

Research Article

What Causes Stock Market Volatility in Pakistan? Evidence from the Field

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Received 10 April 2016; Accepted 5 July 2016

Academic Editor: David E. Giles

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We examined the presence of volatility at the Karachi Stock Exchange (recently changed the name to Pakistan Stock Exchange) (KSE) by fitting Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model to 25 years' index data. We found that the ARCH effects are present in the data indicating the stock market cluster volatility during the period under study. We found persistent high volatility in the stock market and presence of negative *leverage effect*. Moreover, we tried to identify the factors causing stock market volatility by collecting and analyzing the primary data obtained from 246 individual investors of stock market and 28 brokers listed with KSE. Our results show that investors consider political situation as the most important factor causing turbulence in the stock market. Interviews with the brokers also confirmed this. The second most important factor identified by investors is the herd behavior among investors that results in over- and underpricing of stocks and the overall market shows a volatile behavior. Our findings suggest that individual investor's behavioral dimensions of involvement, risk attitude, and overconfidence are significantly associated with factors causing market volatility.

1. Introduction

Financial markets channel the savings to efficient investments to facilitate economic growth and development. However, stock market volatility may be an obstacle in this process especially in an emerging economy where high volatility in prices leads to erosion of capital from the market. As such, what causes high volatility in the stock market is a continued discussion among the market experts and academicians. Volatility, apparently an easy and discerning concept, refers to unexpected return due to unexpected events resulting in huge price movements with nonconstant variance. Consequently, the financial markets develop an unexpected behavior that may confuse the investors.

Stock market in Pakistan is highly volatile as it is very sensitive and reactive to unanticipated shocks and news. It takes no time to affect the market activities. However, at the same time Pakistani stock market is resilient that recovers soon after shocks. We observe increased participation of

the individual investors in the financial markets over time making them more "peopled." As a result, their behavior, actions, reactions, and perceptions have a continuous impact on the stock prices that traditional models fail to explain. The behavioral quirks observed in individual investors do manifest themselves on a much larger scale in the overall stock market. They lead to pricing anomalies and unexplainable movements in stock prices. Behavioral finance seeks to elucidate the unjustifiable stock price volatility.

The objective of this study is to find out the presence of the stock market volatility and its behavioral causes at Karachi Stock Exchange (KSE), the largest and the oldest stock exchange of Pakistan. For this purpose, we use Autoregressive Conditional Heteroskedasticity (ARCH) models and its extension Generalized ARCH (GARCH) model and EGARCH. To the best of our knowledge, this is the first study that applied both the primary (survey) data of 250 investors and brokers and secondary data of 25 year to understand stock market volatility in Pakistani context. We find cluster

volatility in a highly volatile market where political situation and herd behavior are the two most important factors that contribute towards market volatility.

Along with Introduction, we organize this paper in the following manner. Section 2 presents literature review. Section 3 depicts the data and the methodology. Section 4 describes the results and their discussion, and Section 5 presents conclusions. We provide references at the end.

2. Literature Review

Volatility is a vital input to determine the overall cost of capital [1]. Stock prices generally demonstrate nonlinear and probably chaotic behavior. However, some observe that stock prices/returns are predictable imperfectly in the short-run but unpredictable in the long-run and statistical distributions can measure the return unevenness. Literature has identified a number of factors that cause stock market volatility. For example, credit policy, inflation, interest rate, corporate earnings, financial leverage, dividend policies, bonds prices, and many other macroeconomic, social, and political variables. Researchers also find stock market volatility transmission between friendly countries of different regions (e.g., Pakistan and China) having economic links [2]. They find evidence of reduced volatility after implementation of financial liberalization policies in Pakistan [3]. Some suggest that that stock trades' volume causes volatility [4, 5] and an asymmetrical volatility is due to response between volume and price [6]. While others observe that volatility is an outcome of the trading volume followed by arrival of new information regarding new floats or any kind of private information incorporated into market stock prices [7]. Madhavan [8] describes volatility in the form of price divergence and argues that investors demand low volatility to minimize the needless risk borne by them to enable them to liquidate their assets without facing threat of unfavorable huge price movements.

There are a number of negative implications of the stock market volatility. One implication is that market volatility negatively affects the economic growth [9] and business investment [10]. We use econometric techniques, namely, ARCH model [11] and the GARCH model [12] to determine the presence of volatility at KSE. In the past different studies were carried out to check the market volatility at KSE. For example, Ali and Laeeq [13] studied the banking sector of KSE by fitting AR(1), ARCH(1), and GARCH(1, 1) model and they assess the fitness of model by loss function. Kanasro et al. [14] studied the KSE-100 index and KSE all share price by fitting ARCH and GARCH model. They confirm the presence of high volatility in market. Moreover, Saleem [15] studied volatility of KSE-100 index using 9-year data and concluded that ARCH and GARCH best fit the market and confirm volatility clustering.

