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Calendar Anomalies in Pakistani Stock Returns and Return Volatility

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Abstract

Prior studies investigating monthly calendar anomalies in Pakistan have presented contrasting conclusions and not accounted for volatility in returns. This paper investigates monthly anomalies in the Pakistani stock market using an asymmetric GARCH model across a 17-year time period at firm-level to examine whether the mean and volatility of share returns vary across different months. Since the findings of prior studies have been mixed, the current study undertakes further work on this topic to offer some clarity in the area. The paper's major findings offer little statistical evidence of a monthly seasonal anomaly in mean returns however the findings indicate that anomalies are more prominent for monthly patterns in the volatility of returns.

Keywords: Calendar anomalies; conditional volatility; efficient market hypothesis (EMH); Karachi Stock Exchange (KSE); stock returns
1. Introduction
The month of the year effect has been shown to be a persistent anomaly in both developed and emerging capital markets throughout the world. Researchers have documented that the returns in some months (especially January) are consistently higher than in others (Rozeff and Kinney, 1976). Evidence about this anomaly was initially highlighted for US securities, but more recent investigations have noted similar patterns in many international markets (Gultekin and Gultekin, 1983). However, the international evidence in support of the monthly seasonal effect is mixed; different researchers have obtained different results while studying various time periods and using different models of expected returns. Such results are important since, Mills and Coutts (1995) have suggested that the existence of calendar anomalies is one of the clearest contradictions of the Efficient Market Hypothesis (EMH). Any persistence over time of a monthly anomaly can help an investor to predict when share price changes will occur.

A limited number of studies have started to examine whether monthly calendar anomalies are present in emerging stock markets such as the Karachi Stock Exchange (KSE) in Pakistan (Ali and Akbar, 2009; Rafique and Shah, 2012; Zafar et al., 2010). Thus, an analysis of this topic for Pakistan may offer interesting insights because the findings arrived at and the explanations advanced may be different from those which have been reported for developed nations. To date, only a handful of studies have looked at a monthly seasonal effect for the KSE. Yet, monthly seasonality is arguably of interest to investors since no specialist knowledge is needed to exploit this anomaly and the transaction costs of attempting to outperform on the basis of such patterns in returns can be relatively low as compared to anomalies based on day of the week effect. However, the findings from the small number of Pakistani investigations that have investigated whether monthly anomalies are present have arrived at different conclusions about the predictability of equity returns at different times within a year. Since the conclusions of these findings have been mixed, the current study undertakes further work on this topic to offer some clarity in the area.

Studies have documented evidence of volatility shifts in Asian markets (Tan et al., 2015). Volatility is also one of the key characteristics of the KSE (Ahmed and Rosser, 1995; Farid and Ashraf, 1995; Iqbal, 2012). For example, Iqbal (2012) documented that “Pakistan’s stock market operates as a typical emerging market with a high level of returns and volatility...” (p. 88). Nawazish and Sara (2012) examined volatility patterns in the KSE over the period 2004 to 2012 and documented the presence of time varying volatility in the returns of the KSE-100 index. Their findings confirmed the earlier results of Kanasro et al. (2009) which suggested that volatility in the KSE market tended to cluster in certain periods.

This variability in the volatility of Pakistani share returns has been attributed to the impact of the terrorist attacks of 9/11 (Ahmed and Farooq, 2008; Halari et al., 2015; Hameed and Ashraf, 2006; Nguyen and Enomoto, 2009; Suleman, 2012). For example, Ahmed and Farooq (2008) found that the conditional variance, risk premium and the asymmetric response of the conditional variance experienced a significant change from their pre-9/11 levels during the post- 9/11 period. Hameed and Ashraf (2006) argued that, after 9/11, the Security and Exchange Commission of Pakistan (SECP) introduced a number of initiatives to counter high levels of volatility in the market such as: the implementation of a T+3 settlement period and imposition of circuit breakers.¹

In light of the findings from these studies, the present investigation attempts to identify empirically whether any patterns are present in the returns or the volatility of equity returns during certain months across a 17-year time period; hence, both the
risk and return are included in the analysis. As a result, investors can discern more accurately whether the market is efficient in the sense that whether average monthly price changes or their associated volatilities can be predicted on the basis of historic data. Such information may help investors to avoid (or reduce) risk when investing in the Pakistani stock market. The impact on the volatility of KSE share returns of the terrorist attack on the Twin Towers in New York on September 11, 2001 (9/11) which previous studies on calendar anomalies in Pakistan have neglected is also considered. Thus, the current research extends the findings of earlier work by testing data for a large number of firms listed on the KSE and examining a long time period using an asymmetric Generalised Autoregressive Conditional Heteroscedasticity (GARCH) model proposed by Glosten et al. (1993) – known as Threshold GARCH (TGARCH) model which takes account of variations in both risk and return. No previous studies have investigated monthly anomalies in Pakistan have accounted for volatility in returns; hence this study extends the current literature about monthly anomalies in Pakistan. The Karachi Stock Exchange was chosen as the primary source of data since it is the largest and the most active stock exchange in the country (Halari et al., 2015; Khan et al., 2017).

