4. HIGHER REALIZED MOMENTS AND STOCK RETURN PREDICTABILITY

Seema REHMAN[1]
Saqib SHARIF[2]
Wali ULLAH[3]

Abstract

This study exploits information contained in high frequency sample data by computing higher realized moments of individual firms in the emerging stock market of Pakistan. Furthermore, the relation of higher moments with future stock returns is examined by constructing decile portfolios based on weekly realized volatility, skewness and kurtosis to predict the next week return of the trading strategy that takes long position for portfolio of stocks having high realized moment and takes short position for portfolio of stocks having low realized moment. The long short spread is significant for equal weighted weekly returns based on realized volatility. The long short weekly return is positive and highly significant for realized skewness, 1.659 and 1.969 (in bps) with t-statistics of 7.92 and 14.027 for value and equal weighted portfolios respectively. The result for realized skewness is also supported by Carhart's Alphas. Similar results are obtained for realized kurtosis, 0.427 and 0.664 (in bps) of long short return, with t-statistics of 2.079 and 4.049 for value and equal weighted portfolios respectively. The evidence suggests that realized skewness and kurtosis can predict the next week's moment based on cross sectional stock returns.

Keywords: cross-section of equity returns, emerging market, intraday data**,** realized kurtosis, realized skewness

JEL Classification: G11, G12, G17, O16.

1. Introduction

Examining the cross-sectional variation in average stock returns has been considered as one of the salient features of finance researches (Cooper and Maio, 2019). Although, several studies argue that volatility risk is priced at individual firm level, bidding a negative risk premium for fluctuations in volatility (e.g., Da and Schaumburg, 2011; Bansal *et al.,* 2014),

[1] *Department of Management Sciences, Shaheed Zulfiqar Ali Bhutto Institute ofScience and Technology (SZABIST), 90 and 100 Clifton, Karachi-75600, Pakistan. E-mail: seemarehman2014@yahoo.com. Corresponding author.*

[2] *Department of Finance, Institute of Business Administration (IBA),University Road, Karachi-75270, Pakistan. E-mail: ssharif@iba.edu.pk.*

[3] *Department of Economics, Institute of Business Administration (IBA), UniversityRoad, Karachi-75270, Pakistan. E-mail: waliullah@iba.edu.pk.*

such cross-sectional variations are commonly not very strong (Bollerslev *et al.,* 2016). In asset pricing literature, the major goal of many scholars is to enhance the precision of stock return forecasts by accounting for volatility characteristics and its constituents such as persistent leverage effect, trading volume and signed jumps (e.g., Corsi and Reno, 2012; Haugom *et al.,* 2014; Patton and Sheppard, 2015). Meanwhile, others contend the simplicity of conventional linear association of risk-return trade-off and assert that the accuracy of cross-sectional stock return forecasts can be acquired by considering higher order moments (Dittmar, 2002; Conrad *et al.,* 2013). The importance of higher moments in asset pricing cannot be ignored. The extent literature proposes the importance of heavy tailed shocks (kurtosis) and left tailed events (skewness) (e.g., Kraus and Litzenberger, 1976; Rietz, 1988; Barro, 2006) to explain the stock price behavior. Ghysels *et al.* (2016) report analogous findings for emerging stock markets (Neuberger and Payne, 2018). The skewness of a distribution presents bias towards positive or negative returns. If a stock return distribution has positive skewness, there is a greater possibility of higher positive returns than negative returns (Damodaran 2012). Many scholars document that investors prefer positively skewed stocks (e.g., Mitton and Vorkink, 2007; Barberis and Huang, 2008), therefore high demand of such stocks lowers the required rate of return by the investors. Investors are not interested in stocks with high kurtosis, as kurtosis measures the probability of extreme events in the distribution and there is a higher chance of a specific return that is farther from average return, therefore investors command higher risk premium for holding such stocks (Ayadi *et al.,* 2019).

The normality of stock returns distribution is considered as one of the most pronounced assumptions elemental to central theory and statistical techniques employed in financial economics. Though, an immense literature demonstrates that stock returns distributions have negative skewness and excess kurtosis in numerous emerging markets (e.g., Bekaert *et al.,* 1998; Ghysels *et al.,* 2016). Mensi (2020) obtained data of 16 stock market indices to study the path and magnitude of asymmetric volatility connectedness among these markets and show that emerging stock markets of Brazil, Russia, India and China (BRIC) as well as Thailand face higher asymmetric spillovers than developed economies. He argues that emerging economies continue to experience this phenomenon because of global macroeconomic uncertainty, lower growth caused by drop in asset prices, tighter external financing and rebalancing in China. Neglecting asymmetries in stocks returns may underestimate risk leading to mistaken pricing of financial securities like stocks and formalized option contracts. Moreover, conditional left tailed skewness may cause systematic errors in statistical procedures dependent upon time-invariant stock returns distributions.

Volatility, skewness and kurtosis of a stock return distribution helps in understanding the channeling of volatility risk, downside/upside risk and fat tail risk. It is well known that mean variance technique is appropriate in the instance of compactness of returns distribution and frequent or continuous portfolio making decisions, which makes risk parameter satisfactorily small. Nonetheless, in the instance of limits imposed on portfolio making decision to finite time period and also restriction on rebalancing, then need arises to incorporate higher order moments due to the quadratic approximation not being locally of high contact (Briec *et al.,* 2007). In a group of 17 emerging markets including Pakistan, Hwang and Satchell (1999) show that cokurtosis has at least as much explanatory power as coskewness. Do *et al.* (2016) examine the linkages within and between equity and forex markets using higher moments viz., volatility, skewness and kurtosis and find supportive findings of positive relationship within stock markets for all three moments in emerging and developed economies. Other papers have focused more on the third moment, i.e., skewness, for example, study of Narayan and Ahmed (2014) provides evidence for higher returns for a model that incorporates skewness than a model that ignores it after exploring the Indian Stock Exchange. Similarly, Hadhri and Ftiti (2019) find that skewness drives stock returns by covering a sample of 22 individual emerging markets. Five markets exhibit a positive relation and 17 a negative relation between realized skewness and returns and that this relation is significant for all emerging markets under study.

For a long time, fitted parametric econometric techniques such as generalized autoregressive conditional heteroscedasticity (GARCH) of Engle (1982) and Bollerslev (1986) and stochastic volatility approaches (e.g., Taylor, 1986) have been used in financial econometrics. However, in the beginning of this century, instigated by the easy accessibility of high frequency asset prices, Andersen *et al.,* (2001) and Barndorff-Nielsen and Shephard (2002) introduced the concept of realized estimators (Brito *et al.,* 2017). Recent researches show that measuring realized moments using high frequency data can provide better estimates and improve the statistical performances (Amaya *et al.,* 2015; Chen *et al.,* 2019). Realized volatility is a measure of the ex-post volatility of stock prices during a specific time period (Barndorff *et al.,* 2010). However, there is a deep theoretical background. By observing intraday returns at sufficient frequencies, the realized volatility factor converges to the inherent integrated volatility, the aggregate of instant volatility across the time period of interest therefore identified as a natural volatility estimator. Thus practically this measure may be treated as observed volatility which allows for direct examination of its characteristics taking simple approaches rather than developing complex econometric models necessary in the instance of latent volatility (e.g., Andersen and Benzoni, 2009; Barndorff-Nielsen and Shephard, 2002). The estimator's asymptotic properties are dramatic when high frequency data are utilized with trading occurring every few seconds. Particularly, as it is commonly known now that within the context of stochastic procedures, a full observation of the sampling path of an asset will precisely disclose the variance of that sample path in the limit. The nature of this finding is non-parametric due to the convergence of the estimator towards the quadratic variation of the process (Ait-Sahalia and Yu, 2009).

