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The Effect of Kurtosis on the Cross-Section of Stock Returns

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by

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Abstract

In this study, I show an effect of the statistical fourth moment on stock returns. In the mean–variance framework, rational investors follow two strategies: optimize the mean–variance of return and diversify the portfolio. Regarding the first approach, investors intend to generate the maximum level of return while facing a constant level of risk (or, the standard deviation) of return. It is possible that firm specific risk can be concentrated in the portfolio. However, diversification of the assets can eliminate that (idiosyncratic) risk from the portfolio. After a long period of time, in a diversified portfolio the shape of the return distribution appears to be peaked around the average value of the return compared with that of the typical shape of the return distribution. If investors have a preference for skewness in their returns, they also can produce peakedness in the shape of the distribution. The statistical fourth moment (kurtosis) measures the magnitude of peakedness of the distribution. As the kurtosis of the distribution increases the distribution will appear more peaked. I find evidence that kurtosis positively and significantly predicts future stock returns over the period 1981–2011. The effect remains after controlling for other factors in multivariate regressions.

Introduction

A number of studies state that investors who are undiversified commonly hold a few numbers of assets that result in failure to eliminate idiosyncratic risk (see Kelly, 1995; and Goetzmannand and Kumar, 2004). Under standard portfolio theory, those investors capture the same amount of expected returns as those who have a large number of assets. The former type of investors face higher risk than the latter type of investors. Mitton and Vorkink (2007) mention that if investors show under–diversification in their portfolios, they are likely to earn extreme positive returns while experiencing a high value of skewness. Conine and Tamarkin (1981) provide a similar argument in a different way–investors try to avoid diversification in their portfolios when investors realize they are earning extremely large returns. Therefore, in the mean–variance–skewness framework, investors with a preference for skewness may obtain an efficient portfolio.

However, in the mean–variance–skewness framework, stocks that provide extremely large returns ultimately result in portfolio returns that are positively skewed (i.e. skewed to the right). A very low probability is associated with the extreme return above the mean for a positively skewed distribution.

Stocks with positively skewed returns tend to be contemporaneously over-valued, but in future periods are under-valued. This situation results in a return distribution that experiences different risk levels through time.

In order to eliminate the effect of the riskier assets, investors may want to be diversified in their portfolios. They may choose low correlated assets, such as bonds. As a result of diversification returns become less volatile. Consequently, the shape of the return distribution is lower peaked than that of the typical diversified return distribution. The return distribution characterized by lower peakedness is called platykurtic.

Another effect of peakedness, leptokurtosis, is experienced when investors avoid large fluctuations among the individual asset returns in their portfolios. Under the Capital Asset Pricing Model (CAPM) investors expect high returns while facing a minimum level of risk over time. The common measure of risk is the standard deviation of returns. The return distribution that results when investors follow the diversification strategy for a long period of time, namely they minimize risk while facing a constant return, is characterized by high peakedness around the mean. The leptokurtic return distribution has higher peakedness around the mean than the typical return distribution.

I show empirically the significant effect of kurtosis on raw returns and abnormal excess returns with multiple regression analysis. I obtain abnormal excess returns on stocks employing the CAPM model (see Sharpe, 1964) as well as the Fama–French three-factor model (see Fama and French, 1992). I find that the effect of kurtosis on two extreme portfolios is both positive and significant over the period 1981–2011. Kurtosis has the same positive effect on the excess returns obtained from the CAPM.

I perform regression analysis of the return on stock i on lagged kurtosis, as well as the CAPM β, market capitalization ($size$), idiosyncratic volatility, price, and liquidity at time t. In my simple regression analysis, (model (1)), I measure the relation between returns and lagged kurtosis. In model (1), lagged kurtosis positively predicts future returns.

$$R_{i,t} = \alpha + k_{i,t-1} \tag{1}$$

In order to provide further evidence of the effect of kurtosis on future returns, I next conduct two different multiple regressions. First, I synthesize ideas contained in Fama (1970) and Jagedeesh and Titman (1993). Utilizing the method from Fama (1970), I initially consider that current returns and past returns are not independent. In other words, present returns already include all information contained in past returns. Following Fama's semi-strong form market efficiency tests, I assume that the lagged value of kurtosis also contains all publicly available information such as stock splits, financial statements, bond issues, price changes, and so forth. Thus, I add lagged kurtosis to the past return to predict future return in model (2).

