modeling volatility. The study examined the fluctuating nature and the magnitude of the spillover from US and Gulf equity markets to Pakistan stock market KSE 100. The unidirectional spillover effect is found from S&P 500, NASADQ 100, and DJI to KSE 100. The bidirectional spillover effect is found between DFMGI and KSE 100. While there is a bidirectional spillover effect amongst S&P 500, NASADQ 100, DJI, and DFMGI. This study concluded that there is direct and indirect spillover effect from leading foreign markets to Pakistan stock market. One thing that is more important in the study is comparison of GARCH type models and ARDL model. The study concluded that the ARDL model is unable to capture ARCH effect when data are collected on daily and weekly basis. It only captures the ARCH when data are monthly or at less frequency. We may not be able to generalize these finding on this small sample outputs but it is an effort to explore another way to deal with financial series having ARCH effect. We conclude that the investors are using these markets in their diversified portfolios. Despite the war and terror foreign investors are interested in Pakistani stock markets. Particularly the investment in energy sector is more attractive for foreign investors. The boom in KSE 100 is not a bubble created by local investors. This study is an important tool for financial institutions, portfolio managers, market players and academician to diagnose the nature and level of linkages and information transmission between the financial markets. The financial managers get more understanding about the management of portfolio which is badly affected by the stock prices. The market players may use this information for portfolio diversification and hedging. The policy makers can minimize the effects of spread of stock prices. The stability of stock prices is very important for portfolio and foreign direct investments, which improves macroeconomic stability and positively affect the economic growth. Through these results the investors/market players of one market can guess the performance of other markets. This study also provides an alternative way to deal with ARCH effect.

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Appendix

Table 6: Spillover Effect with GARCH Models (Bidirectional Analyses with Daily Data)

The ****, **, and * asterisks indicate the level of significance at 1%, 5%, and 10% respectively.

Parameters / Spillover direction	Mean spillover effect R_t (π_1)	Volatility Spillover effect R_t^2 (π_2)
KSE 100 to S&P 500	0.0472	0.0013
ARMA(1,1) GARCH (1,1)	(0.3931)	(0.3624)
S&P 500 to KSE 100	0.0059***	-0.0174***
ARMA(1,1) GJR (1,1)	(0.0000)	(0.0000)
KSE 100 to NASDAQ 100	0.0136	0.0193*
ARMA(1,1) GARCH (1,1)	(0.5945)	(0.0847)
NASDAQ 100 to KSE 100	0.0113***	-0.0014***
ARMA(1,0) GJR (1,1)	(0.0000)	(0.0000)
KSE 100 to DJI	0.0001	0.0294
ARMA(0,1) GARCH (1,1)	(0.1943)	(0.5734)
DJI to KSE 100	-0.0210***	-0.0019***
ARMA(1,1) GJR (1,1)	(0.0000)	(0.0000)
KSE 100 to DFMGI	0.01846*	0.0147*
ARMA(2,1) GARCH (1,1)	(0.0443)	(0.0788)
DFMGI to KSE 100	0.0201***	-0.0015***
ARMA(1,1) GARCH (1,1)	(0.0000)	(0.0000)
S&P 500 to DFMGI	0.0813***	0.0117
ARMA(1,1) GARCH (1,1)	(0.0028)	(0.5462)
DFMGI to S&P 500	0.0213**	-0.0018
ARMA(1,1) GARCH (1,1)	(0.0328)	(0.1585)
NASDAQ 100 to DFMGI	0.0703***	0.0184
ARMA(1,1) GARCH (1,1)	(0.0056)	(0.7160)
DFMGI to NASDAQ 100	0.0232**	-0.0059
ARMA(1,0) GARCH (1,1)	(0.0257)	(0.6331)
DJI to DFMGI	0.0792***	0.0284
ARMA(1,2) GARCH (1,1)	(0.0056)	(0.5194)
DFMGI to DJI	0.0039**	-0.0283
ARMA(1,1) GARCH (1,1)	(0.0240)	(0.3720)

Null Hypotheses:
"Mean spillover H0:π_1= 0 No mean spillover, volatility spillover H0: π_2= 0 No volatility spillover. P-values are in the parenthesis".

The ****, **, and * asterisks indicate the level of significance at 1%, 5%, and 10% respectively.