Naqvi *et al.,* (2017) account for weighted preferences of investors for higher order moments along with the traditional criterion of risk return at Pakistan Stock Exchange (PSX) and find the importance of the role played by added dimensions of risk to determine the yields of optimal portfolios. Iqbal *et al.,* (2010) find the usefulness of excess kurtosis to explain Pakistan stock market returns over and above the Fama and French three factor model. This study adds to the literature by studying the effects of realized moments on future stock returns in the emerging stock market of Pakistan. The choice of Pakistan stock market for this study is motivated by the improvement in evolution and integration of global emerging financial markets which may initiate right set of circumstances for local and international investors. It's a common observation that emerging markets tend to be more volatile relative to advanced economies because of socio-political and economic conditions which lead to greater market concentration, low liquidity, highly volatile market and larger amount of infrequent trading than advanced economies (e.g., Iqbal *et al.,* 2010). Iqbal *et al.,* (2010) require that due to such conditions, estimating prices of riskier assets is becoming a demanding job in the emerging economies. A number of researches look at the role of skewness and kurtosis considering emerging markets but the equity market of Pakistan is still under researched and demands investigation to examine the effects of higher order moments on investment making decisions.

Based on the above discussion, the following hypotheses are formulated:

H1: Realized volatility predicts cross section of stock returns.

H2: Realized skewness predicts cross section of stock returns.

H3: Realized kurtosis predicts cross section of stock returns.

Set against this background, the aim of this research is to empirically analyze the informative properties of realized higher moments calculated using intraday returns in the emerging stock market of Pakistan. The study differs from researches on developed markets (e.g., Amaya *et al.,* 2015) in two ways. First, this research finds a positive and significant relationship between realized skewness and subsequent week's return. Secondly, it considers the individual firms' co-kurtosis with the market and reports it along with other firm specific characteristics. Azher and Iqbal (2018) show the relevancy of co-kurtosis in the emerging economy of Pakistan because such markets are characterized by thin trading as an outcome of illiquidity and also presence of downside risk linked to sizable extreme deviations.

To the best of authors' knowledge, this is the first study conducted at Pakistan Stock Exchange, which computes realized higher moments with high frequency data to ensure the effectiveness of the measurement of asymmetry and fat tails.

The organization of the subsequent sections is as follows. Section 2 presents the data and methodology, section 3 deals with data analysis and findings and section 4 concludes.

2. Data and Methodology

2.1. Data

Tick by tick data from July 1st, 2008 to August 31st, 2018 of all listed firms are acquired from Pakistan Stock Exchange to calculate returns of five minutes intervals. Taking sample of five minutes interval keeps the daily realized moment estimates mostly free of measurement error and yet as low as not to concern about microstructure biases (Andersen *et al.,* 2001). Along with tick-by-tick data, daily firm-level data of closing prices, daily trading volume (i.e., turnover), value traded, number of shares outstanding and market value is also provided by Pakistan Stock Exchange.

To proxy the risk free rate, one month T-bills' rate is utilized and value weighted KSE-100 index is used to proxy for market returns. Five minute prices of each company are used for calculating weekly realized moments, daily firm level prices are utilized for computing historical skewness (previous month skewness), market model beta, lagged return, idiosyncratic volatility, highest return within the prior week and illiquidity (Amihud, 2002). Monthly prices are obtained by taking end of the month value and are used for computing co-skewness (Harvey and Siddique, 2000) and co-kurtosis. Daily volume is used for computing illiquidity and number of outstanding shares and share prices are used for computing market capitalization/size. This research uses Thomson Reuters Data-stream for extracting book equity BE of individual companies for calculating their book to market ratios.

2.2. Modelling Realized Moments

This study examines the characteristics of higher moments measured by using tick by tick data of Pakistan Stock Exchange from July 1st, 2008 to August 31st, 2018. Five minutes prices are extracted from tick by tick data. Five minutes prices are converted into returns and daily realized moments are constructed by taking sum of squares of five minutes returns.

Weekly values of realized volatility, skewness and kurtosis are obtained by averaging daily realized measures.

2.2.1. Calculation of Realized Moments

Following Amaya *et al.* (2015), nearest neighbor interpolation technique is used to extract 5 minutes prices from tick by tick prices, starting from 9:30am from Monday to Thursday till 3:30pm and from 9:15am for Fridays* till 4:30pm, such as if there is no price in an interval, last observed price in the preceding five minutes time period is used. Only equities, having prices Rs. 5 and more are considered for analysis, to restrict getting larger returns, i.e., prices below five rupees are excluded from the analysis. Furthermore, to maintain sufficient liquidity, only those firms have been included in the sample that have at least 80 transactions in one trading day (e.g., Amaya *et al.,* 2015; Choi and Lee, 2014). There were 559 firms included in the sample initially, based on the aforementioned prescribed criteria but the sample size reduced to 306 companies by deleting those firms for which data was not available for other variables.

The daily log returns for each company are first described by the following equation of *i*th daily return on day *t*:

$$r_{t,i} = P_{t,\frac{i}{N}} - P_{t,\frac{(i-1)}{N}}, \tag{1}$$

where *P* represents the natural log of stock price and *N* is the number of returns observed during a trading day. The day *t* opening log price is $P_{t,0}$ and the day *t* closing log price is $P_{t,1}$. The normal trading timings at Pakistan Stock Exchange are used for better results i.e., 9:30am to 3:30pm, and for Fridays 9:15am to 4:30pm. Friday breaks at PSX from 12:00pm till 2:30pm are incorporated in the data. Five minutes prices have been used in this paper such as *N*=72 for 6 trading hours from Monday to Thursday and *N*=57 for 4 hours and 45 minutes for Fridays. Five minutes prices are converted to five minutes returns by taking log difference with previous period price, as follows:

$$ln(P_t/P_{t-1}) \tag{2}$$

Five minutes returns are squared for facilitating estimation of realized volatility. The famous intraday realized variance (Andersen and Bollerslev, 1998; Andersen *et al.,* 2003) is acquired by adding squares of these high frequency returns.

$$RDVar_t = \sum_{i=1}^{N} r_{t,i}^2 \tag{3}$$

Estimating mean of high frequency pay offs is not a standard practice because it is influenced by the variance at such frequency. The distinct attribute of this volatility calculation is its model free nature relative to other measurement models (Andersen *et al.,* 2001; Barndorff-Nielsen and Shephard, 2002). Furthermore, increasing sampling data frequency cause realized variance to converge to a clearly stated quadratic variation limit.