$$R_{i,t} = \alpha + R_{i,t-1} + k_{i,t-1} \tag{2}$$

In model (2) I provide evidence that past returns ($R_{i,t-1}$) have a negative effect on current returns ($R_{i,t}$) in the presence of lagged kurtosis ($k_{i,t-1}$), while kurtosis has a positive effect. I interpret the positive coefficient on kurtosis as follows: past publicly available information (good news or bad news) related to stock i predicts (positive or negative) current returns in the model.

Second, I consider additional explanatory variables, namely the stock price ($\log(price)$), β, idiosyncratic volatility (σ), market capitalization ($size$) and a liquidity proxy (liq), in order to examine the effect of kurtosis on returns while controlling for those explanatory variables. The following model (3) predicts future return on stock i at time t with the explanatory variables.

$$R_{i,t} = \alpha + k_{i,t-1} + log(price_{i,t-1}) + size_{i,t} + \beta_{i,t} + \sigma_{i,t} + liq_{i,t-1} \tag{3}$$

The variable *size* determines the market capital of the stock over the period of 1981–2011 in the model (3). The data show that the average market capitalization would be categorized as small cap (refer to Table 1). Acharaya and Pedersen (2005) explicitly show the effect of liquidity risk on an asset pricing model. In addition, Amihud (2002) shows that an illiquidity premium has positive predictive ability on returns. In model (3), I include a variable (liq) that measures the amount of liquidity in the market over the period of 1981 to 2011. In my analysis, I proxy the illiquidity premium with liq. My analysis in model (3), confirms the results in Amihud (2002) providing evidence of a negative effect of $liq_{i,t-1}$ on $R_{i,t}$ while controlling for $k_{i,t-1}$.

I include additional variables of risk measurement, such as β and idiosyncratic volatility to measure the effect on returns while also controlling for the effect of lagged kurtosis in model (3). I find the $\beta_{i,t}$ obtained with the

CAPM model is marginally but positively significant. This marginally significant value of β may be explained by Banz's (1981) argument: "The CAPM has been misspecifiecd." Banz proposed the size effect as an additional variable to the market–risk premium (see Banz, 1981). In my study, I implement his idea by including another risk variable, kurtosis.

The rest of the paper is organized as follows. In section 1, I describe the empirical methodology and stock characteristics. I include the univariate analysis in section 2, in which I discuss the nature of portfolio returns and a correlation study of the stock variables. Next, I provide regression results in section 3. Finally, I conclude the paper in section 4. In appendix section, I provide the tables containing my results.

1 Empirical methodology

In 1964, Sharpe proposed the capital asset pricing model (CAPM) as a model to explain asset returns (see Sharpe, 1964). In CAPM only one variable, market return, was used to predict the return on an individual stock. In addition, the return on the stock as well as the market are adjusted by the risk free rate, $R_{f,t}$, and at time t the CAPM model produces a β coefficient. It quantifies the level of risk of an individual stock i compared to that of the whole market. Fama and French (1992) presented a new capital asset pricing model. They considered two additional factors, market capitalization and the book–to–market ratio, with the adjusted market return in the CAPM model. In the model (5), those two additional factors are small–minus–big market capitalization (SMB) and high book–to–market minus low book–to–market (HML), respectively. Model (5) is commonly known as Fama–French three-factor model. These two models are presented as follows:

$$R_{i,t} - R_{f,t} = \alpha_{CAPM} + \beta_{i,t}(R_{m,t} - R_{f,t}) + \epsilon_{i,t} \tag{4}$$

$$R_{i,t} - R_{f,t} = \alpha_{3-factor} + \beta_{i,t}(R_{m,t} - R_{f,t}) + b_s(SMB) + b_v HML + U_{i,t} \tag{5}$$

I employ the above two models to obtain the two types of abnormal excess returns for any given year t due to holding risky assets. In model (4), the excess return on stock i is denoted by α_{CAPM}. In model (5), the excess return is denoted by $\alpha_{3-factor}$. Referring to Table 1, the average negative value of -0.348 excess return explicitly shows that the Fama–French three–factor model suggests underperformance of 34.8% with the 31-year stock data. With same data set, in contrast, an average of 0.003 is the excess return (α_{CAPM}) that is estimated by the CAPM model.