1.1. Previous studies on monthly anomalies in KSE and other Emerging Markets
The substantive literature on the EMH relating to calendar anomalies appear to have investigated the share returns of developed markets such as the UK and the US. However, in the recent decades, an increasing amount of research has focussed on investigating monthly calendar anomalies in Emerging Markets (Floros, 2008; Depenchuk et al., 2010; Compton et al., 2013; Ke et al., 2014; Nwachukwu and Shitta, 2015; Kumar and Pathak, 2016). For example, Aggarwal and Rivoli (1989) investigated seasonal patterns in returns for four emerging markets between 1976 and 1988. Their study confirmed that the January effect was not only prevalent in developed markets but also occurred in emerging markets; returns in the month of January were higher than in any other month for all of the markets examined (with the exception of the Philippines). Ho (1990), using daily returns for a similar period (from 1975 to 1987), arrived at a similar conclusion3. The author also reported evidence of seasonality during the months of April and December which he linked to the tax year ends in those countries. A relatively recent study by Fountas and Segredakis (2002) tested for seasonal effects in the stock returns of 18 emerging markets for the period 1987-1995. Although evidence in favour of the January effect was relatively sparse, the existence of significant differences in monthly returns in several countries was well documented; the strongest evidence of a significant monthly seasonal pattern was reported for equities in Chile (January, February, June, August and December), Colombia (April, May, June, September and December), India (August), Malaysia (February, April, May, and December), Mexico (March, May and July), Nigeria (all 12 months) and Zimbabwe (April, May, July and August). These results confirmed the evidence of a monthly seasonal in emerging market security returns for the 18 emerging markets investigated. Giovanis (2009) investigated 55 stock market indices from 51 countries using a GARCH methodology6. The author discovered a December effect in 19 countries (Austria, Belgium, Brazil, Canada, Denmark, Estonia, Germany, India, Indonesia, Ireland, Luxemburg, Mexico, Netherlands, New Zealand, Philippine, Switzerland, Turkey, UK and finally in Yugoslavia). Furthermore, a January (April) effect was documented in seven (six) stock markets which varied in size from 0.00342 (for Pakistan) to -0.00124 (for Luxemburg). More recently, Keong et al. (2010) investigated security returns in 11 Asian countries using a GARCH (1, 1) model over a 20-year
period from 1990 to 2009. Their results suggested that share prices increased in December for all the countries, with the exception of Hong Kong, Japan, Korea, and China. A positive January effect was documented for five countries (Indonesia, Philippines, Singapore, Taiwan, and Thailand) with open economies and strong trade links with the US. Furthermore, their results documented an April effect for Indonesia, Malaysia, Korea and China while a May effect was reported for Hong Kong, India, Indonesia and Philippines. In addition, their results demonstrated a negative August effect for Indonesia.

These studies have highlighted that monthly seasonal anomalies are present in the share returns for different emerging stock markets around the world. The review will now concentrate on studies about the Pakistani stock market (KSE) since the findings of these investigations are most relevant for the current paper.

Empirical studies regarding monthly anomalies in the Pakistani stock market are relatively sparse when compared with investigations from other regions in the world. A summary of all the Pakistani studies that investigated monthly anomalies in Pakistan are discussed in this section.

Mahmood and Rehman (2007) was one of the earliest studies to investigate monthly seasonality in the KSE market. They analysed monthly share price data from 1996 to 2006 for eight of the KSE-100 index companies. The one-way ANOVA procedure was employed to test for seasonality in the returns of these eight shares. The results indicated that the mean returns in all the months were not significantly different from each other for all the eight companies studied. Hence, the authors suggested that investors could not beat the marked based on the monthly share price information.

More recently, a study by Ali and Akbar (2009) observed a monthly calendar effect in the KSE 100 index over the period 1991 to 2006. The authors employed a one-way ANOVA test, OLS regressions and serial correlation tests. They suggested that no monthly anomalies were present in the KSE index; all the coefficients on the monthly dummy variables in their OLS analysis were insignificant. The authors therefore concluded that the KSE index was weak form efficient. However, the authors only investigated monthly data for a 15 year period which meant they only had 15 values for each month’s returns; thus, the power of any statistical tests was relatively weak.

Zafar et al. (2010) attempted to address this limitation in Ali and Akbar’s work. They tested for monthly calendar anomalies in the KSE using regression analysis based on daily share price data of the KSE-100 index for the period 1991 to 2007. Initial descriptive statistics revealed that the month of May recorded the lowest mean return in comparison to all the other months in the year. The results from their regression analysis revealed that no January effect was present in the market.

More recently, Rafique and Shah (2012) investigated the existence of a calendar anomaly using daily data for the KSE-100 index. OLS regression analysis was conducted for the period of 1997 to 2011 with the month of January subsumed in the constant term. Descriptive statistics revealed that May, June and August were the months in which mean returns were negative. Although no explanation was provided as to why such behaviour might exist. Rafique and Shah’s analysis also revealed that highest average mean return for all the months occurred in January whereas the lowest average was recorded in May. Based on their findings, the authors reported no January effect in the KSE market; however negative May returns were documented.

Three of these four studies of calendar anomalies in the Pakistani market have used data for the KSE-100 index; an investigation of data for individual companies’ shares might offer a clearer understanding into the nature of any seasonality in the
Pakistani stock market; it might indicate whether any monthly seasonality was more pronounced in different sectors or among different sized firms. Furthermore, prior studies have failed to address the issue of time varying volatility; volatility needs to be modelled in order to provide a clearer picture of whether any monthly seasonal pattern in the Pakistani equity markets is an anomaly or the rational response to shifts in volatility over time. Prior studies that have focussed on calendar anomalies in the Pakistani stock market have not examined: (i) whether the volatility of returns varies from month to month in Pakistan; and (ii) whether this change in volatility could explain any seasonal pattern which may be present in equity price changes. Thus, this examination of monthly anomalies which takes account of return volatility for individual firm returns might help clarify if the Pakistani stock market is inefficient or rationally responding to risk. Hence, the current study is the first to undertake a detailed firm-level analysis of calendar anomalies on firm return and firm return volatility.