To measure the asymmetry of the distribution of daily return, a measuring technique of ex post realized daily skewness is constructed using intraday returns divided by realized variance for standardizing them:

$$RDSkew_t = \frac{\sqrt{N}\sum_{i=1}^{N} r_{t,i}^3}{RDVar_t^{3/2}} \tag{4}$$

The negative values of this measuring technique are indicative of a fatter left tail and positive values are indicative of fatter right tail.

The extremes of the return distribution i.e. realized daily kurtosis is measured as follows:

$$RDKurt_t = \frac{N\sum_{i=1}^{N} r_{t,i}^4}{RDVar_t^2} \tag{5}$$

The $RDSkew_t$ and $RDKurt_t$ are scaled by $\sqrt{N}$ and N for ensuring their magnitudes' conformity to daily skewness and kurtosis.

The cross sectional analysis is performed at weekly frequency therefore weekly realized moments are constructed from the daily realized moments. The weekly realized measure is constructed by simply taking average of the daily realized moment measure, therefore at least one valid day of the realized moment is needed for computing weekly measure. To avoid the impact of day-of-the-week effect or calendar anomalies, the average of the available daily estimators is taken from Wednesday through Tuesday, similar to Amaya *et al.* (2015). If *t* stands for Tuesday then:

$$RVol_t = \left(\frac{252}{5}\sum_{i=0}^{4} RDVar_{t-i}\right)^{1/2}, \tag{6}$$

$$RSkew_t = \frac{1}{5}\sum_{i=0}^{4} RDSkew_{t-i}, \tag{7}$$

$$RKurt_t = \frac{1}{5}\sum_{i=0}^{4} RDKurt_{t-i}. \tag{8}$$

The trading days from Monday till Thursday have 72 five minute observations and Fridays have 57 observations, therefore weekly realized moments for each company consists *t* of 345 intervals. As the weekly frequency is used to conduct the cross sectional asset pricing analysis, therefore *t* denotes a week. Following the standards, annualizing the realized volatility measure simplifies the interpretation of findings.

Portfolios are constructed by ranking stocks into deciles based on the three moments, that is, volatility, skewness and kurtosis. Each decile's equal weighted characteristics are calculated over the same week. This process is iterated for every week from July 2008 to August 2018. Portfolios' characteristics mean values are not only reported for realized volatility, realized skewness and realized kurtosis but also for control variables in each decile of firms. These include size, BE/ME, historical skewness, market beta, lagged return, idiosyncratic volatility, co-skewness, co-kurtosis, maximum return, illiquidity, stock's market price and number of stocks for each decile. This procedure may help in examining whether firm specific realized moments carry unique information related to the cross section of equity returns.

Next, value and equal weighted portfolios are constructed by using the returns over the coming week. The long-short average raw returns of the decile portfolios along with long-short Carhart's alpha are computed. The empirical linkage between realized moments and equity returns is also assessed by observing alphas from the Carhart (1997) four factor model to adjust for standard measures of risk.

3. Data Analysis and Findings

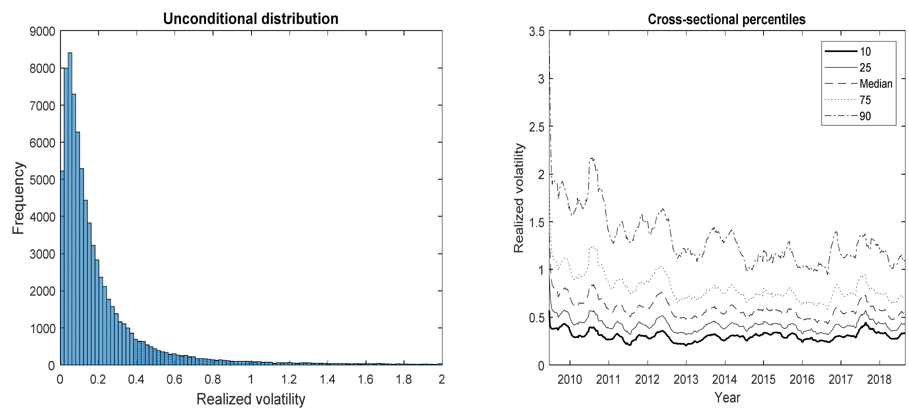
Higher realized moments are computed for one hundred and fifty seven thousand firm week observations for the period of July 2008 till August 2018. The left panel of Figure 1 depicts the realized measures pooled across firms and weeks and the right panel displays three month moving averages of cross-sectional percentiles. In consistence with existing literature, the realized volatility distribution is highly skewed to right. According to Andersen *et al.*

(2001), such distribution captures meaningful facets of return generating process and show time variations in volatility. The cross-sectional percentiles for realized volatility clearly depict that the dispersion has decreased through the time period under study, suggesting improving stability in stock returns during this period. Theoretically, the conditional variance of asset return is dependent on the conditional variance of expected cash flow (Schwert, 1989). The realized skewness distribution is strongly peaked around zero. Skewness explains the effects of large rare disasters on stock returns and actually magnifies through time period, up to a year (Neuberger, 2012).

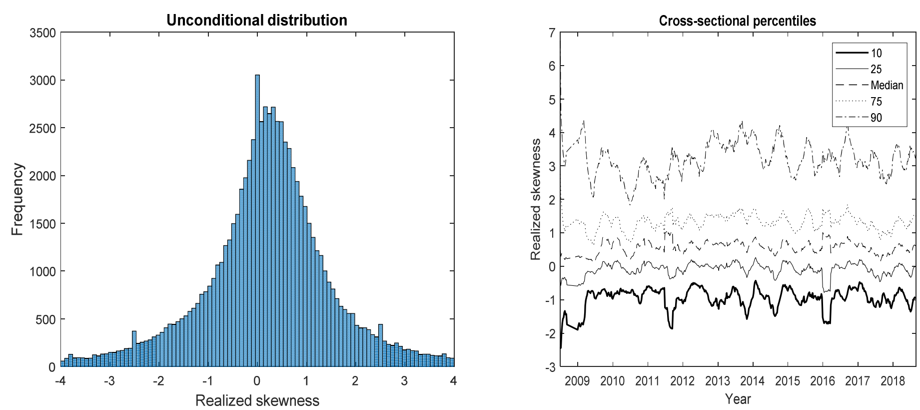
Figure 1

Histograms and quantiles (three month moving averages) of Realized Volatility, Skewness and Kurtosis for the period between July 2008 and August 2018, based on 157,000 firm week observations.