1.1 Stock characteristics

The detail descriptions of stock characteristics are given below. I present summary statistics of the stock characteristics in Table 1.

1.1.1 Kurtosis(k)

The measurement of kurtosis is measured by the 4^{th} moment of each stock i at year t divided by variance of that stock i. The general formula of it is

$$k_{i,t} = \frac{\sum_{i=1}^{242473} \sum_{t=1}^{31} (R_{i,t} - \overline{R_{i,t}})^4}{(\sum_{i=1}^{242473} \sum_{t=1}^{31} (R_{i,t} - \overline{R_{i,t}})^2)^2} \quad (6)$$

I use lagged kurtosis $k_{i,t-1}$ of return as a predictor of return on stock i. Table 1 shows a summary of statistics of average stock characteristics. It shows that the average kurtosis is 7.69 with a standard deviation of 15.26 for the aggregated stocks across the period of 1981–2011. A high average value of kurtosis compared with a standard cut-off point of 3 supports that returns have high peakedness around the average returns of 12%. Kurtosis values bigger than 3 are called leptokurtic. The leptokurtic return is typically present, when investors have an inclination to avoid large return resulting in high variation in their portfolios. The data also show that kurtosis has a high value of standard deviation.

1.1.2 Risk variable(β)

Model (4) includes the risk variable, $\beta_{i,t}$ calculated as follows. Ranking the stocks at each year, the CAPM model is employed on the adjusted return with risk free rate $R_{f,t}$. In model (4) the $\beta_{i,t}$ is the slope of the adjusted market return ($R_{m,t}$-$R_{f,t}$). The slope (β) is estimated as the ratio of covariance between the return on individual stock i and the market return to the variance of the market return. Looking at Table 1, the 31–year data suggests that the average is 1.006 with standard deviation of 6.11. I interpret the β of 1.006 to mean that the movement of the stock and the underlying index (S&P 500) is approximately the same.

1.1.3 Size

The measurement of $size_{i,t}$ for stock i at year t is the number of outstanding shares of stock i multiplied by log(price). The general formula is $size_{i,t}$ =

$share_{i,t} \times log(price_{i,t})$. Table 1 shows the average size is about \$134 m with standard deviation of \$745 m. Across the period from 1981 to 2011, the average market capitalization appears to be small cap. Generally speaking, the smaller the market capitalization, the riskier the investment is and the greater the return may be. Hence, for the small market capital the data demonstrate that partial correlation between β and return is 0.02115 and partial correlation between return and kurtosis is 0.0086. These correlations are statistically significant (referring to Table 4). Interestingly, the correlation matrix presented in Table 4 shows size and β are independent. In other words, the risk of an asset is not a determinant of market capital, or vice-versa. I propose here that the degree of kurtosis can be a proxy for identifying the riskiness of an asset. Small market cap stocks have low variation in return which lead a high value of kurtosis that eventually gives a high return.

1.1.4 Idiosyncratic volatility(σ)

The idiosyncratic volatility is included in model (4). The CAPM model (4) provides the residual of each stock i at year t, and it is obtained by taking the difference between actual return and the expected return of stock i. Mathematically, it can be presented as,

$$\epsilon_{i,t} = R_{i,t} - E(R_{i,t}) = \beta_{i,t}(R_{m,t} - E(R_{m,t})) \quad (7)$$

Equation (7) is the idiosyncratic risk of the CAPM model (4). Standard deviation measures the degree of idiosyncratic volatility, σ of each stock i at year t. Sharpe pointed out that the effect of the idiosyncratic risk will disappear with diversification of the assets. Under the situation of arbitrage, Ross (1976) explained the influence of that risk when we have a large number of assets in a portfolio.

1.1.5 Additional variables

Liquidity (liq) is calculated by the volume of share i traded as total number of share listed on year t. I use another variable, $log(price_{i,t})$, to predict market return on stock i at year t. In Table 1, the data suggest that across the period 1981–2011, the average value of liquidity at year t and $log(price_{i,t})$ is \$14.863m and \$2.169m, respectively.