Behavioral finance seeks to elucidate the unjustifiable stock price volatility. Studies on the stock market [16, 17] and on the bond market [18] found excess volatility in these markets and observed that asset prices are far more unstable than could be explained by traditional financial model. Proper justification of extreme volatility is still missing

because researchers do not have complete knowledge about all the aspects of the valuation models used by investors. However, financial economists believe that disagreement in the investor opinion directly affects the security-price volatility and trading volume [19]. Standard finance fails to enlighten an ample divergence of opinion except to call it the effect of asymmetrical information. We argue that studying behavior related factors might help explain the phenomenon. While probing the volatility-volume phenomenon, researchers found the relationship between volatility and investor trades [20]. However, majority of volatility-volume studies have ignored the impact of heterogeneous behavior of investor trades. Nevertheless, some argue that herd behavior can result in over- or underpricing and can act as a source of stock market volatility. Individual investors may not invest proper time and effort to evaluate the market but choose to follow the aggregated assessment of the majority and consequently the true value of the market may be incorrect [17].

Some studies attribute the excess volatility to investors' overconfidence. They argue that overconfident investors feel it is a justifiable act to trade often [21]. A survey of the 1987 market crash notices investors' strong confidence and an insightful outlook about the postcrash course the market would take [22] suggesting that overconfidence might explain the phenomenon of volatility and huge price deviations. Shefrin and Statman [23] observe that investors commit two common mistakes: either they consider recent observations more important and do not give due importance to the prior information; or they commit a gambler's fallacy and develop a belief that recent events more closely resemble long term probabilities, thereby distorting prices and causing increased volatility while reducing market efficiency.

Asset pricing theory suggests that if investors are rational then stock price should equal the present value of the stock's expected cash distributions to shareholders. However, empirical evidences suggest that stock prices are more volatile than what standard asset pricing models can explain [16, 18]. Shiller [18] further attributes it to psychology or irrationality. Finding a connection between investor behavior and the dynamics of asset prices is an important challenge facing behavioral finance. The proponents of behavioral paradigm are of the view that a large number of investors act irrationally and are prone to behavioral heuristics that result in less than optimal investment choices [24].

3. Data and Methodology

The objective of study is to identify the presence of stock market volatility at KSE and to find the reasons of volatility from individual investors' behavior perspective. For this purpose, we collected both secondary and primary data. For secondary data, we obtained the daily changes in KSE-100 index (from <http://www.kse.com.pk/>) from January 1, 1990, to October 1, 2014. Consequent to the decline in KSE index to very low levels, the market remained frozen from August 27, 2008, to December 12, 2008. As these values may distort our results, we conducted a reality check by including the dormant values (when the market remained frozen) during

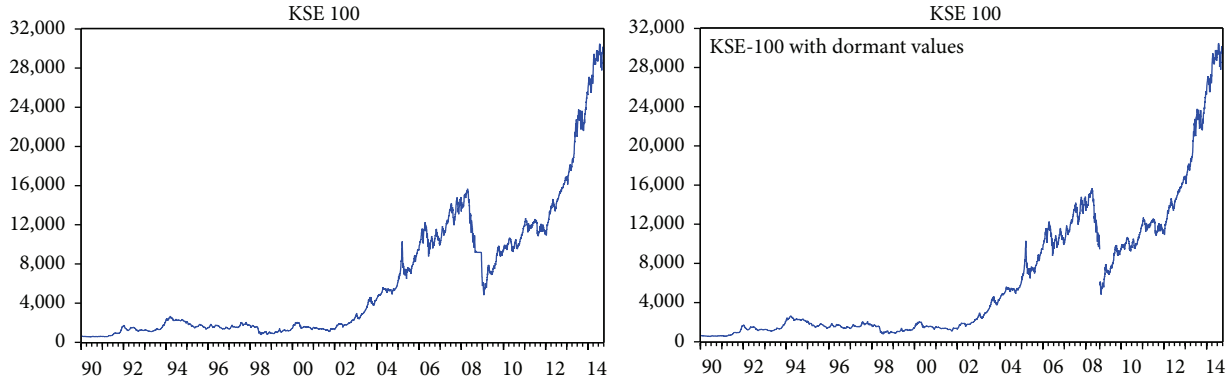


FIGURE 1: KSE-100 index.

this period and then by excluding these observations to draw sound conclusions. Both data sets exhibit almost the same behavior. We also used an alternative statistical method called winsorization that also yielded the same results.