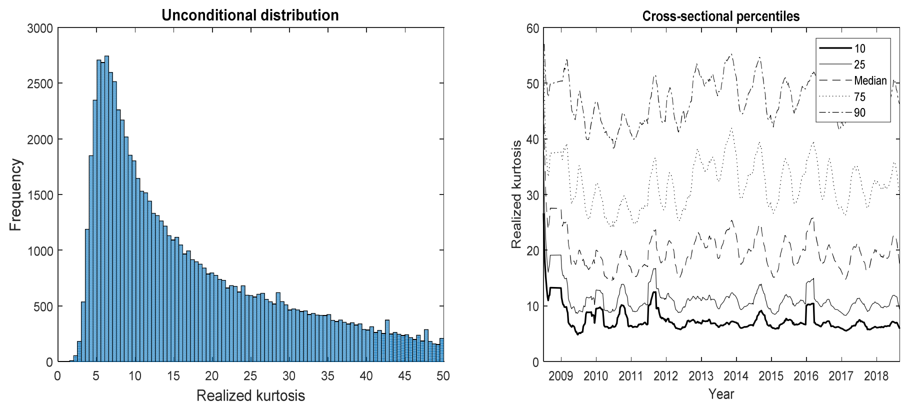
Panel A: Realized Volatility



Panel B: Realized skewness



Panel C: Realized Kurtosis



Finally, analogous to realized volatility, the distribution of realized kurtosis, as can be seen in the left side of Panel C of Figure 1, is approximately log-normal. Time variations are obvious in cross-sectional percentiles of realized skewness and kurtosis as well. As compared to researches from developed countries such as Amaya *et al.* (2015), the realized kurtosis values are way higher (1.75-57) for PSX, which suggest fat tailed returns. Kurtosis measures extreme episodes of returns in the tails. A large value for kurtosis stipulates higher risk in investment. Mei *et al.* (2017) show that realized skewness and kurtosis are helpful in predicting volatility by taking index level data of China and United States. Empirical evidence proves that stocks showing more sensitivity to market kurtosis earn higher expected returns (Chang *et al.,* 2013).

Decile portfolios are formed every Tuesday by ranking stocks on their weekly realized moments. Time series mean values for realized moments and firm control variables have been reported in Table 1. Panel A shows the time series mean values of factors based on realized volatility. Panel B reports results on the basis of realized skewness and Panel C on realized kurtosis. First column consists of portfolio of stocks having lowest average realized moment and last column consists of portfolio of stocks having highest realized values. Due to the sample size of 306 companies in PSX, the number of average companies per decile is low i.e., 30 in each decile.

Panel A of Table 1 exhibits results for the decile portfolios formed by relying on realized volatility measure. The value of realized volatility for the first decile is 19.9% and has increased to 174.4% for the tenth decile. Realized skewness values ranked by realized volatility, show interesting patterns as all values are positive and increase gradually over deciles. Which elaborates that the riskier firms have earned higher average returns over time period under study. Since, PSX is an emerging stock exchange, hence the realized kurtosis values are higher than developed market evidence (e.g. Amaya *et al.,* 2015), such as 16 for the first five deciles and increased to 23 for the tenth decile, implying higher expected returns. Hwang and Satchell (1999) provide evidence to assert the relevancy of kurtosis within the context of emerging markets. It is suggestive that non normal returns are a manifestation of kurtosis and are not driven by skewness as mostly discovered in developed countries. Moreover, the presence of outliers in emerging economies suggest that the extreme returns have greater likelihood of happening in emerging economies. Moreover, the findings show that firms with higher realized volatility happen to be small, have low and negative co-skewness with the market and they also have low stock prices, clearly providing an explanation for low required rate of return by the investors. Harvey (2000) asserts the importance of coskewness in explaining the emerging stock market returns in the cross section beside other risk determinants. Kraus and Litzenberger (1976) introduce a modeling approach in which investors get compensation for exposure to systematic risk and co-skewness risk, desiring high (low) return at whatever time the systematic risk is high (low) and the co-skewness risk is low (high). A positive relationship is evident between realized volatility values and book to market ratio, historical skewness, lagged return, idiosyncratic volatility and maximum weekly return. The observed higher volatility values for distressed firms are consistent with the existing literature. Size and book to market particularly absorb the roles played by leverage and earnings/price and act as proxies for typical risk factors related to equity returns. Fama and French (1993) offer some possible reasons to explain the role of book to market ratio in measuring risk. For example, high BE/ME represent a distressed equity that sells at low price because of dubious future returns. It could also show a capital intensive equity that is commonly more susceptible to low returns during economic downturns.

Panel B of Table 1 displays a value of -2.98 for realized skewness in the first decile and 3.20 in the tenth decile. Highly skewed firms, both negative and positive are small sized, having high illiquidity values (e.g., Amaya *et al.,* 2015). The other variables also show similar patterns of having higher values for higher negatively or positively skewed firms. The observed values imply that small, illiquid firms have earned extreme returns, both negative and positive during the time period under study.

Panel C of Table 1 exhibits results for the decile portfolios formed by relying on realized kurtosis measure. The kurtosis values range from 5.15 to 46.88 over the deciles. In the emerging economies, infrequent trading for most stocks results in excessive zero returns leading to large kurtosis (Azher and Iqbal, 2018). The variables that show positive relationship with realized kurtosis are book to market values, historical skewness, idiosyncratic volatility, illiquidity and price. Firm characteristics having negative relationship with realized kurtosis are realized volatility, realized skewness, firm size, lagged return and maximum weekly return. However, no relation is observed between realized kurtosis and co-skewness and co-kurtosis. Realized kurtosis show consistent higher pattern for small sized and low beta firms. This can partially explain the higher reward to hold stocks having low beta values (Frazzini and Pedersen, 2014).

Figure 2 complements Table 1 by displaying the three months moving averages of the cross-sectional percentiles of realized moments ranked on three well known determinants of return i.e., size, book to market ratio and market beta. Right and left column of Figure 2 clearly depict the relationship between realized volatility and kurtosis with size, book to market ratio and market beta. Realized volatility tends to be high for small firms, firms having low book to market ratio and firms with high market beta values, implying that such firms generate higher returns on average. The imperfect capital market theories proposed (Bernanke and Gertler, 1989; Gertler and Gilchrist, 1994; Kiyotaki and Moore, 1997), argue that the changes in credit market conditions impact the risk related to small and large firms differently. Thus, small firms have more volatile business environment as compared to large firms. The cross-sectional variations in realized kurtosis are high for small sized firms, for firms having high book to market ratio and firms having low market beta values. Realized skewness turns out to have the most potential to drive the variation in cross-sectional stock returns, independently. Table 2 further clarifies the role of realized skewness and kurtosis in explaining future returns.

Each Tuesday, value and equal weighted decile portfolios are formed based on realized estimates. The time series mean values of weekly returns for deciles ranked on realized volatility are reported in Table 2, Panel A. The value weighted returns are -0.255 basis points for decile 1 and -0.189 basis points for decile 10. The long short return is positive but insignificant for value weighted portfolios, suggesting high return for high volatile stocks but negative and significant for equal weighted portfolios (i.e., -0.487). This finding leads to the conclusion that giving the same weight to small firms in the portfolio as large firms, increase the riskiness of the portfolios and generates negative risk premium on average, during time period under study. Fama and French (1988) find that fluctuations in dividend payments, term premium and default premium have more impact on the returns of equal weighted portfolios in relation to returns on value weighted portfolios where more weight is put on large firms. The Carhart alphas also show the same pattern. Because of mixed evidence for equal and value-weighted decile portfolios, it is concluded that realized volatility is not a good or accurate measure of next week's returns. Thus *H1* is rejected.