2 Univariate analysis

2.1 Portfolio analysis

I divide returns and excess returns on stocks into four equal portfolios. The lagged kurtosis (k_{t-1}) serves as an instrument and the quantile distribution of it is implemented to rank four portfolios. Literally, the quantile probability assigns equal weight of 0.25 to each of the portfolios. Therefore, the 1^{st} portfolio contains raw returns, as well as excess returns measured by the α_{CAPM} and $\alpha_{3-factor}$ on stocks below 25% of the values of k_{t-1}, whereas the 4^{th} portfolio has raw returns, α_{CAPM} and $\alpha_{3-factor}$ above 75% of the values of k_{t-1}. I define those portfolios in the analysis as the extreme portfolios.

The significant difference of returns of the two extreme portfolios is determined by the t-statistic. The t-statistic is obtained from a statistical hypothesis test that assumes the return is same in the two portfolios. Similarly, regarding excess return on stock i, it presumes same hypothesis of the portfolios. For example, excess return measured by the α_{CAPM} is same in the two portfolios. Table 2 and 3 report the standard errors of the t statistics, including the difference of return of the two portfolios.

I extend the same analysis described above for each year starting from 1981. Table 3 contains the results of those analyses. In the analysis and illustration to come, I specify that if the differences of returns are negative, it indicates returns on stocks of the 4^{th} portfolio are higher compared to those of the 1^{st} portfolio across the years.

In Table 2, it is evident that the difference of return in the two extreme portfolios is negative across the 31-year period. Similarly, across all time periods, one of the excess return measurements, α_{CAPM} is negative. The standard errors associated with all of the differences reported in Table 2 are very low. Thus, it leads to a general conclusion that the distribution of return (for both α_{CAPM} and $\alpha_{3-factor}$ respectively) is significantly different in the two extreme portfolios. In case of the difference of return on stock, the negative value of -0.0233 exposes that market has a high expected return on stock in the 4^{th} portfolio. For example, if an investor prefers kurtosis of return and he constructs his portfolios based on kurtosis, then on average he will gain 2% more return on each stock from the 4^{th} portfolio than from the 1^{st} portfolio. In Table 2 the significant difference of excess return (for either model (4) or (5)) shows that across the period of 1981–2011 the overall market generates abnormal excess returns.

Looking at Table 3 for the recent time period (especially from 2000 to 2009) the returns on stocks in the 4^{th} portfolio are statistically different than those of the 1^{st} portfolio. In terms of excess returns such as α_{CAPM} and $\alpha_{3-factor}$, they vary year to year.

2.2 Correlation analysis

The correlation results presented in Table 4 show that return depend on the lagged kurtosis. The significant and positive correlation of 0.0086 between them implies that a high lagged kurtosis is positively associated with stock return. Stock return is positively associated with β, $size$, liq and $price$. Their degrees of correlations are also statistically significant. The significant association of 0.0124 between return and market capitalization signifies that size can predict return.

Firm specific risk (σ) and β also predict return. In the Table 4, the positive association of 0.0212 between β and return suggests that return is sensitive to change in its risk compared to market risk. According to Zang et al (2006, 2009) returns are negatively correlated with idiosyncratic volatility (or firm specific risk). From the Table 4, the negative correlation between return and firm specific risk of -0.01966 indicates that the return is negatively associated with the firm specific risk. This negative association can be explained when the firm becomes riskier than the overall market, return related to that firm falls. Although the idiosyncratic risk has a negative association with return, in the correlation study it has a positive association with lagged kurtosis. The positive association of 0.06009 between idiosyncratic volatility and lagged kurtosis indicates lower volatility leads to the leptokurtic shape in return. The leptokurtic return at present period may lead to gains in return in future. Hence, I propose that idiosyncratic volatility is a confounding factor. After removing the effect of idiosyncratic volatility my analysis provides the significant and positive partial correlation between kurtosis and return of about 0.07443. This value of partial correlation is seven times higher than that of the pearson correlation of kurtosis and return reported in Table 4.