We also collected primary data by obtaining direct responses from 246 individual investors of the stock market and 28 brokers listed with KSE. While doing so, we first identified recurring themes and factors that may cause volatility through preliminary interviews with the investors and brokers. After identifying recurring themes, we developed structured questionnaires administered to the individual investors and brokers selected using random sampling technique from four major cities: Lahore, Islamabad, Karachi, and Multan. We used quantitative methods to analyze responses obtained from individual investors, whereas we used qualitative method to analyze brokers' responses to our open-ended questions based interviews. We examined the presence of volatility at KSE by fitting ARCH, GARCH, and EGARCH models ([11, 12, 25]).

Engle [11] proposed the ARCH model to specify conditional volatility that incorporates the common sense logic that observations belonging to the recent past should get higher weights than those belonging to the distant past. The ARCH process often requires large number of parameters to explain the dynamic structure of financial phenomenon. To overcome these problems, Bollerslev [12] proposed GARCH model that essentially generalizes the ARCH by modelling the conditional covariance as an ARMA process. The GARCH model helps find cluster volatility of financial markets, thicker tail distribution, and predictability of volatility from past patterns. The following system of (1) represents the ARMA(m, n)-GARCH(p, q) for stock returns (r_t) and stock return volatility (h_t):

$$\begin{aligned}
 r_t &= \mu + \sum_{i=1}^m \phi_i r_{t-i} + \sum_{i=0}^n \theta_i u_{t-i}, \\
 \theta_0 &= 1, \\
 u_t &= z_t \sqrt{h_t} \\
 h_t &= \alpha_0 + \sum_{i=1}^p \alpha_i h_{t-i} + \sum_{j=1}^q \beta_j u_{t-j}^2,
 \end{aligned} \tag{1}$$

where $\alpha_i > 0$, $\beta_j > 0$, and $\lambda_k > 0$ for all i, j , and k and $Z_t \sim iid$ with mean 0 and variance 1

The virtue of this approach is that GARCH model with a small number of terms appears to perform better than ARCH with many terms. The EGARCH model has no such constraint of parameters [25]. The variance equation has an advantage over the ARCH and GARCH that it tends to be automatically positive without imposition of restriction of nonnegativity on parameters and it captures the "leverage effect." Moreover, EGARCH allows the asymmetric response of volatility to downside and upside market movements. The system of (2) specifies EGARCH model:

$$\begin{aligned}
 r_t &= \mu + \sum_{i=1}^m \phi_i r_{t-i} + \sum_{i=0}^n \theta_i u_{t-i}, \\
 \theta_0 &= 1, \\
 u_t &= z_t \sqrt{h_t} \\
 \log(h_t) &= \alpha_0 + \sum_{i=1}^p \alpha_i \log(h_{t-i}) + \sum_{j=1}^q \beta_j \left| \frac{u_{t-j}}{h_{t-j}} \right| \\
 &\quad + \sum_{k=1}^r \gamma_k \frac{u_{t-k}}{h_{t-k}},
 \end{aligned} \tag{2}$$

where $Z_t \sim iid$ with mean 0 and variance 1. Since β_j show the asymmetric function, that is, current volatility which is influenced by the past standardized residuals, the term $\alpha_i + \beta_j$ shows the effect of magnitude and γ_k is for the representation of sign effect. The volatility persistence is equal to $\sum \alpha_i$ and for unconditional variance, it should be less than 1.

Furthermore, we employ Analytical Hierarchical Process (AHP) to rank the factors causing volatility and analysis of variance (ANOVA) to obtain the results of this study.

4. Results and Their Discussion

Before fitting ARCH and GARCH, we conducted preliminary graphical analysis of the data for heteroskedasticity. Figures 1 and 2 reveal huge unevenness in the observations.

We present descriptive statistics in Table 1.

TABLE I: Descriptive statistics.

	KSE-100 with dormant values	KSE-100 without dormant values
Mean	0.000615	0.000606
Median	0.000000	0.000000
Maximum	0.127622	0.127622
Minimum	-0.49417	-0.13214
Std. dev.	0.015869	0.014607
Skewness	-4.96136	-0.28648
Kurtosis	155.59290	9.84641
ARCH-LM test	97.14249	99.98743
Jarque-Bera test	6202352.00	12699.21
Observations	6366	6457