The time series mean values of weekly returns for deciles ranked on realized skewness are reported in Table 2, Panel B. The weekly value weighted and equal weighted returns reveal an increasing pattern. The value weighted return for decile 1 is – 0.825 bps and the equal weighted return for decile 1 is -0.782 bps, however for decile 10, the value weighted return is 0.834 and the equal weighted return is 1.187. The weekly spread between high and low deciles is 1.659 for value weighted returns and 1.969 for equal weighted returns. Both spreads are at 1% level of significance. The higher value of equal weighted return spread suggests that the relation between realized skewness and next week's returns is greater for small companies. The interesting point to note is, all values reported for realized skewness across most deciles including Carhart Alphas are statistically significant. The long short Alphas are 1.660 bps and 1.935 bps for value and equal weighted deciles respectively. Table 2 also reports the return difference between decile 9 and 2 and between decile 8 and 3. Thus, there is a strong evidence of realized skewness in predicting future stock returns in the cross section and hypothesis *H2* is accepted.

The time series mean values of weekly returns for deciles ranked on realized kurtosis are reported in Table 2, Panel C. The long short spreads and values for Carhart Alphas are significant for both value and equal weighted portfolios. So, it means that in the Pakistani emerging market, realized kurtosis of weekly returns is a good predictor of expected returns and *H3* is accepted. Chaudhary *et al.* (2020) provide similar evidence for existence of risk premium for skewness and kurtosis in the Indian stock market. Wu *et al.* (2020) use the Real EGARCH-SK model to forecast the VaR for Chinese stock market that accounts for time varying higher moments and suggest the extension of this model by incorporating realized skewness and kurtosis.

Table 1

Characteristics of Portfolios sorted by Realized Moments

Panel A: Characteristics of Portfolios sorted by Realized Volatility

Deciles	1	2	3	4	5	6	7	8	9	10
Realized volatility	0.199	0.357	0.454	0.539	0.627	0.723	0.831	0.963	1.161	1.744
Realized skewness	0.057	0.137	0.153	0.162	0.194	0.177	0.278	0.326	0.343	0.221
Realized kurtosis	16.157	16.348	16.293	16.681	16.903	17.786	18.498	19.752	21.416	23.344
Size	81.789	73.121	52.42	35.954	26.159	19.996	14.489	10.442	8.201	5.582
BE/ME	0.711	0.731	0.790	0.791	0.792	0.826	0.862	0.895	0.833	1.037
Historical skewness	0.02	0.018	0.021	0.022	0.024	0.026	0.027	0.03	0.032	0.041
Market beta	0.872	0.927	0.936	0.939	0.955	0.957	0.963	0.945	0.921	0.863
Lagged return	-0.004	-0.002	-0.0016	-0.001	-0.001	-0.0003	0.0026	0.0043	0.0078	0.0146
Idiosyncratic volatility	0.018	0.016	0.018	0.019	0.021	0.022	0.024	0.026	0.029	0.037
Co-skewness	0.017	0.019	-0.002	0.009	-0.02	-0.044	-0.036	-0.062	-0.058	-0.036
Co-kurtosis	0.131	0.192	0.274	0.453	0.845	0.373	0.77	0.496	0.257	-0.598
Maximum return	-0.0048	-0.0034	-0.0022	-0.0032	-0.0015	0.0002	0.0011	0.0041	0.0077	0.0149
Illiquidity	2.06	2.097	4.034	9.585	8.495	7.892	7.395	21.482	38.002	223.117
Price	215.617	175.806	144.816	132.188	128.015	112.563	123.736	123.136	130.017	103.048
Number of stocks	30	31	30	31	30	31	30	31	30	30

Panel B: Characteristics of Portfolios sorted by Realized Skewness

Deciles	1	2	3	4	5	6	7	8	9	10
Realized skewness	-2.988	-1.093	-0.503	-0.141	0.135	0.384	0.633	0.942	1.462	3.202
Realized volatility	0.727	0.800	0.753	0.747	0.739	0.750	0.768	0.756	0.770	0.804
Realized kurtosis	33.89	21.024	16.347	13.851	12.502	12.03	12.371	14.089	18.785	31.592
Size	13.412	22.788	28.851	33.328	34.026	35.347	33.144	29.531	24.536	15.086
BE/ME	1.028	0.943	0.804	0.801	0.860	0.826	0.804	0.819	0.784	0.936
Historical skewness	0.028	0.026	0.025	0.024	0.024	0.024	0.025	0.026	0.027	0.029
Market beta	0.676	0.831	0.927	0.994	1.031	1.05	1.06	1.017	0.934	0.753
Lagged return	0.002	0.002	0.001	0.001	0.001	0.002	0.002	0.003	0.003	0.003
Idiosyncratic volatility	0.026	0.023	0.022	0.021	0.021	0.021	0.021	0.022	0.023	0.027
Co-skewness	-0.022	-0.018	-0.028	-0.023	-0.011	-0.023	-0.012	-0.008	-0.028	-0.019
Co-kurtosis	0.459	0.454	0.206	0.317	0.443	0.099	0.368	0.359	0.191	0.486
Maximum return	0.0012	0.0014	0.0005	0.0009	0.0015	0.0003	0.0016	0.0025	0.0026	0.0028
Illiquidity	34.954	10.48	10.335	13.717	10.157	6.237	13.784	14.84	25.6	92.49
Price	163.348	141.396	134.907	127.352	124.656	130.591	123.29	131.205	144.283	174.494
Number of stocks	30	31	30	31	30	31	30	31	30	30