The remainder of this paper is organised as follows. Section 2 describes the data and reports on the descriptive statistics. The modelling is described in Section 3 while the results are presented in Section 4. Finally, Section 5 concludes.

2. Data and Sample Description

Daily share returns for 106 companies listed on the KSE over the 17-year period from January 1, 1995 to December 31, 2011 were used in this study. Individual companies’ data instead of KSE index returns that have been analysed in most previous studies (Ali and Akbar, 2009; Zafar et al., 2010) allows an examination of calendar anomalies which can be useful for investment strategies.

This sample of companies covers a broad spectrum of the KSE market and ensures that the results are not specific to a particular sector or size of company. There were a total of 638 companies listed on the KSE at the end of December 2011; out of these, only 564 had data available on the Datastream database. From this sample of 564 firms, only 176 companies had a start date before January 1995. Of those 176 companies, 39 firms did not have adjusted prices and 31 companies were found to be inactively traded. Hence, a final sample of 106 companies was available for analysis.

Share returns were computed as the first differences of the natural logarithm of prices:

$$R_{it} = \ln(P_{it}) - \ln(P_{it-1})$$

(1)

Where Ln is the natural logarithm; R_{it} is the return on share i for day t; P_{it} and P_{it-1} are the prices of firm i for day t and t-1, respectively.
Table 1: Summary Statistics for the Average Returns over the 17-year Period

<table>
<thead>
<tr>
<th>Month</th>
<th>MEAN</th>
<th>SD</th>
<th>MIN</th>
<th>MAX</th>
<th>SKEW</th>
<th>KURT</th>
<th>JB</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>0.00135</td>
<td>0.0125</td>
<td>-0.045</td>
<td>0.046</td>
<td>-0.25</td>
<td>4.75</td>
<td>47.70*</td>
</tr>
<tr>
<td>February</td>
<td>0.00085</td>
<td>0.0117</td>
<td>-0.052</td>
<td>0.060</td>
<td>0.42</td>
<td>6.64</td>
<td>178.10*</td>
</tr>
<tr>
<td>March</td>
<td>-0.00003</td>
<td>0.0119</td>
<td>-0.046</td>
<td>0.052</td>
<td>-0.03</td>
<td>5.14</td>
<td>66.65*</td>
</tr>
<tr>
<td>April</td>
<td>0.00053</td>
<td>0.0100</td>
<td>-0.038</td>
<td>0.039</td>
<td>-0.28</td>
<td>5.00</td>
<td>61.26*</td>
</tr>
<tr>
<td>May</td>
<td>-0.00192</td>
<td>0.0137</td>
<td>-0.060</td>
<td>0.067</td>
<td>-0.31</td>
<td>6.44</td>
<td>177.62*</td>
</tr>
<tr>
<td>June</td>
<td>-0.00333</td>
<td>0.0131</td>
<td>-0.051</td>
<td>0.061</td>
<td>0.09</td>
<td>5.70</td>
<td>109.14*</td>
</tr>
<tr>
<td>July</td>
<td>0.00082</td>
<td>0.0104</td>
<td>-0.041</td>
<td>0.033</td>
<td>-0.53</td>
<td>5.25</td>
<td>94.73*</td>
</tr>
<tr>
<td>August</td>
<td>-0.00102</td>
<td>0.0104</td>
<td>-0.047</td>
<td>0.033</td>
<td>-0.45</td>
<td>4.97</td>
<td>69.75*</td>
</tr>
<tr>
<td>September</td>
<td>0.00044</td>
<td>0.0098</td>
<td>-0.039</td>
<td>0.036</td>
<td>-0.28</td>
<td>5.84</td>
<td>112.75*</td>
</tr>
<tr>
<td>October</td>
<td>0.00007</td>
<td>0.0100</td>
<td>-0.034</td>
<td>0.039</td>
<td>-0.45</td>
<td>4.29</td>
<td>34.14*</td>
</tr>
<tr>
<td>November</td>
<td>0.00045</td>
<td>0.0102</td>
<td>-0.032</td>
<td>0.061</td>
<td>0.53</td>
<td>6.88</td>
<td>210.69*</td>
</tr>
<tr>
<td>December</td>
<td>0.00056</td>
<td>0.0109</td>
<td>-0.047</td>
<td>0.032</td>
<td>-1.33</td>
<td>7.48</td>
<td>369.80*</td>
</tr>
</tbody>
</table>

Note: This table shows the descriptive data for the average daily returns across 106 sample firms. The mean is the equally-weighted average of all daily observations over the 17-year period. SD, Min and Max donate the standard deviation, the minimum daily return and the maximum daily return, respectively. Skew refers to the Kendall-Stuart measure of skeweness while Kurt is the Kendall-Stuart measure of kurtosis. JB refers to the Jarque-Bera test for normality. An * indicates significance at the 0.05 significance level.

Monthly descriptive statistics for the average daily returns across the sample firms is presented in Table 1. The table presents the mean, the standard deviation, the minimum and the maximum return, a measure of skewness (SKEW) and kurtosis (KURT) as well as the Jarque-Bera normality test statistics (JB) for the whole 17-year period.