Table 7: Residual Analysis Modeling with GARCH Model (Daily Data)

Parameter / Series	Jarque Bera	Q-Stat (5)	Q-Stat (10)	Q^2-Stat (5)	Q^2-Stat (10)	LM -ARCH (1-2)	LM-ARCH (1-5)

KSE 100 to S&P 500	319.13*** (0.0000)	5.5842 (0.9413)	1.5873 (0.4959)	1.1844 (0.5935)	3.8345 (0.8544)	0.8745 (0.9859)	0.6853 (0.8541)
S&P 500 to KSE 100	4522.1*** (0.0000)	1.2841 (0.7494)	7.8534 (0.9593)	0.8420 (0.3448)	1.9531 (0.8593)	0.7433 (0.7534)	0.7853 (0.9832)
KSE 100 to NASDAQ 100	732.74*** (0.0000)	2.3843 (0.8364)	4.5832 (0.8534)	2.3893 (0.5947)	9.1954 (0.0843)	1.0380 (0.3266)	0.9053 (0.9371)
NASDAQ 100 to KSE 100	8724.5*** (0.0000)	1.4285 (0.4855)	14.923* (0.0593)	0.6135 (0.6815)	3.7594 (0.5935)	0.1305 (0.3751)	0.7435 (0.6403)
KSE 100 to DJI	421.64*** (0.0000)	14.752* (0.0845)	14.776 (0.1404)	2.6165 (0.5154)	11.854* (0.0532)	8.7824* (0.0794)	2.9305* (0.0911)
DJI to KSE 100	1298.0*** (0.0000)	2.5874 (0.7993)	11.864 (0.1334)	0.8635 (0.6422)	1.5934 (0.9503)	0.6340 (0.5564)	0.8350 (0.8513)
KSE 100 to DFMGI	14511*** (0.0000)	3.3345 (0.4947)	12.571* (0.0953)	1.8542 (0.5721)	4.8503* (0.1583)	0.7238 (0.8453)	0.8953 (0.9475)
DFMGI to KSE 100	4513.3*** (0.0000)	0.4632* (0.0534)	6.8347 (0.4865)	1.5834 (0.9420)	1.7543 (0.7539)	0.5482 (0.8843)	0.8934 (0.5731)
S&P 500 to DFMGI	2134.2*** (0.0000)	2.4341 (0.4749)	14.759* (0.0905)	4.7582 (0.5793)	3.7604 (0.8530)	0.7635 (0.4365)	0.9240 (0.1011)
DFMGI to S&P 500	1432.2*** (0.0000)	3.3489 (0.3460)	9.7594 (0.9535)	5.8354* (0.0884)	10.753* (0.0953)	1.8754 (0.1039)	0.2017 (0.7430)
NASDAQ 100 to DFMGI	1354*** (0.0000)	2.6332 (0.3843)	12.947* (0.0964)	1.8534 (0.9858)	4.7592 (0.7502)	0.8350 (0.7635)	0.5877 (0.4021)
DFMGI to NASDAQ 100	1921.5*** (0.0000)	5.5753 (0.9738)	10.743 (0.7534)	3.6356 (0.8635)	8.8541* (0.0964)	1.7845 (0.1631)	1.5437 (0.7536)
DJI to DFMGI	1653.1*** (0.0000)	2.8543 (0.5534)	11.532 (0.8573)	1.7530 (0.7583)	3.7594 (0.8543)	0.8553 (0.0955)	0.7325 (0.4920)
DFMGI to DJI	4743.3*** (0.0000)	1.8454 (0.8434)	5.4853 (0.9491)	2.8525 (0.7424)	7.8996* (0.0971)	0.8915 (0.8420)	0.0441 (0.1475)

Null Hypotheses:
"Q-stat (return series) there is no serial autocorrelation. Q^2-stat (square return series) H0: there is no serial autocorrelation. Jarque-Bera H0: distribution of series is normal. LM-ARCH H_0: there is no ARCH effect. P-values are in the parenthesis".

The ****, **, and * asterisks indicate the level of significance at 1%, 5%, and 10% respectively.