Panel C: Characteristics of Portfolios sorted by Realized Kurtosis

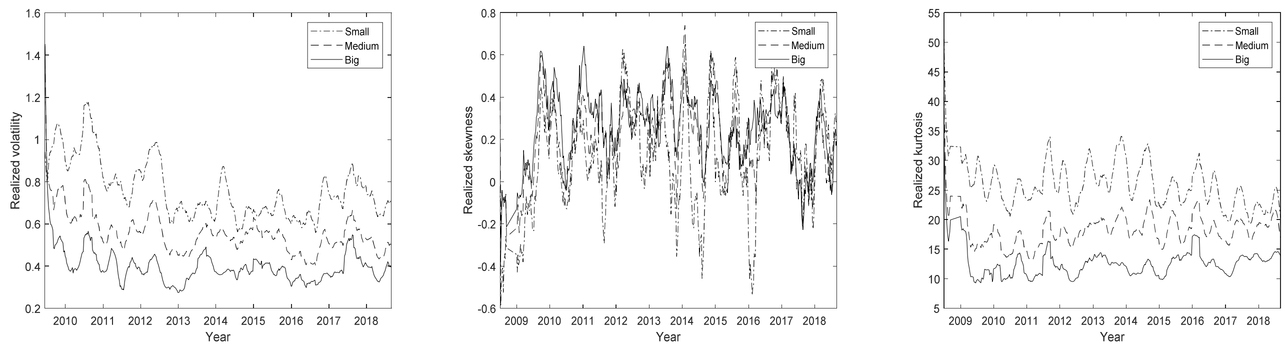
Deciles	1	2	3	4	5	6	7	8	9	10
Realized kurtosis	5.155	6.833	8.388	10.286	12.774	16.047	20.305	25.84	33.764	46.885
Realized volatility	0.696	0.709	0.754	0.749	0.813	0.825	0.855	0.855	0.802	0.692
Realized skewness	0.226	0.314	0.368	0.318	0.318	0.222	0.146	0.092	0.044	-0.004
Size	59.493	48.049	40.622	32.388	24.961	20.268	14.586	11.815	9.346	10.094
BE/ME	0.803	0.809	0.819	0.843	0.739	0.847	0.878	0.896	1.004	1.116
Historical skewness	0.024	0.024	0.025	0.025	0.025	0.025	0.026	0.027	0.027	0.029
Market Beta	1.252	1.197	1.134	1.062	0.974	0.89	0.81	0.727	0.656	0.556
Lagged return	0.003	0.004	0.003	0.004	0.003	0.003	0.002	0.002	0.001	-0.004
Idiosyncratic volatility	0.02	0.02	0.021	0.021	0.022	0.022	0.023	0.024	0.026	0.028
Co-skewness	0.0138	-0.0187	-0.0262	-0.0542	-0.0316	-0.0233	-0.0112	0.0066	0.0002	-0.0071
Co-kurtosis	0.02	-0.088	0.415	0.878	0.348	0.354	-0.022	0.593	0.502	0.495
Maximum return	0.002	0.003	0.002	0.004	0.002	0.003	0.001	0.002	-0.001	-0.003
Illiquidity	0.0107	0.0193	0.4326	0.2758	0.6024	0.7059	8.3299	26.6551	73.3305	123.3233
Price	91.454	104.023	110.368	123.591	146.844	153.661	158.56	161.538	159.859	183.886
Number of stocks	30	31	30	31	30	31	30	31	30	30

Note: Every week, stocks at Pakistan Stock Exchange (PSX) are sorted into deciles based on their realized moments and their equal weighted characteristics are calculated from July 1, 2008 to August 31, 2018. Panel-A reports average results for realized volatility, Panel-B for realized skewness and Panel-C for realized kurtosis. Average portfolio characteristics are also reported for size (in billions Rs.), book to market ratio, historical skewness (one month skewness from daily returns), market beta, lagged return, idiosyncratic volatility, co-skewness, co-kurtosis, maximum return (from the prior month), illiquidity (Amihud, 2002), stock price and number of stocks.

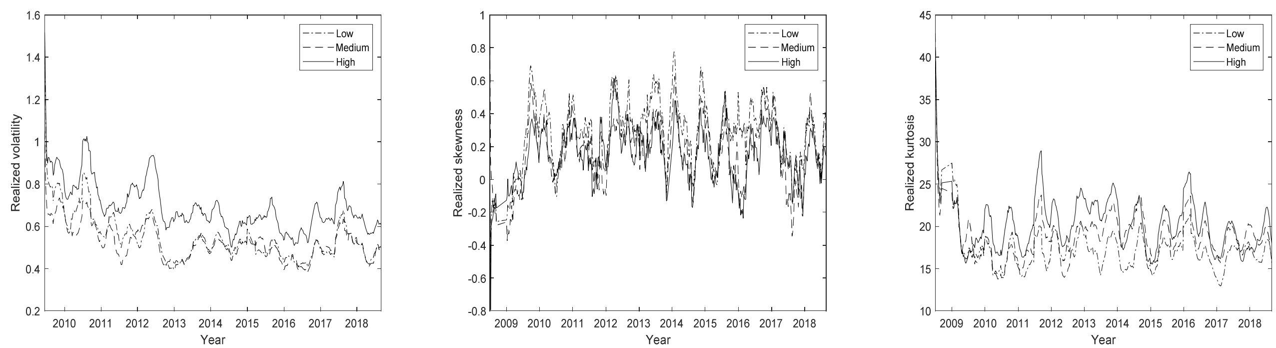
Figure 2

Three months moving averages of the terciles of realized moments, ranked by size, book to market ratio and market beta are reported. Panel A exhibits the low, medium and high groups based on size, Panel B based on book to market ratio and Panel C on market beta.

Panel A: Moments ranked on size



Panel B: Moments ranked on book to market



Panel C: Moments ranked on market beta

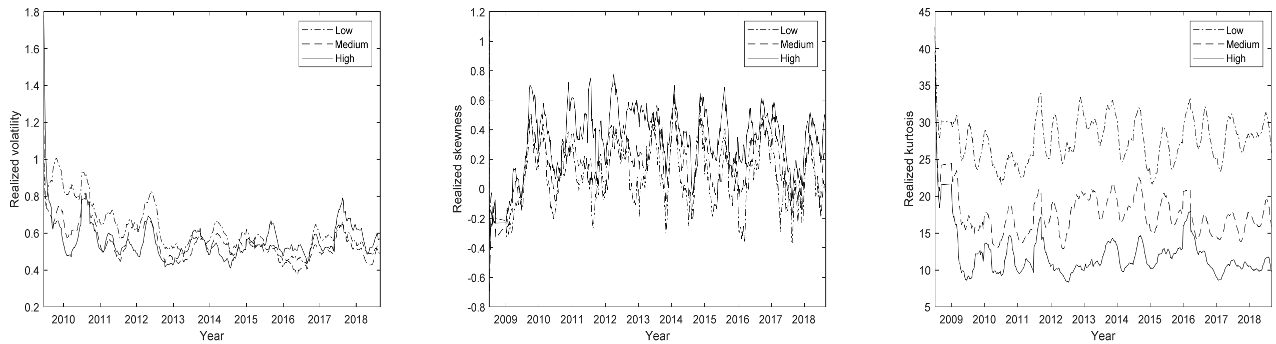


Table 2

Realized moments and the cross-section of stock returns

Panel A: Realized volatility and the cross-section of stock returns

	Low	2	3	4	5	6	7	8	9	High	High-low	9-2	8-3
						Value weighted							
Raw returns	-0.2552	-0.1752	-0.1266	-0.0245	-0.1121	-0.0465	-0.0116	-0.1235	-0.1212	-0.1888	0.0664	0.0541	0.0031
	(-1.963)	(-1.209)	(-0.861)	(-0.148)	(-0.670)	(-0.255)	(-0.065)	(-0.642)	(-0.580)	(-0.728)	(0.266)	(0.300)	(0.019)
Alpha, C4	-0.3209	-0.2651	-0.2318	-0.1389	-0.2334	-0.1727	-0.1215	-0.2537	-0.2536	-0.2870	0.0339	0.0116	-0.0220
	(-3.012)	(-2.461)	(-2.007)	(-1.120)	(-1.880)	(-1.168)	(-0.867)	(-1.615)	(-1.477)	(-1.239)	(0.139)	(0.065)	(-0.138)
						Equal weighted							
Raw returns	0.0939	-0.1477	-0.0818	-0.0110	-0.1456	-0.0639	0.0102	0.0023	0.0733	-0.3931	-0.4870	0.2210	0.0841
	(0.741)	(-1.143)	(-0.596)	(-0.073)	(-0.917)	(-0.391)	(0.060)	(0.013)	(0.368)	(-1.850)	(-2.789)	(1.520)	(0.754)
Alpha, C4	-0.0126	-0.2488	-0.2031	-0.1453	-0.2723	-0.2105	-0.1513	-0.1852	-0.1052	-0.5854	-0.5901	0.1436	0.0179
	(-0.128)	(-2.558)	(-2.006)	(-1.338)	(-2.303)	(-1.673)	(-1.185)	(-1.342)	(-0.674)	(-3.469)	(-3.587)	(1.055)	(0.168)