A close examination of Table 1 suggests that over the 17-year period investors earned the highest mean return in the month of January; the average return for this month was 0.135 percent while the average return for the whole year was 0.015 percent. This finding appears similar to the results documented for other developed markets (Agnani and Aray, 2011; Agrawal and Tandon, 1994; Boudreaux, 1995; Brown et al., 1983; Gultekin and Gultekin, 1983; Rozeff and Kinney, 1976). However, the size of this positive return in January is less than that reported in other studies. For example, Rozeff and Kinney (1976) found that the average January monthly return for US equities was approximately 3.5 percent while the average return over the other months was only 0.5 percent. The lowest mean for the sample firms was for the month of May at -0.192 percent. This finding supports the results of Zafar et al. (2010) and Rafique and Shah (2012) which documented that the lowest mean return for the KSE-100 index occurred in the month of May.

As per Table 1, the highest return volatility occurred in May whereas the lowest return volatility occurred in September. Through analysis of maximum and minimum values, the volatile behaviour of equity prices for the KSE is clearly shown. Results of the Jarque-Bera normality test suggest that the daily average returns across 106 firms are not normally distributed. The fifth and sixth columns of the table suggest that returns were negatively skewed in 9 of the 12 months; out of the 106 firms, 97 had negative skewness statistics that were significant at the 5 percent level. In addition, the kurtosis
statistics were all higher than the critical value of 3 suggesting that the return distributions were characterised by fat-tails; there were more observations in the tail than one would normally expect.

3. Modelling

Before deciding to use a GARCH model, the Engle (1982) test for Autoregressive Conditional Heteroscedasticity (ARCH) effects was conducted to ascertain whether a GARCH model was appropriate for the data. The test statistic is distributed as \( \chi^2 \) under the null hypothesis of no ARCH effects. In addition, an autoregressive (AR) model was also fitted for each firm’s return; the model was tested for the ARCH effect. The results at lag 6, 12 and 20 confirmed that an ARCH effect was present in the data for all firms. Hence, the use of GARCH-type model was deemed appropriate for this research.

TGARCH (1, 1) model is applied to test for the presence of monthly calendar anomalies in KSE equities under the assumptions of time-varying return volatility\(^{16}\). This model allows for time-varying volatility and takes account of any leverage effect (Black, 1976) which may be present where the impact of good news may be different from the effect of bad news on the variance of returns.

To estimate any monthly seasonality in share returns and volatility, the following TGARCH (1, 1) model was estimated:

\[
R_t = \mu + \sum_{i=1}^{11} \kappa_i D_{it} + \varepsilon_t \quad (2)
\]

\[
h_t = \theta + \sum_{i=1}^{11} \lambda_i D_{it} + \rho_j D_{ct} + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma \varepsilon_{t-1}^2 I_{t-1} \quad (3)
\]

Equation (2) is the mean equation where \( R_t \) is the stock return at time \( t \) for each firm examined. \( \varepsilon_t \) is the random error term where \( \varepsilon_t \) is normally distributed with a mean of zero and a time-varying variance of \( h_t \). Equation (3) is the variance equation that captures the time-varying volatility in the return series where \( h_t \) is the conditional variance since it is a one-period ahead estimate for the variance calculated on the basis of past information. \( \varepsilon_{t-1}^2 \) is the unexpected return during the previous period, known as the ‘ARCH term’. \( h_{t-1} \) is the conditional variance in the previous period, also referred to as the ‘GARCH term’. \( I_{t-1} \) is a dummy variable for the leverage effect i.e. \( I_{t-1} = 1 \) if \( \varepsilon_{t-1} < 0 \) (bad news) and 0 otherwise. \( \gamma \) is the asymmetric leverage effect. A positive value of \( \gamma \) implies that negative shocks have a larger impact on volatility than positive shocks; whereas, a negative value of \( \gamma \) indicates that positive shocks have a larger impact on volatility than their negative counterparts. The news impact is symmetric if \( \gamma = 0 \).

The model is specified such that eleven monthly dummy variables in the mean and variance equations of the share returns are included to proxy for January through November with intercept terms \( \mu \) in equation (2) and \( \theta \) in equation (3) representing the 12th month (December)\(^{17}\). In other words, December becomes the reference month against which all the other months are compared. In both equations, \( D_{it} \) is a set of 11 dummy variables for each of the 11 months from January to November where \( D_{1t} = 1 \).
for all January observations and 0 otherwise, $D_{2t} = 1$ for all February observations and 0 otherwise and so on.

Furthermore, after analysing the volatility of the sample firms, a structural break was identified in the time series after 9/11 (Halari et al., 2015). It is clear from Figure 1 that while the mean value of stock returns was not affected by the 9/11 attack, their volatility was relatively lower and more stable after 9/11. This observation is consistent with previous studies that have documented a significant shift in the volatility of share returns in Pakistan after the terrorist attack of 9/11 (Ahmed and Farooq, 2008; Halari et al., 2015; Hameed and Ashraf, 2006; Nguyen and Enomoto, 2009; Suleman, 2012). A 9/11 crisis dummy “$D_{ct}$” is therefore introduced into the variance equation (equation 3), but not the mean equation (equation 2) where $D_{ct}$ has a value of zero for the period before September 11, 2001 and a value of 1 for observations after that date. Equation (2) and equation (3) are estimated simultaneously allowing both risk and return to vary across the months of the year in order to uncover whether any seasonality is present in both stock returns and volatility. The results from this investigation are discussed in the next section.