Table 8: Spillover Effect by using ARDL models (Bidirectional Analyses for Daily Data)

Spillover direction	F-stat	Spillover direction	F-stat
S&P 500 to KSE 100	6.6834 *** (0.0000)	**KSE 100 to S&P 500**	4.6734*** (0.0012)
NASDAQ 100 to KSE 100	9.7642*** (0.0000)	**KSE 100 to NASDAQ 100**	0.8964 (0.1021)
DJI to KSE 100	7.6735*** (0.0000)	**KSE 100 to DJI**	3.6324** (0.0352)
DFMGI to KSE 100	2.1102 (0.9440)	**KSE 100 to DFMGI**	2.8972 (0.8091)
S&P 500 to DFMGI	10.822*** (0.0000)	**DFMGI to S&P 500**	3.0234* (0.0724)
NASDAQ 100 to DFMGI	8.7534*** (0.0000)	**DFMGI to NASDAQ 100**	0.4245 (0.7824)

DJI to DFMGI	5.7352*** (0.0000)	**DFMGI to DJI**	1.8204 (0.2031)

The ****, **, and * asterisks indicate the level of significance at 1%, 5%, and 10% respectively.

Table 9: Residual Analysis of ARDL model (Daily data)

Spillover direction	AR 1-7 test	ARCH 1-7 test	Hetero test
S&P 500 to KSE 100	3.7322 ** (0.0141)	144.02*** (0.0000)	74.642*** (0.0000)
KSE 100 to S&P 500	0.7425 (0.1035)	19.424*** (0.0000)	62.742*** (0.0000)
NASDAQ 100 to KSE 100	0.2812 (0.7489)	17.239*** (0.0000)	23.642*** (0.0000)
KSE 100 to NASDAQ 100	0.9472 (0.2133)	35.362*** (0.0000)	9.6423*** (0.0000)
DJI to KSE 100	0.0013 (0.9475)	24.845*** (0.0000)	11.648*** (0.0000)
KSE 100 to DJI	0.7052** (0.0472)	32.874*** (0.0000)	25.828*** (0.0000)
DFMGI to KSE 100	2.9371* (0.0740)	72.046*** (0.0000)	19.632 (0.0000)
KSE 100 to DFMGI	12.674*** (0.0000)	732.32*** (0.0000)	35.623*** (0.0000)
S&P 500 to DFMGI	9.732*** (0.0000)	232.83*** (0.0000)	23.642*** (0.0000)
DFMGI to S&P 500	5.7324*** (0.0030)	63.674*** (0.0000)	11.833*** (0.0000)
NASDAQ 100 to DFMGI	0.7922 (0.1033)	43.624*** (0.0000)	9.7522*** (0.0000)
DFMGI to NASDAQ 100	0.6482 (0.4421)	28.872*** (0.0009)	2.7423*** (0.0024)
DJI to DFMGI	11.487*** (0.0000)	294.74*** (0.0000)	13.742*** (0.0000)
DFMGI to DJI	0.0313 (0.4681)	61.752*** (0.0000)	16.084*** (0.0000)

Null Hypotheses:
"LM-ARCH H0: there is no ARCH effect. P-values are in the parenthesis. AR H0: there is no autocorrelation in residuals. P-values are in the parenthesis. Hetero test H0: there is no Heteroscedasticity in residuals. P-values are in the parenthesis".

The ****, **, and * asterisks indicate the level of significance at 1%, 5%, and 10% respectively.

Table 10: Spillover Effect by using GARCH models (Bidirectional Analyses for Weekly Data Analysis)

Parameters	Mean spillover effect R_t	Volatility Spillover effect R_t^2

Spillover direction	(π_1)	(π_2)
KSE 100 to S&P 500 **ARMA(1,1) GARCH (1,2)**	0.0273 (0.3237)	0.0102 (0.7818)
S&P 500 to KSE 100 **ARMA(1,2) GJR (1,1)**	0.0134*** (0.0002)	-0.0022*** (0.0003)
KSE 100 to NASDAQ 100 **ARMA(1,0) GARCH (1,1)**	0.0212 (0.3232)	0.0060 (0.1973)
NASDAQ 100 to KSE 100 **ARMA(1,1) GJR (1,1)**	0.0322*** (0.0005)	-0.0020*** (0.0009)
KSE 100 to DJI **ARMA(0,0) GARCH (1,1)**	0.0201 (0.2891)	0.0027 (0.4091)
DJI to KSE 100 **ARMA(1,1) GJR (1,1)**	-0.0031*** (0.0000)	-0.0029*** (0.0004)
KSE 100 to DFMGI **ARMA(1,1) GARCH (1,1)**	0.0691** (0.0413)	0.0191 (0.2081)
DFMGI to KSE 100 **ARMA(1,0) GARCH (1,1)**	0.0230*** (0.0009)	-0.0017*** (0.0021)
S&P 500 to DFMGI **ARMA(1,1) GARCH (1,1)**	0.1435*** (0.0020)	0.0034*** (0.7123)
DFMGI to S&P 500 **ARMA(1,1) GARCH (2,1)**	0.0278** (0.0231)	-0.0007*** (0.3459)
NASDAQ 100 to DFMGI **ARMA(1,1) GARCH (1,1)**	0.0693*** (0.0033)	0.0028 (0.7865)
DFMGI to NASDAQ 100 **ARMA(0,0) GARCH (1,1)**	0.0213** (0.0178)	-0.0004 (0.3341)
DJI to DFMGI **ARMA(1,1) GARCH (1,1)**	0.0820*** (0.0055)	0.0048 (0.4908)
DFMGI to DJI **ARMA(1,0) GARCH (2,1)**	0.0226** (0.0178)	-0.0005 (0.1345)