Panel B: Realized skewness and the cross-section of stock returns

						Value weighted							
Raw returns	-0.8255	-0.5830	-0.4562	-0.3757	0.0576	-0.0617	0.0071	0.0494	0.2970	0.8338	1.6593	0.8800	0.5056
	(-5.106)	(-3.526)	(-2.898)	(-2.371)	(0.350)	(-0.378)	(0.045)	(0.293)	(1.819)	(4.170)	(7.920)	(6.016)	(3.789)
Alpha, C4	-0.9177	-0.6827	-0.5486	-0.5058	-0.0630	-0.1861	-0.0949	-0.0476	0.2083	0.7426	1.6602	0.8909	0.5010
	(-6.428)	(-4.959)	(-4.8060)	(-4.340)	(-0.526)	(-1.557)	(-0.802)	(-0.391)	(1.710)	(4.282)	(7.9103)	(6.163)	(3.821)
						Equal weighted							
Raw returns	-0.7823	-0.4258	-0.5026	-0.3026	-0.0463	-0.1656	-0.1139	0.0797	0.3302	1.1867	1.9689	0.7559	0.5823
	(-5.541)	(-2.694)	(-3.077)	(-1.967)	(-0.283)	(-0.971)	(-0.693)	(0.474)	(1.934)	(6.722)	(14.027)	(6.542)	(5.345)
Alpha, C4	-0.8925	-0.5667	-0.6339	-0.4472	-0.2015	-0.3421	-0.2569	-0.0840	0.1809	1.0425	1.935	0.7476	0.5499
	(-7.670)	(-4.477)	(-5.086)	(-3.888)	(-1.687)	(-2.799)	(-2.086)	(-0.695)	(1.400)	(7.205)	(14.011)	(6.497)	(5.102)

Panel C: Realized kurtosis and the cross-section of stock returns

	Low	2	3	4	5	6	7	8	9	High	High-low	9-2	8-3
						Value weighted							
Raw returns	-0.2023	-0.0286	-0.1581	-0.1624	-0.1059	-0.0906	0.0487	0.0665	0.0633	0.2243	0.4266	0.0919	0.2246
	(-1.340)	(-0.1793)	(-0.999)	(-0.964)	(-0.630)	(-0.547)	(0.272)	(0.387)	(0.392)	(1.287)	(2.079)	(0.558)	(1.586)
Alpha, C4	-0.3193	-0.1274	-0.2638	-0.3048	-0.2365	-0.1771	-0.0446	-0.0030	-0.0098	0.1500	0.4693	0.1176	0.2608
	(-2.978)	(-1.186)	(-2.441)	(-2.517)	(-1.875)	(-1.400)	(-0.299)	(-0.021)	(-0.070)	(0.9070)	(2.351)	(0.751)	(1.876)
						Equal weighted							
Raw returns	-0.3224	-0.1722	-0.2194	-0.0911	-0.1619	-0.1310	-0.0291	0.0929	-0.0304	0.3417	0.6641	0.1418	0.3122
	(-1.824)	(-0.994)	(-1.278)	(-0.530)	(-0.981)	(-0.791)	(-0.184)	(0.587)	(-0.199)	(2.247)	(4.049)	(1.035)	(2.520)
Alpha, C4	-0.4823	-0.3407	-0.3814	-0.2552	-0.2991	-0.2926	-0.1708	-0.0516	-0.1850	0.2341	0.7164	0.1557	0.3405
	(-3.797)	(-2.801)	(-3.088)	(-2.060)	(-2.397)	(-2.291)	(-1.343)	(-0.399)	(-1.558)	(1.815)	(4.631)	(1.209)	(2.809)

Note: Value and equal weighted weekly returns (in bps) with their t-statistics (in parentheses) of decile portfolios are reported, constructed on the basis of realized moments. The spread between high and low decile, 9 and 2 and 8 and 3 is reported based on data of listed firms at Pakistan Stock Exchange (PSX) from July 2008 to August 2018.

Table 3

Realized moments and returns for different subsamples

Panel A: Realized volatility effects for different subsamples

			Value weighted raw returns								
	Low	2	3	4	5	6	7	8	9	High	High-low
1st	-0.247	-0.3979	-0.2577	-0.0723	-0.2236	-0.0997	0.066	-0.166	-0.0215	-0.3821	-0.1351
	(-1.149)	(-1.695)	(-1.145)	(-0.283)	(-0.862)	(-0.369)	(0.252)	(-0.565)	(-0.068)	(-0.9)	(-0.331)
2nd	-0.2634	0.0474	0.0045	0.0233	-0.0005	0.0067	-0.0892	-0.081	-0.2208	0.0046	0.2679
	(-1.794)	(0.28)	(0.023)	(0.111)	(-0.002)	(0.027)	(-0.372)	(-0.325)	(-0.802)	(0.015)	(0.933)
			Equal weighted raw returns								
	Low	2	3	4	5	6	7	8	9	High	High-low
1st	0.0357	-0.3567	-0.2536	-0.1487	-0.3717	-0.2027	-0.084	-0.0352	-0.1019	-0.561	-0.6495
	(0.177)	(-1.747)	(-1.237)	(-0.66)	(-1.534)	(-0.836)	(-0.336)	(-0.129)	(-0.339)	(-1.765)	(-2.382)
2nd	0.1521	0.0614	0.09	0.1268	0.0806	0.0749	0.1045	0.0398	0.2485	-0.2252	-0.3773
	(0.993)	(0.389)	(0.493)	(0.645)	(0.394)	(0.341)	(0.448)	(0.163)	(0.948)	(-0.802)	(-1.785)