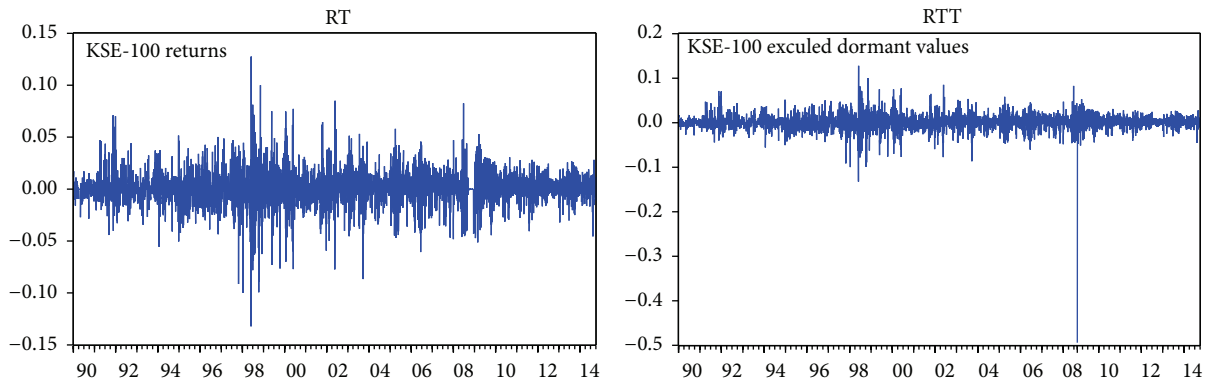


FIGURE 2: Daily change in KSE-100 index.

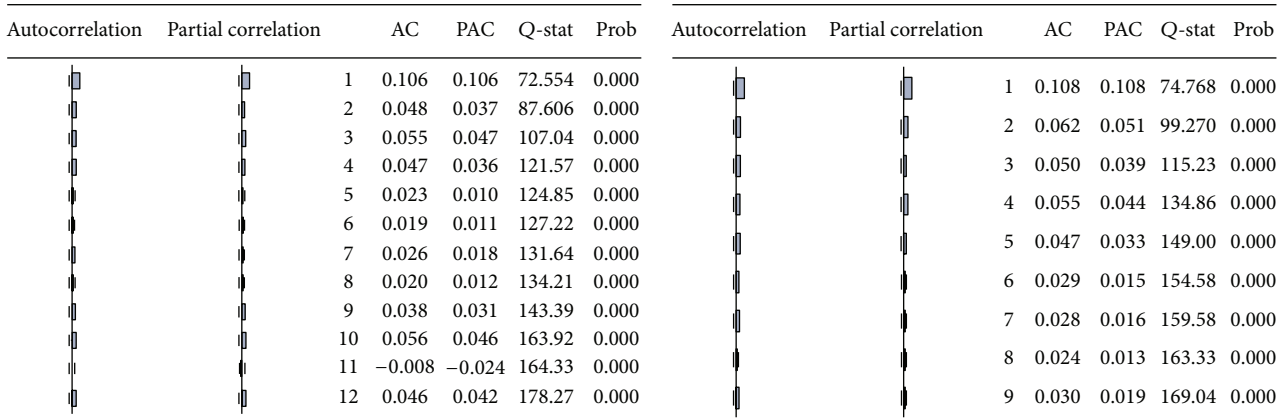


FIGURE 3: Results of ACF test of KSE-100 index (with and without dormant values).

Excess kurtosis and negative skewness result in high Jarque-Bera statistic that indicates the nonnormality of the distribution. Moreover, the high values of ARCH-LM statistic [11] also suggest the presence of ARCH effect in the conditional variance. Even after excluding those abnormal observations there exist signs of presence of heteroscedasticity and huge variations among the observations and the presence of volatility clustering in returns revealing presence of ARCH in the data. Moreover, we applied Auto Correlation Function (ACF) test to check the presence of autocorrelation in the data. If there is no ARCH in the residuals, the

autocorrelations (AC) and partial autocorrelations (PAC) should be zero at all lags and the Q-statistic should be insignificant. We present the results of ACF test in Figure 3 that confirm the existence of ARCH effect and presence of cluster volatility in returns.

We followed the Box-Jenkins methodology for the identification of the mean model. For the identification of appropriate models, we used ACF, PACF, and Ljung-Box statistics of the standardized residuals and the squared standardized residuals and ARCH-LM test. We found ARMA(1, 1)-GARCH(1, 1) process to be the appropriate model for

TABLE 2: Results of ARMA, GARCH, and EGARCH.

Parameters	Mean equation			Variance equation				SBC	AIC
	μ	ϕ	θ	α_0	α_1	β_1	γ		
GARCH(1, 1)	0.00075 (0.0000)	0.766781 (0.0000)	-0.6697 (0.0000)	0.000005 (0.0000)	0.834785 (0.0000)	0.146561 (0.0000)		-5.97	-5.977
EGARCH(1, 1)	-0.0007 (0.0000)	0.87746 (0.0000)	-0.7791 (0.0000)	-0.80484 (0.0000)	0.92974 (0.0000)	0.26901 (0.0000)	-0.0634 (0.0000)	-5.95	-5.9641

ARCH-LM test for GARCH.