According to Table 4 the correlation of return with $price$ and $size$, respectively, is significant and positive. On the other hand, between $price$ and lagged kurtosis (k_{t-1}) the negative association of -0.15893 indicates a high peakedness at present year may lower the future price of the stock. Additionally, from the definition of kurtosis (equation (1)) leptokurtic return in portfolio is a result of a low variation in return. This idea of low variation in return satisfies the diversification performance of an investor by constructing a portfolio with low correlated assets to increase the sharpe ratio.

The negative correlation of -0.0397 between lagged kurtosis and *size* from the correlation matrix presented in Table 4 indicates that past leptokurtic return determines the small capitalization at the present time. The data state a positive association of 0.0124 between *size* and return. In contrast *size* negatively associates with σ.

In correlation Table 4, I also report the association of the abnormal excess returns (α_{CAPM} and $\alpha_{3-factor}$) with the stock variables. Surprisingly, the $\alpha_{3-factor}$ does not show statistical association with lagged kurtosis. But, the α_{CAPM} provides positive and significant association of 0.00954 with lagged kurtosis. Both of the excess returns negatively and significantly associate with the β.

3 Regression analysis

The regression results presented in Table 5 support the idea that the lagged kurtosis has a positive predictive ability on current return. Referring to Table 5 from panel A and B, for the two models (1) and (2) the intercept (α) of 0.1223 suggests that over the period of 1981–2011 market generates a positive excess return of 12%. In both panels A and B, the positive slope of lagged kurtosis(k_{t-1}) evidences that the current return is positively associated with the past kurtosis. The interpretation for panels A and B is that each unit increment of lagged kurtosis results in increasing return by 0.04%. In panel B I find a momentum effect between lagged return (R_{t-1}) and current return (R_t). This effect is negative. Therefore, based on the estimated value of -0.05169, one unit increment of the lagged return will decrease the current return by 5%.

Results of model (3) are presented in panel C of Table 5. The negative intercept of -0.5226 indicates that stocks do not generate positive excess returns. Instead, they produce high negative abnormal return of 52%. Stock returns at period t show under performance when including all factors: lagged kurtosis, β, σ, *size*, *price*, and *liq*. Controlling with those factors, the multiple regression provides positive and significant coefficient of 0.0027 for the lagged kurtosis. The lagged kurtosis positively and significantly predicts future stock return. This suggests that kurtosis may have sufficient power for predicting stock return.

The negative slope of -2.997E-8 for size in model (3) indicates that the market has small capital at present time. Moreover, with a small standard error of 1.727E-9 it suggests that smaller captial stcoks have a statistical effect on achieving large return. In terms of liquidity, from Table 5, model (3) provides a negative and significant estimate. The negative estimate of -0.00014 describes that the illiquid stock i at time t-1 generates about 0.014% of return at time t. The result of the liquidity proxy is in the line with the finding of Amihud (2002), in which he showed current return is positively related to the past illiquidity premium.

Regarding the two risk measurement components, β and σ, I find they have a positive effect on return at period t. A high positive estimate of σ of 5.15 indicates that high current stock return depends on firm specific volatility, estimated from the CAPM model. In addition, with each positive movement in volatility, the expected current return gains 51.5%. The β also provides a positive slope. However, the coefficient of 0.0016 and the standard error of 0.00021 show a marginaly significant effect in predicting stock return.

My next two regression analyses of models (1), (2) and (3) are with the excess returns, obtained from the CAPM model and the Fama–French three-factor model. In these regression studies, I consider α_{CAPM} and $\alpha_{3-factor}$, respectively, as my dependent variable without changing the independent variables in the models.

In Table 6, it is evident lagged kurtosis significantly predicts abnormal excess return (α_{CAPM}). In panels A to C,the estimate of kurtosis remains positive. From Table 6 panel C, the estimate of β is -0.042. The negative value of β explicitly states that the lower the systematic risk of stock i, the higher will be the abnormal excess return. The positive σ of 1.1803 asserts that the excess positive return also can be produced by a high firm specific error σ.