Panel B: Realized skewness effects for different subsamples

			Value-weighted raw returns								
	Low	2	3	4	5	6	7	8	9	High	High-low
1st	-0.9065	-0.7378	-0.5223	-0.6242	0.2417	-0.0242	-0.156	0.0851	0.0004	0.805	1.7115
	(-3.7)	(-2.764)	(-2.052)	(-2.496)	(0.922)	(-0.093)	(-0.635)	(0.319)	(0.001)	(2.415)	(5.199)
2nd	-0.7445	-0.4283	-0.3901	-0.1271	-0.1266	-0.0992	0.1702	0.0136	0.5935	0.8625	1.6071
	(-3.522)	(-2.192)	(-2.1)	(-0.655)	(-0.638)	(-0.504)	(0.875)	(0.066)	(3.011)	(3.893)	(6.183)
			Equal-weighted raw returns								
	Low	2	3	4	5	6	7	8	9	High	High-low
1st	-0.9429	-0.5512	-0.5551	-0.4469	0.0351	-0.1921	-0.384	-0.092	0.0132	1.0153	1.9581
	(-4.282)	(-2.305)	(-2.26)	(-1.939)	(0.144)	(-0.742)	(-1.559)	(-0.361)	(0.05)	(3.681)	(8.537)
2nd	-0.6217	-0.3004	-0.4501	-0.1583	-0.1277	-0.1392	0.1562	0.2514	0.6471	1.3581	1.9797
	(-3.521)	(-1.453)	(-2.085)	(-0.776)	(-0.586)	(-0.624)	(0.721)	(1.144)	(3.033)	(6.159)	(12.195)

Panel C: Realized kurtosis effects for different subsamples

			Value-weighted raw returns								
	Low	2	3	4	5	6	7	8	9	High	High-low
1st	-0.3096	0.0057	-0.0866	-0.3245	-0.2936	-0.0757	-0.0555	0.0715	-0.0618	0.4145	0.724
	(-1.293)	(0.023)	(-0.348)	(-1.203)	(-1.119)	(-0.276)	(-0.185)	(0.263)	(-0.253)	(1.532)	(2.266)
2nd	-0.0951	-0.0629	-0.2296	-0.0002	0.0818	-0.1055	0.153	0.0615	0.1884	0.0342	0.1292
	(-1.516)	(-0.314)	(-1.173)	(-0.001)	(0.389)	(-0.566)	(0.777)	(0.292)	(0.89)	(1.155)	(1.963)
			Equal-weighted raw returns								
	Low	2	3	4	5	6	7	8	9	High	High-low
1st	-0.5908	-0.2968	-0.2736	-0.1879	-0.4096	-0.3157	-0.1486	0.0274	-0.125	0.2476	0.8384
	(-2.245)	(-1.16)	(-1.073)	(-0.72)	(-1.711)	(-1.236)	(-0.623)	(0.111)	(-0.507)	(1.052)	(3.245)
2nd	-0.0541	-0.0475	-0.1652	0.0058	0.0857	0.0536	0.0903	0.1583	0.0642	0.4357	0.4899
	(-0.23)	(-0.203)	(-0.717)	(0.026)	(0.378)	(0.254)	(0.433)	(0.798)	(0.353)	(2.261)	(2.424)

Note: Value and equal weighted weekly returns (in bps) of decile portfolios (ranked on realized moments) and their t-statistics (in parentheses) are reported for two equal sub samples, 1st sample spans 1 July 2008 till 31 July 2013 and 2nd sample spans 1 August. 2013 till 31 Aug. 2018 based on data of listed firms at Pakistan Stock Exchange (PSX). The spread between high and low decile portfolio is also reported.

Robustness Analysis

To check if the results for realized moments are consistent across different sub samples, data is divided into two equal parts. The 1st sample comprises of data from 1 July 2008 till 31 July 2013 and 2nd sample comprises of data from 1 August 2013 till 31 August 2018. The value and equal weighted weekly raw returns (in bps) of portfolios constructed on the basis of realized volatility, realized skewness and realized kurtosis for the two sub samples are reported in Panels A, B and C of Table 3 respectively. The long short value weighted return based on realized volatility for 1st sub sample reverses sign but still insignificant as shown in Panel A of Table 3. Though, the long short equal weighted returns maintain the same positive signs but are marginally significant. The results for realized skewness are consistent with Table 2, positive long short returns for both value and equal weighted portfolios at 1 percent level of significance as presented in Panel B of Table 3. There's no effect on magnitude but slight decrease is observed in their significance. Similarly, the results for long short returns based on realized kurtosis are still positive but less significant as shown in Panel C of Table 3. Thus the cross sectional relationship between realized skewness and kurtosis and future stock returns is robust.

4. Conclusion

This research analyzes the cross sectional properties of realized higher moments' estimates, relying on methodology introduced by Amaya *et al.* (2015). Firm level tick by tick data from July 1st, 2008 to August 31st, 2018 is used to construct weekly realized moments and based on these measures, value and equal weighted decile portfolios are formed. Equal weighted characteristics of well documented determinants of stock returns are also reported to show that the role of realized moments in stock return predictability is not a manifestation of already identified factors. It is evidenced that firms with higher realized volatility are small distressed firms, having low and negative coskewness with the market and have low stock prices depicting low required rate of return by the investors (e.g., Luu Duc and Nguyen, 2018). The observed pattern for highly right or left skewed firms insinuates that such firms are small and illiquid and receive extreme returns (either positive or negative) from market ups and downs. The large kurtosis values for small firms having low beta suggest higher profit for holding low beta stocks (e.g., Bekaert *et al.,* 1998).

The relationship between realized moments of stocks and their future returns is further investigated in the cross section. It is found that realized volatility has a significant relation with subsequent week's stock return only for equal weighted decile portfolios. A reliable and highly significant relationship is found between realized skewness and subsequent week's cross sectional stock returns. Positive and significant relationship is found between realized kurtosis and the subsequent week's cross sectional stock returns. The robustness tests further supports the evidence found for predictability power of realized skewness and kurtosis in this study for the whole sample and the two sub samples. However, realized skewness emerges as the most robust measure to predict the cross sectional future stock returns.

Many researchers report negative relationship between realized skewness and future stock returns (e.g., Barberis and Huang, 2008; Conrad *et al.,* 2013) and some find that the relation is positive (e.g., Rehman and Vilkov, 2012; Bali *et al.,* 2014), this study finds highly significant evidence of a positive relation between realized skewness and expected stock returns using zero investment strategy, which buys stocks in the highest decile portfolio and sells stocks in the lowest decile portfolio. Thus, the evidence suggests that the investors should take a short position in decile1 with low (negative) realized skewness and take a long position in decile10 with the high (positive) realized skewness to earn positive returns. These results are consistent with Choi and Lee (2014) who find strong positive relation between realized skewness and future stock returns after incorporating the role of information. This study contributes to finance literature by finding a positive relation of realized skewness with expected stock returns within the context of emerging stock market of Pakistan portraying greater possibility of making abnormal returns. Iqbal (2012) asserts that Pakistani stock market tends to be extremely volatile due to noisy market makers and speculators. However, on a positive side, investors are compensated by yielding enormous profits for exposure to high market volatility. The primary motivation behind working on Pakistan stock market data is the lack of empirical researches that have checked multifactor asset pricing models in the past. Existing literature provides evidence about non-normality of asset returns in emerging markets because of the presence of skewness and kurtosis. Since Pakistan stock market is an emerging market, incorporating higher moments is beneficial for risk-return analysis.

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