Figure 1: Share Returns for ACB, AGR, CPB and PRE during 1995 to 2011

Note: The firms shown in the figure are Askari Bank (ACB), Agriauto Industries (AGR), Century Paper (CPB) and Pakistan Refinery (PRE).
4. Results

Table 2 and Table 3 display the distributions of the coefficients for the TGARCH model across 106 firms. Table 2 reports monthly results for the mean equation while Table 3 documents monthly findings from the variance equation. Table 3 also presents statistics for the ARCH, GARCH, leverage effect and the 9/11 dummy. There are nine columns per table; the first simply highlights the name of the variables for which the coefficient’s descriptive statistics are being provided. In both tables, the variables include the constant term (December) and the 11 months for which dummy variables are included. The second column highlights the average coefficients for each variable across all 106 companies. The next two columns report the percentage of these coefficients that were (i) significant; and (ii) negative. The fifth and sixth columns document the minimum and maximum values for each coefficient respectively while the seventh column reports the standard deviation for each coefficient around its mean. Finally, the last two columns describe the skewness and kurtosis of each coefficient’s distribution.

Table 2: TGARCH Summary Table: Mean Equation

<table>
<thead>
<tr>
<th>Mean</th>
<th>Avg</th>
<th>% Sig</th>
<th>% Neg</th>
<th>MIN</th>
<th>MAX</th>
<th>SD</th>
<th>SKEW</th>
<th>KURT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan</td>
<td>0.0113</td>
<td>6.60</td>
<td>45.28</td>
<td>-0.7823</td>
<td>0.6818</td>
<td>0.26</td>
<td>-0.23</td>
<td>0.21</td>
</tr>
<tr>
<td>Feb</td>
<td>-0.0806</td>
<td>3.77</td>
<td>59.43</td>
<td>-2.2348</td>
<td>0.7031</td>
<td>0.32</td>
<td>-2.95</td>
<td>19.02</td>
</tr>
<tr>
<td>Mar</td>
<td>-0.1127</td>
<td>3.77</td>
<td>66.98</td>
<td>-1.1985</td>
<td>0.3572</td>
<td>0.24</td>
<td>-0.99</td>
<td>3.18</td>
</tr>
<tr>
<td>Apr</td>
<td>-0.0710</td>
<td>3.77</td>
<td>58.49</td>
<td>-0.6858</td>
<td>0.4198</td>
<td>0.23</td>
<td>-0.34</td>
<td>0.15</td>
</tr>
<tr>
<td>May</td>
<td>-0.2723</td>
<td>12.26</td>
<td>86.79</td>
<td>-2.2155</td>
<td>0.1662</td>
<td>0.35</td>
<td>-3.36</td>
<td>15.96</td>
</tr>
<tr>
<td>Jun</td>
<td>-0.1303</td>
<td>4.72</td>
<td>73.58</td>
<td>-0.9358</td>
<td>1.1090</td>
<td>0.25</td>
<td>0.73</td>
<td>5.84</td>
</tr>
<tr>
<td>Jul</td>
<td>-0.0751</td>
<td>2.83</td>
<td>62.26</td>
<td>-0.9063</td>
<td>0.4193</td>
<td>0.25</td>
<td>-0.74</td>
<td>1.05</td>
</tr>
<tr>
<td>Aug</td>
<td>-0.1628</td>
<td>8.49</td>
<td>76.42</td>
<td>-0.8767</td>
<td>0.2594</td>
<td>0.24</td>
<td>-0.62</td>
<td>0.37</td>
</tr>
<tr>
<td>Sep</td>
<td>-0.0829</td>
<td>4.72</td>
<td>64.15</td>
<td>-1.0886</td>
<td>0.5945</td>
<td>0.25</td>
<td>-1.03</td>
<td>2.58</td>
</tr>
<tr>
<td>Oct</td>
<td>-0.0812</td>
<td>6.60</td>
<td>65.09</td>
<td>-1.0192</td>
<td>1.3359</td>
<td>0.31</td>
<td>0.40</td>
<td>4.62</td>
</tr>
<tr>
<td>Nov</td>
<td>-0.0836</td>
<td>1.89</td>
<td>55.66</td>
<td>-1.6798</td>
<td>0.3912</td>
<td>0.27</td>
<td>-2.87</td>
<td>13.57</td>
</tr>
<tr>
<td>µ</td>
<td>0.0856</td>
<td>8.49</td>
<td>33.01</td>
<td>-0.4373</td>
<td>0.6771</td>
<td>0.17</td>
<td>0.33</td>
<td>1.82</td>
</tr>
</tbody>
</table>

Note: This summary table shows the average coefficients for the 106 sample firms for the mean equation. µ represents the effect of December. % Sig refers to the percentage of statistical significance of sample firms at 5 per cent level while % Neg implies the percentage of negative values for all the sample firms across different months. Min, Max and SD donate the minimum daily return, the maximum daily return and the standard deviation, respectively. Skew refers to the Kendall-Stuart measure of skeweness while Kurt is the Kendall-Stuart measure of kurtosis. * notes the rejection of the null hypothesis of the normality at the 0.05 significance level.