Null Hypotheses:
"Mean spillover H0:π_1= 0 No mean spillover, volatility spillover H0: π_2= 0 No volatility spillover. P-values are in the parenthesis".

The ****, **, and * asterisks indicate the level of significance at 1%, 5%, and 10% respectively.

Table 11: Residual Analysis with GARCH Model with (Weekly Data)

Parameter / Series	Jarque Bera	Q-Stat (5)	Q-Stat (10)	Q^2-Stat (5)	Q^2-Stat (10)	LM -ARCH (1-2)	LM-ARCH (1-5)
KSE 100 to S&P 500	498.10*** (0.0008)	4.3039 (0.2198)	7.4352 (0.4013)	5.2762 (0.2171)	6.5741 (0.1178)	0.2891 (0.5961)	0.1562 (0.1617)
S&P 500 to KSE 100	3264.1*** (0.0013)	1.1451 (0.4112)	7.5221 (0.1109)	0.7889 (0.4230)	3.731 (0.7676)	0.2956 (0.7011)	0.3138 (0.1898)
KSE 100 to NASDAQ 100	210.71*** (0.0049)	2.3456 (0.7298)	5.7174 (0.4870)	5.0332 (0.5239)	13.717 (0.1239)	3.9131 (0.2134)	1.4319 (0.2134)
NASDAQ 100 to KSE 100	5651.3*** (0.0014)	2.5621 (0.1265)	14.267 (0.1237)	0.2456 (0.5721)	1.8165 (0.7619)	0.6713 (0.3134)	0.1245 (0.7189)
KSE 100 to DJI	436.67*** (0.0000)	11.665 (0.1567)	12.101 (0.2231)	6.231 (0.1513)	14.786 (0.2124)	4.841 (0.2018)	1.7856 (0.213)
DJI to KSE 100	1203.2*** (0.0010)	5.1391 (0.2364)	15.651 (0.3561)	0.9198 (0.6152)	3.103 (0.7176)	0.1761 (0.7820)	0.301 (0.2018)
KSE 100 to DFMGI	13451*** (0.0001)	6.69561 (0.1451)	11.6132 (0.1431)	3.832 (0.9856)	8.7456 (0.4989)	0.5139 (0.5116)	0.5879 (0.7228)

DFMGI to KSE 100	2651.2*** (0.0000)	10.31 (0.1451)	25.021 (0.1638)	2.1897 (0.756)	5.4786 (0.4324)	0.3234 (0.6981)	0.6561 (0.6741)
S&P 500 to DFMGI	12431*** (0.0019)	9.391 (0.3890)	13.6715* (0.0981)	3.5861 (0.3989)	8.6758 (0.6732)	0.5314 (0.1536)	0.8284 (0.6123)
DFMGI to S&P 500	4867.2*** (0.0015)	4.69871 (0.1671)	7.5549 (0.4760)	5.4311* (0.0983)	11.654 (0.1267)	2.6070 (0.1642)	1.5623 (0.1090)
NASDAQ 100 to DFMGI	12415*** (0.0000)	4.6247 (0.1676)	12.879 (0.1534)	3.2167 (0.5345)	6.8767 (0.4764)	0.2178 (0.1789)	0.6245 (0.4656)
DFMGI to NASDAQ 100	151.56*** (0.00036)	7.5613 (0.1456)	8.6781 (0.6178)	5.5671 (0.6671)	11.342 (0.1872)	1.7657 (0.1867)	1.1251 (0.4671)
DJI to DFMGI	14165*** (0.0000)	7.3924 (0.2452)	13.2861 (0.6891)	3.4521 (0.5639)	8.1342 (0.1989)	0.2815 (0.8210)	0.6700 (0.4159)
DFMGI to DJI	367.61*** (0.0003)	5.7172 (0.4671)	6.2191 (0.7011)	2.2234 (0.5234)	5.2398 (0.176)	1.2976 (0.5089)	0.9231 (0.6789)