My regression study on $\alpha_{3-factor}$ is summarized in Table 7. In Table 7 lagged kurtosis is not strongly associated with the $\alpha_{3-factor}$. However, the estimates of it are positive in all panels. The regression results for the $\alpha_{3-factor}$ provide opposite results from the analysis of the return ($R_{i,t}$) and the α_{CAPM}. A possible explanation may be that employing the Fama-French three-factor model gives a negative value of the abnormal excess return from 1981 to 2011.

4 Conclusion

In a world where portfolios are exposed to the effect of kurtosis, regardless of the diversification of the assets, the CAPM beta (β) may not properly capture the risk of an asset. When macroeconomic variables are strongly related to changing the kurtosis of return, ignoring the effect of kurtosis one cannot obtain a precise risk estimator for predicting return. Indeed, kurtosis might be a fundamental factor for all financial securities and assets in predicting future returns.

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Appendix

Table 1: Summary statistics of the stock characteristics

	Mean	Standard deviation
Return (R)	0.1233	0.6259
α_{CAPM}	0.0034	0.3165
$\alpha_{3-factor}$	-0.0343	3.8630
kurtosis(k)	7.689	15.2566
β	1.006	6.1100
Market cap (size)	$134m	$745m
Idiosyncratic risk (σ)	0.0368	0.0326
Liquidity(liq)	$14.863m	$111.677m
Log(price)	$2.169m	$1.443m

Summary statistics of the stock characteristics described in section 1 are presneted. The value weighted stock return is directly observed from The Center for Research in Security Prices (CRSP) database from 1981 to 2011. R stands for stock return. The α_{CAPM} and the $\alpha_{3-factor}$ are the measurements of the excess returns, measured by the CAPM and the Fama–French three-factor model, respectively. k stands for kurtosis of return is calculated by $k_{i,t} = \frac{\sum_{i=1}^{242473}\sum_{t=1}^{31}(R_{i,t}-\overline{R_{i,t}})^4}{(\sum_{i=1}^{242473}\sum_{t=1}^{31}(R_{i,t}-\overline{R_{i,t}})^2)^2}$. The σ is an idiosyncratic volatility. The Beta (β) is the mesurement of risk reward on stock. σ and β are directly obtained from the CAPM model. Market capitalization (*size*) and liquidity (*liq*) are measured from data. $size$ = number of outstanding shares $\times$ log(price) and liq is measured by volume of outstanding shares at time t.

Table 2: Portfolio analysis with returns

	Mean difference	*Standard error*
Return	-0.0233 $**$	0.0039
α_{CAPM}	-0.0055 $**$	0.0014
$\alpha_{3-factor}$	0.0585 $**$	0.0235

$**$ represents 5% level of significance.
We make the 1^{st} and 4^{th} portfolios, respectively, based on the 25% and 75% quantile of lagged kurtosis. The negative value of the mean difference indicates that raw return, and α_{CAPM} are higher in the 4^{th} portfolio.

Table 3: Portfolio analysis of the returns by yearly

Year	*Return*	α_{CAPM}	$\alpha_{3-factor}$
1981	0.0762	-0.0003	-0.0006
	(0.0460)	(0.0056)	(0.0068)
1982	-0.1341**	-0.0193**	0.0036
	(0.0193)	(0.0045)	(0.0133)
1983	-0.0025	0.0032	0.0043
	(0.0164)	(0.0024)	(0.0030)
1984	0.0342	-0.0100	-0.0280
	(0.0185)	(0.0022)	(0.0054)
1985	0.0088	-0.0033	-0.0020
	(0.0213)	(0.0037)	(0.0058)
1986	-0.0202	-0.0006	-0.0053
	(0.0205)	(0.0025)	(0.0044)
1987	0.0275	-0.0058	-0.0080
	(0.0166)	(0.0171)	(0.0174)
1988	0.0719 **	0.0045	-0.0018
	(0.0179)	(0.0323)	(0.0229)
1989	-0.0179	-0.0004	-0.0007
	(0.0219)	(0.0071)	(0.0147)
1990	-0.1120	-0.0173	0.1463
	(0.0281)	(0.0088)	(0.2531)
1991	-0.432	-0.0202	-0.0027
	(0.0276)	(0.0071)	(0.0104)
1992	-0.0254	-0.0034	-0.0025
	(0.0196)	(0.0025)	(0.0031)
1993	-0.0067	-0.0014	-0.0012
	(0.0168)	(0.0022)	(0.0027)
1994	0.0270	-0.0011	-0.0065
	(0.0179)	(0.0053)	(0.0059)
1995	0.0212	0.0068	0.0027
	(0.0168)	(0.0026)	(0.0042)
1996	0.1068	0.0121	0.0033
	(0.0176)	(0.0023)	(0.0028)
1997	0.0294	-0.0109	-0.0266
	(0.0195)	(0.0242)	(0.0271)
1998	-0.1639**	-0.012	-0.0064
	(0.0267)	(0.0047)	(0.0067)
1999	0.1210**	0.0011	-0.0122**
	(0.0261)	(0.0041)	(0.0052)