Table 2 indicates that apart from January, all the months have a lower average return for the sample firms relative to the return in December; the January coefficient was the highest at 0.0133. January also reported the least negative number of
coefficients; relative to the month of December, only 45.28 per cent of the sample firms had a negative January mean return even after taking volatility into account. However, after allowing the volatility of returns to vary, the results in Table 2 indicate that the January effect is no longer as strong as other studies have documented. In fact, only a relatively small percentage of firms (6.60 per cent) had a significant coefficient for this month. These firms are Al-Abbas Cement, Fauji Fertilizer, Indus Motor Company, Nestle Pakistan, Pakistan Refinery, Sui Northern Gas and Sui Southern Gas. Apart from Fauji Fertilizer and Nestle Pakistan, all other firms were small relative to the size of the typical firm in the KSE. The insignificance of the coefficient for the month of January for most cases suggests that there is no January effect present in the KSE; such a finding confirms the results of previous Pakistani studies that documented no January effect on share returns whilst taking account of volatility (Ali and Akbar, 2009; Mahmood and Rehman, 2007; Rafique and Shah, 2012; Zafar et al., 2010). Thus, the current study arrives at a firm conclusion about the January anomaly in Pakistani stock market after taking account for time varying volatility.

A second feature of the results is that the mean returns for the month of May are the lowest reported; at -0.2723 the average coefficient for May in Table 2 is 67 per cent larger in absolute terms than the next lowest coefficient (August). This finding seems consistent with the results of prior Pakistani studies that investigated monthly anomalies (Rafique and Shah, 2012; Zafar et al., 2010) where a strong negative May seasonality was reported. Such studies associated the negative May returns with the budget announcement in the month of June. For example, Zafar et al. (2010) argued that:

“Investors predict a change in general prices and in monetary policy as well with new budget and so in month of May they keep on selling their holdings” (p. 25).

According to Table 2, a staggering 86.79 per cent of the sample firms had a negative coefficient in May. Furthermore, the skewness and kurtosis statistics reveal that (relative to December) May returns were negatively skewed (-3.36). However, in the current investigation, only 12.26 per cent of the sample firms had a significant negative coefficient value for May (Askari Bank, Adamjee Insurance, Al-Ghazi Tractors, Bata Pakistan, Dawood Hercules Chemicals, English Leasing, GlaxoSmithKline Pakistan, MCB Bank, Nishat Mills, Nestle Pakistan, Pak Packages, Dewan Cement and Pakistan Refinery). Apart from MCB Bank and Nestle Pakistan, all other firms were small relative to the size of the typical firm in the KSE. The insignificance of the coefficient for the month of May in most of the firms suggest that no May effect is present in the KSE which is in fact inconsistent with the results of Zafar et al. (2010) and Rafique and Shah (2012); the results in prior studies which did not take the return volatility into account may be due to misspecification or the implicit effect of time-varying market volatility.
Table 3: TGARCH Summary Table: Variance Equation

<table>
<thead>
<tr>
<th>Variance</th>
<th>Avg</th>
<th>% Sig</th>
<th>% Neg</th>
<th>MIN</th>
<th>MAX</th>
<th>SD</th>
<th>SK EW</th>
<th>KURT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan</td>
<td>0.0002</td>
<td>82.08</td>
<td>49.06</td>
<td>-0.2664</td>
<td>0.5089</td>
<td>0.06</td>
<td>4.80*</td>
<td>51.91*</td>
</tr>
<tr>
<td>Feb</td>
<td>0.0021</td>
<td>70.75</td>
<td>43.40</td>
<td>-0.2579</td>
<td>0.1989</td>
<td>0.04</td>
<td>-1.36*</td>
<td>23.92*</td>
</tr>
<tr>
<td>Mar</td>
<td>0.0000</td>
<td>87.74</td>
<td>52.83</td>
<td>-0.2387</td>
<td>0.1077</td>
<td>0.04</td>
<td>-2.94*</td>
<td>21.02*</td>
</tr>
<tr>
<td>Apr</td>
<td>-0.0050</td>
<td>75.47</td>
<td>59.43</td>
<td>-0.2621</td>
<td>0.1067</td>
<td>0.03</td>
<td>-4.06*</td>
<td>31.24*</td>
</tr>
<tr>
<td>May</td>
<td>-0.0014</td>
<td>78.30</td>
<td>43.40</td>
<td>-0.2640</td>
<td>0.2157</td>
<td>0.05</td>
<td>-1.91*</td>
<td>17.21*</td>
</tr>
<tr>
<td>Jun</td>
<td>0.0042</td>
<td>77.36</td>
<td>49.06</td>
<td>-0.2617</td>
<td>0.5898</td>
<td>0.07</td>
<td>5.84*</td>
<td>57.28*</td>
</tr>
<tr>
<td>Jul</td>
<td>-0.0035</td>
<td>69.81</td>
<td>58.49</td>
<td>-0.2575</td>
<td>0.3735</td>
<td>0.05</td>
<td>2.96*</td>
<td>42.25*</td>
</tr>
<tr>
<td>Aug</td>
<td>-0.0038</td>
<td>76.42</td>
<td>52.83</td>
<td>-0.2647</td>
<td>0.2151</td>
<td>0.04</td>
<td>-1.25*</td>
<td>26.02*</td>
</tr>
<tr>
<td>Sep</td>
<td>-0.0035</td>
<td>75.47</td>
<td>52.83</td>
<td>-0.2285</td>
<td>0.0869</td>
<td>0.03</td>
<td>-3.84*</td>
<td>27.77*</td>
</tr>
<tr>
<td>Oct</td>
<td>0.0005</td>
<td>73.58</td>
<td>40.57</td>
<td>-0.2502</td>
<td>0.1803</td>
<td>0.04</td>
<td>-2.13*</td>
<td>31.01*</td>
</tr>
<tr>
<td>Nov</td>
<td>0.0043</td>
<td>87.74</td>
<td>59.43</td>
<td>-0.2356</td>
<td>0.4216</td>
<td>0.06</td>
<td>3.65*</td>
<td>25.57*</td>
</tr>
<tr>
<td>0</td>
<td>0.0277</td>
<td>97.17</td>
<td>3.77</td>
<td>-0.0265</td>
<td>0.5486</td>
<td>0.06</td>
<td>5.94*</td>
<td>42.93*</td>
</tr>
</tbody>
</table>