Null Hypotheses:

"Q-stat (return series) there is no serial autocorrelation. Q^2-stat (square return series) H0: there is no serial autocorrelation. Jarque-Bera H0: distribution of series is normal. LM-ARCH H_0: there is no ARCH effect. P-values are in the parenthesis".

The ****, **, and * asterisks indicate the level of significance at 1%, 5%, and 10% respectively.

Table 12: Spillover Effect by using ARDL Models (Bidirectional Analyses for ARDL Weekly Data)

Spillover direction	F-stat	Spillover direction	F-stat
S&P 500 to KSE 100	6.6541*** (0.0000)	**KSE 100 to S&P 500**	4.7145*** (0.0098)
NASDAQ 100 to KSE 100	9.5182*** (0.0000)	**KSE 100 to NASDAQ 100**	2.4231 (0.3416)
DJI to KSE 100	9.1006*** (0.0000)	**KSE 100 to DJI**	2.2314** (0.0101)
DFMGI to KSE 100	1.3451 (0.3156)	**KSE 100 to DFMGI**	2.3415 (0.2140)
S&P 500 to DFMGI	7.5123*** (0.0000)	**DFMGI to S&P 500**	3.0651* (0.08971)
NASDAQ 100 to DFMGI	8.4512*** (0.0000)	**DFMGI to NASDAQ 100**	1.3214 (0.5681)
DJI to DFMGI	7.8978*** (0.0000)	**DFMGI to DJI**	1.8765 (0.1678)

The ****, **, and * asterisks indicate the level of significance at 1%, 5%, and 10% respectively.

Table 13: Residual Analysis of ARDL model with Weekly Data

Spillover direction	AR 1-7 test	ARCH 1-7 test	Hetero test
S&P 500 to KSE 100	5.6782** (0.0251)	471.76*** (0.0008)	32.532*** (0.0018)
KSE 100 to S&P 500	1.1765 (0.4521)	50.231*** (0.0000)	14.213*** (0.0020)
NASDAQ 100 to KSE 100	0.18675 (0.9810)	45.452*** (0.0006)	9.0134*** (0.0001)

KSE 100 to NASDAQ 100	1.7671 (0.4156)	74.6781*** (0.0001)	7.5641*** (0.0001)
DJI to KSE 100	0.18671 (0.8971)	64.561*** (0.0001)	13.612*** (0.0000)
KSE 100 to DJI	3.6018 (0.1671)	70.178*** (0.0001)	14.671*** (0.0000)
DFMGI to KSE 100	1.6123 (0.6751)	51.431*** (0.0001)	12.810*** (0.0000)
KSE 100 to DFMGI	11.342*** (0.0001)	189.231*** (0.0001)	20.701*** (0.0000)
S&P 500 to DFMGI	17.167*** (0.0001)	178.10*** (0.0001)	17.516*** (0.0000)
DFMGI to S&P 500	1.3817 (0.7312)	60.156*** (0.0001)	12.234*** (0.0023)
NASDAQ 100 to DFMGI	0.8976 (0.7989)	64.785*** (0.0001)	8.5610*** (0.0002)
DFMGI to NASDAQ 100	3.6940 (0.3756)	64.6786*** (0.0009)	2.651*** (0.0043)
DJI to DFMGI	16.445*** (0.0001)	184.12*** (0.0001)	12.567*** (0.0002)
DFMGI to DJI	1.5543 (0.5124)	70.102*** (0.0000)	16.070*** (0.0002)

Null Hypotheses:
"LM-ARCH H0: there is no ARCH effect. P-values are in the parenthesis.AR H0: there is no autocorrelation in residuals. P-values are in the parenthesis. Hetero test H0: there is no Heteroscedasticity in residuals. P-values are in the parenthesis".

The ****, **, and * asterisks indicate the level of significance at 1%, 5%, and 10% respectively.