F-test 0.389836 (0.8561); Obs * R^2 1.9504 (0.8560).

conditional variance on the bases of Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC). In addition, the EGARCH model outperformed the GARCH counterpart especially with Student's t error as the error distribution. Therefore, we use EGARCH(1, 1) specification for variance equation. In Table 2, we report the results of the mean and the variance equation.

The results reveal that estimated parameters of GARCH(1,1) are highly significant. The parameter β_1 is positive and significant. This suggests that the measure of risk, measured by own conditional variance, indicates the positive and significant autocorrelation in return. The parameter α_1 is also significant implying higher degree of persistence. Furthermore, the condition $\alpha_1 + \beta_1$ is a measure of volatility persistence and an estimation of the decay rate of response function on daily basis. This condition reflects how the historical conditional volatility affected the current conditional variance of stock returns. The $\alpha_1 + \beta_1$ should be less than one but in this case, it is near to unity. It suggests that estimated conditional variance can be an integrated GARCH (IGARCH) process and is nonstationary. The presence of IGARCH suggests the persistence of volatility and a shock has indefinite influence on volatility level. To assess the "leverage effect" we carried out normality test of standardized residuals. The JB-statistic rejected the hypothesis of normality due to the presence of "leverage effect." The coefficient β_1 corresponds to the asymmetric function and is statistically significant indicating that current volatility is moderately influenced by the past standardized residuals. Moreover, the "leverage effect" term γ_1 is negative and significant demonstrating the presence of negative "leverage effect" implying that negative returns are associated with higher volatility than positive returns of equal magnitude.

Robustness of Estimation. GARCH(p, q) models are fitted to the return series using maximum-likelihood estimation. In the Gaussian quasi MLE method, this estimation is done under the assumption that the innovations $[Z_t]$ have a Gaussian distribution. The estimations are robust if the estimations of the parameters depend on the distributional assumption of the innovations Z_t and if the residuals of the estimated process have the same distribution as the assumed distribution of the innovations. When the estimation of the unknown parameters is done, estimates of the standard deviation series can be calculated recursively via the definition of the conditional variance for the GARCH(p, q) process.

In Figures 4(a) and 4(b), the log-return process and the estimated conditional standard deviation process for KSE-100 index are plotted. The estimated conditional standard deviation process is derived from a EGARCH(1, 1) fit. The estimated conditional standard deviation process reflects the behavior of the log-return process. Based on Figure 4, the EGARCH model seems to be reasonable.

Further, with a QQ-Plot (Figure 5) one can examine the distribution of the residuals to verify the robustness in the estimation. With GARCH(1, 1) fit using MLE under the assumption of Gaussian innovations, the residuals from the fit on the simulated data are computed and plotted in a QQ-Plot against the normal distribution. The fit is good which indicates the process exhibits the Gaussian distribution and shows model robustness with $\alpha_0 = -0.805$, $\alpha_1 = 0.930$, $\beta_1 = 0.269$, and $\gamma_1 = -0.063$.

4.1. Factors Causing Market Volatility. After confirming presence of market volatility, with the help of existing literature and preliminary interviews we identified the following seven factors that can cause market volatility in Pakistan:

- (i) News stories in the media
- (ii) Forecasts of the analysts
- (iii) Change in earnings of listed companies
- (iv) Herd behavior (individual investors following the majority)
- (v) Government policies
- (vi) Political situation
- (vii) Manipulation by big investors

Majority of the brokers put political instability at the first rank to cause market volatility. Among other major factors that they identified are poor government policies, big investors and their manipulations, and herd behavior as the factors causing volatility in stock market.

We then asked the investors to rate the above seven factors on a scale from 1 (least important) to 7 (most important). In response to the role of media news stories to cause stock market volatility, 15.9% of the investors considered it to be among the most important factor while only 3.7% of the investors gave it the lowest rating. Overall, 65.9% of the investors (gave a rate of 5 or more) consider that news stories in the media are an important factor causing stock market