Table 3 continued

Year	*Return*	α_{CAPM}	$\alpha_{3-factor}$
2000	-0.2026 **	-0.0353 **	1.534 **
	(0.0214)	(0.0045)	(0.5139)
2001	-0.0488 **	-0.0067	0.0806
	(0.0224)	(0.0066)	(0.3564)
2002	-0.1416 **	-0.0141 **	-0.0089
	(0.0299)	(0.0046)	(0.0055)
2003	-0.0530 **	0.0021	0.0077
	(0.0153)	(0.0031)	(0.0402)
2004	0.0721 **	0.0078 **	0.0116 **
	(0.0139)	(0.0015)	(0.0047)
2005	0.0296 **	0.0033 **	-0.0012
	(0.0127)	(0.0014)	(0.0023)
2006	0.0586**	0.0043	0.0046
	(0.0156)	(0.0018)	(0.0022)
2007	0.0621 **	0.0113 **	0.0144 **
	(0.0201)	(0.0025)	(0.0027)
2008	-0.2061 **	-0.0425 **	-0.0377 **
	(0.0268)	(0.0103)	(0.0107)
2009	-0.0222 **	-0.0053 **	-0.00677 **
	(0.0162)	(0.0019)	(0.0062)
2010	0.0686**	0.0043	0.0036
	(0.0256)	(0.0038)	(0.0012)
2011	0.0223	-0.0012	-0.0060
	(0.0158)	(0.0028)	(0.0039)

** represents 5% level of significance. Standard error is enclosed into parenthesis.

Table 4: Correlation Matrix

	β	σ	*log(price)*	k	*liq*	*size*
R	0.0212 $**$	-0.01966 $**$	0.2815 $**$	0.0086 $**$	0.003 $**$	0.0124 $**$
α_{CAPM}	-0.80401 $**$	0.02692 $**$	0.03853 $**$	0.00954 $**$	-0.0006	0.00201
$\alpha_{3-factor}$	-0.07308 $**$	-0.03878 $**$	0.02091 $**$	-0.00093	0.00073	0.00250
β		0.02875 $**$	-0.00378	-0.0085 $**$	0.0083 $**$	0.0015
σ		1	-0.63128	0.06009	0.0133	-0.09676
log(price)				-0.15893$**$	0.05725$**$	0.16375$**$
k					-0.0111 $**$	-0.0397 $**$
liq						0.007 $**$

The Pearson correlation coefficients are reported in Table 4. Based on the 5% level of test, the significant stock variable is identified by $**$.

Table 5: Regression analysis of raw return

Panel A $R_{i,t} = \alpha + k_{i,t-1}$

	Estimate	*Standard error*
Intercept	0.1223 **	0.00152
$k_{i,t-1}$	0.0004 **	0.00009

Panel B $R_{i,t} = \alpha + R_{i,t-1} + k_{i,t-1}$

	Estimate	*Standard error*
Intercept	0.1223**	0.00152
$R_{i,t-1}$	-0.05169**	0.00220
$k_{i,t-1}$	0.00047 **	0.000088

Panel C $R_{i,t} = \alpha + k_{i,t-1} + \log(\text{price}_{i,t-1}) + \text{size}_{i,t} + \beta_{i,t} + \sigma_{i,t} + \text{liq}_{i,t-1}$