ARCH 0.1253 | 100 | 0.00 | 0.0171 | 0.3695 | 0.07 | 1.01* | 1.13* |
Leverage 0.0011 | 72.64 | 41.51 | -0.1929 | 0.1457 | 0.06 | -0.58* | 0.99* |
GARCH 0.7464 | 99.06 | 1.88 | -0.0935 | 0.9757 | 0.02 | -2.10 | 5.38* |
9/11 -0.0047 | 89.62 | 71.7 | -0.0871 | 0.9068 | 0.09 | 9.20* | 90.50* |

Note: This summary table shows the average coefficients for the 106 sample firms for the variance equation. \( \theta \) represents the effect of December. 9/11 is a dummy variable representing the observations in the period after 9/11. % Sig refers to the percentage of statistical significance of sample firms at 5 per cent level while % Neg implies the percentage of negative values for all the sample firms across different months. Min, Max and SD donate the minimum daily return, the maximum daily return and the standard deviation, respectively. Skew refers to the Kendall-Stuart measure of skeweness while Kurt is the Kendall-Stuart measure of kurtosis. * notes the rejection of the null hypothesis of the normality at the 0.05 significance level.

Although there is very little statistical evidence of a seasonal anomaly in mean returns, a different picture emerges when the variances of returns are analysed. The results of the variance equations in Table 3 confirm that the volatility of stock returns in the KSE varies with the trading month. The average value of the coefficients of December (\( \theta \)) is 0.0277 and less than 5 per cent of December’s coefficients are negative. Even though the average values of the coefficients for some months are negative, their size is much smaller than 0.0277. Thus, the result indicates that in all months, the variance of share returns are on average positive.

The January coefficient was positive (0.0002) and was significant for 82.08 per cent of the sample firms. The conditional volatility of returns in this month was positively skewed at 4.80 which was significant. However, January was not the only month with volatility that was significantly higher than volatility in December. In fact, four other months had positive coefficients (February, June, October and November). The average coefficient for November was the highest at 0.0043 (relative to December) and the dummy variable for this month was significant in 87.74 per cent of cases. However, November was only 2.38 per cent higher than the month of June when the budget is announced. For five months (April, May, July, August and September) the average coefficient for the dummy variable was negative (relative to December). The least volatile month was the month of April at -0.0050 (relative to December) and the
coefficient was significant for 75.47 per cent of the firms; April was 31.57 per cent larger in absolute terms than the next lowest coefficient (August). Thus, it can be concluded that whatever monthly seasonality may be present in the equity returns of Pakistani companies, it is more pronounced in the volatility data than in the mean return numbers.

The last panel of Table 3 indicates that the ARCH term has a statistically significant coefficient for most of the sample companies (99.06 per cent of these terms are significant) and the GARCH term’s coefficient is statistically significant for all of the firms; these findings suggest that volatility of share returns depends on previous unexpected returns as well as variances. Second, the TGARCH model suggests that Pakistani investors appear to respond in an asymmetric fashion to positive and negative news (Halari et al., 2015). Table 3 indicates that 72.64 per cent of firms reported a significant leverage effect. Whilst 58.49 percent firms reported a positive and statistically significant leverage effect which suggests that, on average, it is bad news rather than good news which generates higher volatility in the returns. Thus, this finding suggest that academic researchers need to take account of good and bad news on share prices when investigating returns and volatility of Pakistani equities to eliminate any risk of spurious results; previous research has failed to consider leverage effect when modelling the equity returns to test for monthly seasonality in Pakistan.

Finally, an analysis of the 9/11 effect reveals that the volatility of the shares listed in the KSE market changed considerably after the attacks on the World Trade Centre in the US. After 9/11, stock exchange reforms were introduced in the KSE which it could be argued, attributed to the results showing that 89.62 per cent of the sample firms experienced a decline in return volatility. As Figure 1 indicates, post 9/11, their stock return volatility has since declined. A visual inspection of Table 3 suggests that the volatility declined on average. A negative coefficient for majority of the firms indicate the volatility of share returns was lower in the post-9/11 period for most firms. Such a finding is consistent with the studies by Hameed and Ashraf (2006), Nguyen and Enomoto (2009) and Halari et al (2015).

5. Conclusion
This paper employs a TGARCH model to analyse the existence of monthly calendar anomalies in the share returns for 106 Pakistani firms listed on the KSE. The results offer little statistical evidence of a monthly seasonal anomaly in mean returns however monthly seasonal anomaly does exist in the return volatility. This finding is consistent with the findings reported by Halari et al. (2015) and Khan et al. (2017) in their investigation of Islamic calendar anomalies in the Pakistani stock market.

In the current investigation, positive returns occur in January while negative returns are present in May; however, these are not significant for most of the individual firms. On the contrary, the calendar anomaly for return volatility was found to be significant. In particular, whilst the return volatility in April is lower than other months (relative to December), the return volatility is highest in November. Therefore, the current research challenges our current knowledge about calendar anomalies in Pakistan and opens up an avenue for further research. Furthermore, the KSE market clearly displays asymmetric behaviour for good and bad news. Overall, it was found that good news had a lower volatility of returns than bad news. The significance of the estimators in the TGARCH models highlights the fact that volatility clustering and asymmetric response to news are clearly present in the Pakistani stock market, which in turn emphasises the need for suitable risk models to be used that would specifically
take account of these affects. In the course of this research, it was discovered that the return volatility has significantly reduced in Pakistan since 9/11. This brings into question the validity of previous research that omitted this effect in their analysis of monthly anomalies in Pakistan (Halari, 2015).