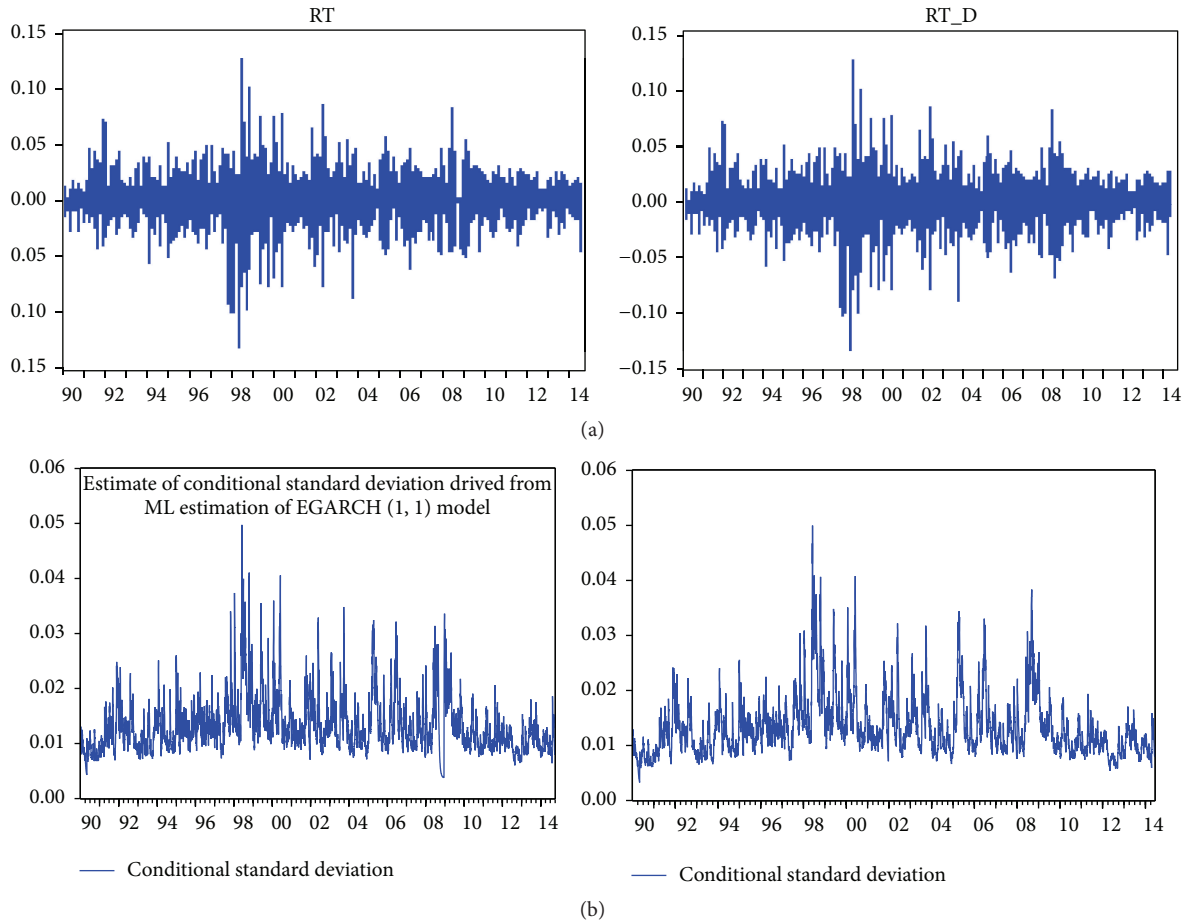


FIGURE 4: (a) Log return of KSE-100 with dormant values (RT) and without dormant values (RT_D). (b) Estimate of conditional standard deviation drive from ML estimation of EGARCH(1, 1) model with and without dormant values.

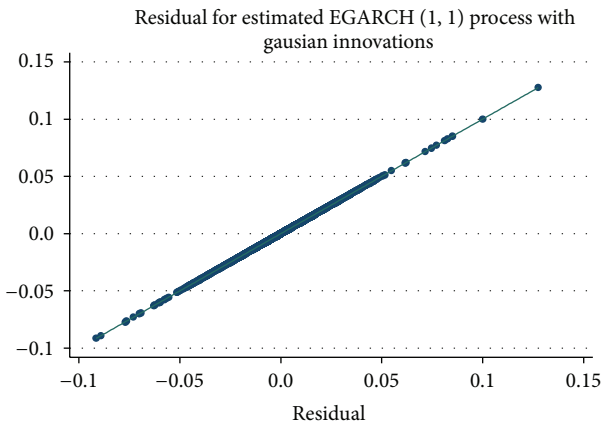


FIGURE 5: The QQ-Plot. Quantile-Quantile Plot.

volatility. Majority of the investors (63% gave rate of 4 or less) did not consider the forecasts of the analysts as an important factor to cause volatility in the stock. Regarding the importance of changes in the earnings of the listed companies in causing stock market volatility, 13.8% of the investors considered it as the most important factor in causing volatility

in the market while just 2.4% of the investors considered it as the least important factor. Overall, 56.9% of the investors gave rating of 5 or above while 43.1% of the investors gave rating of 4 or less.