	Estimate	*Standard error*
Intercept	-0.5226 **	0.0043
$k_{i,t-1}$	0.0027 **	0.00008
$log(price_{i,t-1})$	0.2036 **	0.0012
$size_{i,t}$	-2.997E-8 **	1.72E-9
$\beta_{i,t}$	0.0016 **	0.00021
$\sigma_{i,t}$	5.150 **	0.0518
$liq_{i,t-1}$	-0.00014 **	0.0000113

Panel A predicts current return on stock, $i = 1, 2, 3, \ldots, 242473$, on lagged kurtosis ($k_{t-1}$) of return at $t = 1, 2, 3, \ldots, 31$. Panel B predicts current return (R) at time t with lagged kurtosis and past return, R_{t-1}, on stock i. In Panel C, lagged kurtosis, *price*, market capitalization (*size*), idiosyncratic volatility (σ), β, and liquidity (*liq*) predcit return (R). 5% level of significant test is identified to determine significant regression estimates by **.

Table 6: Regression analysis of α_{CAPM}

Panel A $\alpha_{CAPM\,i,t} = \alpha + \mathrm{k}_{i,t-1}$

	Estimate	*Standard error*
Intercept	0.0019 **	0.00077
$k_{i,t-1}$	0.0002 **	0.000045

Panel B $\alpha_{CAPM\,i,t} = \alpha + \mathrm{R}_{i,t-1} + \mathrm{k}_{i,t-1}$

	Estimate	*Standard error*
Intercept	0.00275 **	0.00077
$\mathrm{R}_{i,t-1}$	-0.0085 **	0.00113
$k_{i,t-1}$	0.00022 **	0.000045

Panel C $\alpha_{CAPM\,i,t} = \alpha + \mathrm{k}_{i,t-1} + \log(\mathrm{price}_{i,t-1}) + \mathrm{size}_{i,t} + \beta_{i,t} + \sigma_{i,t} + \mathrm{liq}_{i,t-1}$

	Estimate	*Standard error*
Intercept	-0.0550 **	0.00136
$k_{i,t-1}$	0.0002 **	0.000027
log(price$_{i,t}$)	0.0254 **	0.00037
$size_{i,t}$	-1.367E-9 **	5.435E-10
$\beta_{i,t}$	-0.042 **	0.000065
$\sigma_{i,t}$	1.1803 **	0.01592
$liq_{i,t-1}$	-0.000005 **	0.0000036

** stands for significant regression estimate at 5% level.
Panel A predicts excess abnormal return (α_{CAPM}) on stock, $i = 1, 2, 3, \ldots, 242473$, with lagged kurtosis at $t = 1, 2, 3, \ldots, 31$. Panel B predicts current excess abnormal return with lagged kurtosis and lagged return, R_{t-1}. In Panel C, lagged Kurtosis, *price*, *size*, idiosyncratic volatility (σ), β and liquidity (*liq*) predict stock return.

Table 7: Regression analysis of $\alpha_{3-factor}$

Panel A $\alpha_{3-factor\,i,t} = \alpha + \mathrm{k}_{i,t-1}$

	Estimate	*Standard error*
Intercept	-0.0332 **	0.00941
$k_{i,t-1}$	-0.00026	0.000555

Panel B $\alpha_{3-factor\,i,t} = \alpha + \mathrm{R}_{i,t-1} + \mathrm{k}_{i,t-1}$

	Estimate	*Standard error*
Intercept	-0.0508 **	0.0095
$R_{i,t-1}$	0.1679 **	0.01378
$k_{i,t-1}$	-0.00065	0.00055

Panel C $\alpha_{3-factor\,i,t} = \alpha + \mathrm{k}_{i,t-1} + \log(\mathrm{price}_{i,t-1}) + \mathrm{size}_{i,t} + \beta_{i,t} + \sigma_{i,t} + \mathrm{liq}_{i,t-1}$

	Estimate	*Standard error*
Intercept	0.2098 **	0.02827
$k_{i,t-1}$	0.00006	0.00056
$log(price_{i,t})$	-0.012	0.00772
$size_{i,t}$	-2.86E-9	1.133E-8
$\beta_{i,t}$	-0.045 **	0.00136
$\sigma_{i,t}$	-4.7136 **	0.3321
$liq_{i,t-1}$	0.000074	0.000075

** stands for significant estimate at 5% level.