It could be argued that the findings of this study could prove useful for trading strategies and investment decisions which investors may look to employ for monthly prices; investors can formulate their investment strategies and time their trading thereby earning abnormal returns (although transaction costs may impact the profitability). The month that offers investors the greatest chance to make a risk-adjusted profit is January while the month that the investor should avoid because of the relatively high chance of making a loss is May. Therefore, investors may be able to use the monthly seasonality information supplied to buy shares in May and sell in January. However, it must be noted that this strategy is only true for a minority of the sample firms. For investors interested in avoiding (or reducing) risk when investing in the Pakistani stock market, the current findings suggest that investing in April may be a good strategy. Reduction in volatility in April is true for the majority of the sample firms. Therefore, investors may alter their portfolios to respond to this shift in volatility in certain months to manage their risk adjusted portfolios. However, further work is needed to identify the reasons behind low volatility in the month of April. A possible investigation can take account of economic factors to examine this anomalous behaviour.

Notes

1. Farag (2013) argued that strucits on shares structurally affects stock returns and asymmetric volatility in the Egyptian and Thai stock markets. Mookerjee and Yu (1999) were of a similar view for the Chinese stock market. There is further evidence of high volatility and asymmetric information in emerging markets (Snoussi and El-Aroui, 2012; Javaira and Hassan, 2015).
2. The Countries considered included: Hong Kong, Singapore, Philippines and Malaysia.
3. Ho (1990) found that six out of his eight Asian Pacific emerging stock markets exhibited significantly higher daily returns in January than in other months of the year. These markets included Hong Kong, Korea, Malaysia, Philippines, Singapore and Taiwan.
4. Countries included: Argentina, Chile, Colombia, Greece, India, Jordon, Korea, Malaysia, Mexico, Nigeria, Pakistan, Philippines, Portugal, Taiwan, Thailand, Turkey, Venezuela and Zimbabwe.
5. The authors observed that share returns for January were significantly higher than the returns for the remaining 11 months only in Chile, Greece, Korea, Taiwan and Turkey.
6. Countries included: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Croatia, Denmark, Egypt, Estonia, Finland, France, Germany, Greece, Hong Kong, India, Indonesia, Ireland, Israel, Italy, Japan, Jordan, Kuwait, Latvia, Lithuania, Luxemburg, Malaysia, Mexico, Netherlands, New Zealand, Norway, Pakistan, Peru, Philippine, Portugal, Russia, Singapore, South Korea, Spain, Sri Lanka, Sweden, Swiss, Taiwan, Thailand, Turkey, UK, US, Yugoslavia and Zambia.
7. Countries included: Hong Kong, India, Indonesia, Japan, Malaysia, Korea, Philippines, Singapore, Taiwan, China and Thailand.
8. The companies included were: Engro Chemicals, Fauji Fertilizer, Sui Northern Gas, Sui Southern Gas, Adamjee Insurance, Indus motors, ICI and Pakistan State Oil. All of these firms were large relative to the size of the typical firm in the KSE.
9. The start date was chosen in order to maximise the number of companies included in the data set whilst having a long enough time frame to investigate monthly calendar anomalies for the KSE market.
10. An ‘adjusted price’ is the price of a company’s share after taking into account any stock dividends, stock splits or share issues. It was decided to use adjusted prices since stock dividends, stock splits and share issues were relatively common for the KSE equities over the 17-year period of this research.
11. Inactive shares are shares listed on the stock exchange that are not traded frequently. In the case of some of the shares excluded from the sample, trades were not apparent for periods of over nine months at a time. For the purpose of this study, a cut-off point of 33 percent was employed which meant that if 33 percent or more of the returns for a share were different from zero the share was included in the sample.
12. Details about the sample companies are available upon request from the author.
13. According to Section 249 of the Ordinance of the SECP, “No dividend shall be paid by a company other than out of the profits of the company” (The Securities and Exchange Ordinance, 1969). Thus, a dividend payment is an indication of profitability (Khan, 2011).
14. Descriptive statistics for individual companies are available upon request from the author.
15. Values of skewness were deemed significant if they were more than twice their standard errors. In the current analysis, the standard error values documented for the skewness statistics varied from -4.97 for Fazal Textile Mills to 1.47 for Pakistan National Shipping.
16. A pilot study on a random selection of 30 sample firms was conducted to select an appropriate GARCH model. The Ljung – Box test result indicated that compared with GARCH (1,1), the EGARCH (1,1) and the TGARCH-M (1,1) models, the TGARCH (1, 1) model best fitted the data for this investigation. An analysis for all the sample firms confirmed that the TGARCH model does not have serial correlations in the standardized and the squared standardized residuals indicating the appropriateness of TGARCH specification for data under investigation.
17. This is consistent with the study by Beller and Nofsinger (1998) using Gregorian calendar that had 11 dummy variables and December as the intercept (constant) term to avoid the perfect multicollinearity problem.
18. Due to the large amount of sample firms, only four firms are shown in Figures 1; however, similar observations were made for the majority of other firms.
19. Results for each individual firm are available upon request.
References