In response to our question regarding herd behavior causing stock market volatility, 26% of the investors considered it as the most important factor while just 3.7% of the investors considered it as the least important factor. Overall, 82.5% of the investors gave high rating of 5 or above to herd behavior and only 17.5% gave a rating of 4 or below. Regarding the role of government regulations and policies in causing volatility, 28.9% of the investors gave highest rating to this factor while just 0.4% of the investors gave the lowest rating. Overall, 55.7% of the investors gave rating of 5 or above while 44.3% of investors gave rating of 4 or less. Moreover, 55.3% of the investors regarded political situation of the country as the most important factor causing stock market volatility and just 1.2% of the investors considered it the least important (gave rating of 1). On the whole, 88.6% of the investors considered it as more important factor (gave rating of 5 or above) whereas 11.4% of the investors considered it as less important factor (gave rating of 4 or less) that causes market volatility. Finally, 61.8% (highest frequency) of the investors considered the role

TABLE 3: Relationship between determinants of investors' behavior and market volatility.

Explanatory variables	Coefficients	SE of coeff.	Beta	<i>t</i> value	<i>p</i> value
Intercept	2.551*	0.308		8.293	0.000
Involvement	0.173*	0.028	0.335	6.146	0.000
Risk attitude	0.164*	0.048	0.187	3.423	0.001
Optimism	0.023	0.037	0.034	0.623	0.534
Overconfidence	0.221*	0.040	0.311	5.545	0.000

*Significant at 1% level.

of manipulations by big investors as the most important factor (gave a rating of 7) in causing volatility but only 0.4% of the investor as the least important factor (gave a rating of 1).

We used Analytic Hierarchy Process (AHP) to find the relative weights and ranking of these seven factors by adopting the following procedure.

Step 1. We developed the hierarchical representation of the problem by defining the factors perceived as most important by the investors.

Step 2. We compared all the factors in pairs. On a scale of 1 to 7, respondents assigned different degrees of relative importance. For example, if a respondent replies that factor (i) is more important than factor (ii) then factor (i) has a relative weight of 7 times than that of factor (ii). We created a pairwise comparison matrix for each factor by dividing each element of the matrix by its column total.

Step 3. We calculated the eigenvalue to determine the relative weight of each factor in relation to the one immediately above in the hierarchy. The priority vector is established by calculating the row averages. At this point, the consistency index is calculated by the following equation: $CR = CI/RI$. Consistency index is calculated by the following equation: $CI = \text{LEMDA} \max - n/n - 1$, where n is the number of subcriteria of each criterion. The design of the AHP hierarchy must satisfy the goal of developing a model that allows respondent to decide which factor they regard most important in assessing factors causing market volatility.

Step 4. We examined the consistency of the created pairs. For this purpose, consistency ratio is used to check whether a criterion can be used for decision-making. The CR value of less than 0.1 is considered acceptable for estimating the priority vector, whereas the bigger value means that it should not be used for estimating the priority vector.

Step 5. The factor priorities are combined to disclose the most important factor in order to develop an overall priority ranking. In order to set weights of the elements in a hierarchy, we prefer the geometric means, as the most common approach to set priorities.

Following these AHP specified steps we determined the relative weights and rankings of the factors causing volatility in KSE that we present in Figure 6.

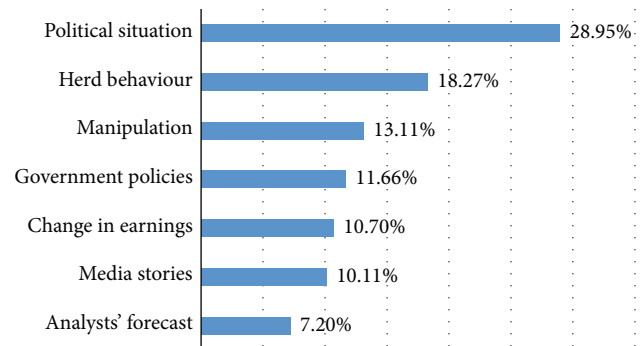


FIGURE 6: AHP results for factors causing market volatility.

The results suggest that political situation and herd behavior are the most important factors to have major impact on the stock market in terms of volatility. Alternatively, forecasts of the analysts cast least impact on market. Moreover, we used the data on investor behavior obtained from an earlier study (Awan et al. 2011) that identified determinants of investor behavior (Figure 7) to find the impact of investor behavior on the factors causing market volatility.

We use Ordinary Least Squares (OLS) model to identify the possible relationship of the investors' behavior with the factors causing volatility and present the results in Table 3.

The results of the model suggest that the behavioral dimensions of investor involvement, risk attitude, and overconfidence are significantly associated with factors causing market volatility as the p values for these dimensions (0.000, 0.001, and 0.000) are less than the alpha value (0.05) that supports our argument that investor behavior is associated with factors causing volatility. Moreover, considering R^2 and adjusted R^2 we find that investor behavior has an impact of 32 to 35 percent on the factors causing volatility.

We also conducted ANOVA in order to check for differences in responses regarding factors causing volatility of investors belonging to different age groups. We observed that investors with 50+ ages gave high rates to the factors of herd behavior and political situation as the determinants of volatility as compared to investors with age ≤ 50 years. Investors with education level of high-school or lower gave higher rates to factors of media stories, herd behavior, and political situations as determinants of volatility as compared to their relatively higher educated peers. We also analyzed the responses of investors with different levels of income and do

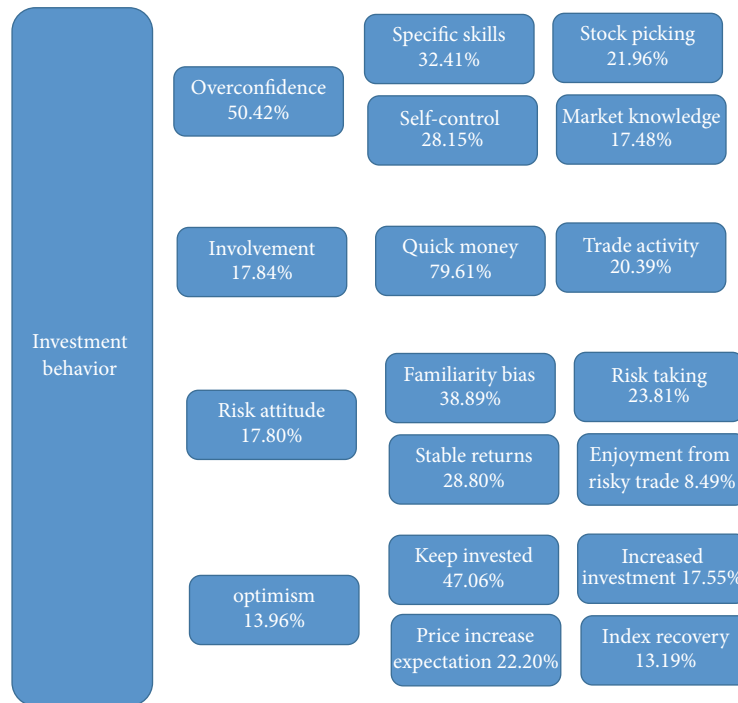


FIGURE 7: Determinants of investors' behavior.

not find any significant difference of opinions among them regarding the factors contributing towards market volatility.

5. Conclusion

The objective of this study was to identify and investigate the volatility at KSE from a behavioral finance perspective. For this purpose, we used the data of return series from January 1, 1990, to October 1, 2014, to specify ARCH, GARCH, and EGARCH models to estimate volatility of KSE-100 index returns. We found that the KSE-100 index returns series exhibited the stylized characteristics such as volatility clustering, excess kurtosis, fat-tiredness, time-varying conditional heteroskedasticity, and "leverage effect." The results indicate that volatility is highly persistent at KSE implying that new shocks will have influence on returns for the shorter periods. EGARCH demonstrated the presence of negative "leverage effect" suggesting that negative returns are associated with higher volatility than positive returns of equal magnitude.

Our results show that according to investors the factor of political situation is the most important in causing turbulences in the stock market. The interviews with the brokers also conform political situation as the most important factor causing volatility. The second most important factor identified by investors is the herd behavior among investors that result in over- and underpricing of stocks and the overall market shows a volatile behavior. According to investors, manipulations by the big investors also play a major role in causing stock market volatility. Moreover, the government policies and change in the earnings of listed companies and media stories also contribute towards the

market volatility. Forecasts by the analysts are at the lowest rank. Furthermore, our findings of OLS model suggest that individual investor's dimensions of involvement, risk attitude, and overconfidence are significantly associated with factors causing market volatility.

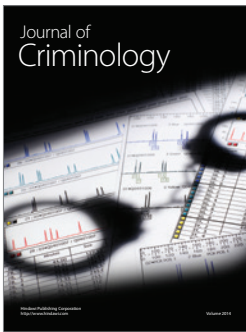
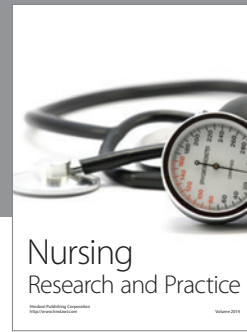
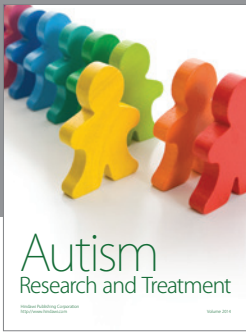
Competing Interests

The authors declare that they have no competing interests.

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