Towards Disentangling Sentiment from Risk Premia

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Abstract

Previous research suggests that the cross-section of stock returns has exposure to market risk captured by higher moments. Intuitively, if a stock has positive (negative, positive) exposure to the market volatility (skewness, kurtosis) innovations, it is assumed to have a high price and a low expected return. However, empirical studies show that stocks have low expected returns if they are positively exposed to market volatility and skewness risk, negatively exposed to market kurtosis risk. Using higher risk-neutral moments implied by S&P500 index option prices, we study this puzzling feature of the data. We find that each of the higher moment prices of risk is time-varying and has significantly different patterns under different market conditions, proxied by investor sentiment. In particular, our results suggest that only in down-markets (low sentiment), the exposure to the market volatility innovations is priced significantly negative, while this significance disappears in up-markets (high sentiment). Furthermore, we find that in down-markets, market skewness and kurtosis are not priced risk factors, while the price of market skewness risk is significantly negative and the price of kurtosis risk is positive in up-markets. Importantly, our findings confirm the previous results for volatility in the cross-section of stocks, but suggest that the previously reported counterintuitive results for skewness and kurtosis are mainly a feature of the data in up-markets, caused by a substantially lower risk-aversion in the market. The results persist even after controlling for the Fama-French and Carhart factors, or orthogonalizing the investor sentiment index with macroeconomic variables. We interpret the evidence as suggesting that the Baker-Wurgler type sentiment indices do not really measure investor sentiment, but instead simply measure time-variation in risk-aversion, and, therefore, pick up risk premia.

Keywords: Investor Sentiment, Market Moment Risk Prima, Option Implied Moments, Cross-Section of Expected Returns (*JEL* G10, G12, G14)

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1. Introduction

In this paper, we combine two controversial streams in the literature, sentiment and risk premia. We analyze the impact of market moment risk factors on the cross-section of stocks under different market conditions, proxied by an investor sentiment index. The first research area identifies the price of different sources of risk in the stock market, and the latter investigates the impact of investors' sentiment on stock returns. However, sentiment is likely to go hand in hand with time-variation in the price of risk. When behavioral researchers talk about high sentiment, efficient-market types tend to describe the same phenomenon by saying that risk premia are low, and vice versa. In this paper, we aim to disentangle sentiment from risk premia.

Assets that pay off well in bearish markets, when the consumption is low and the marginal utility of each dollar is high, are more desirable than assets with high payoff in bullish markets. Merton (1973) introduces the intertemporal capital asset pricing model [ICAPM] to address the static drawback in CAPM (Sharpe 1964; Lintner 1965) and argues that the pricing kernel should be adjusted for continuous improvement or deterioration in the investment opportunity set. Therefore, more elaborate asset pricing models, with state variables that project future investment opportunity sets, have been developed.[1]

Especially as market volatility, skewness and kurtosis are crucial indicators of the market-wide risk, researchers have formulated various pricing kernels that compensate investors for

[1] See for example: Hansen and Singleton (1982), Hansen and Singleton (1983), Brown and Gibbons (1985), Chapman (1997), Campbell and Cochrane (1999), Chabi-Yo (2012), Campbell, Giglio, Polk, and Turley (2013)

bearing the risk of higher market moments.[2] Market-wide risk matters for the cross-section of returns, because it allows risk-averse investors to hedge themselves against adverse changes in future investment opportunities. The prices of market moment risks should be positive or negative, depending on whether they reflect deteriorations or improvements in the economy's (future) opportunity set. Based on Merton (1973), negative shifts in the investment opportunity set reduce the consumption for a given level of future wealth. Intuitively, we formulate the following expectations:

(1) When investors are risk-averse, we expect the price of market volatility risk to be *negative*, because higher market volatility today can be associated with a deterioration of the future investment opportunity set. Stocks which are positively exposed to (correlated with) the market volatility will offer higher return when the investment opportunity set is shrinking. When investors are risk-averse, the hedge provided by the stock is desirable. This attractive property raises their current price and reduces their future expected return. Therefore, the difference between the expected return of a high volatility exposure portfolio and a low volatility exposure portfolio should be negative. Alternatively, following the same reasoning, when investors are risk-neutral (risk-seeking), we expect the price of volatility risk to be zero (positive).

(2) Negative skewness reflects market participants' fear about a negative jump in the stock market. We expect the price of market skewness risk to be *positive*, because lower (more negative) market skewness today can be associated with an increase in the negative

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[2] See for example: Kraus and Litzenberger (1976), Campbell (1996), Fang and Lai (1997), Harvey and Siddique (2000), Chen (2002), Bakshi and Madan (2006), Ang, Hodrick, Xing and Zhang (2006), Adrian and Rosenberg (2008), Chabi-Yo (2012), Chang, Christoffersen, and Jacobs (2013)

jumps risk and, therefore, a deterioration of the future investment opportunity set. The stocks that are negatively correlated with changes in market skewness provide a hedge against this unfavorable scenario. Because of this attractive feature, risk-averse investors would require lower returns. The difference between the expected return of a high (positive) skewness exposure portfolio and a low (negative) skewness exposure portfolio should be positive. Alternatively, following the same reasoning, when investors are risk-neutral (risk-seeking), we expect the price of skewness risk to be zero (negative).

(3) The prices of market kurtosis and volatility risk are related. We expect the price of market kurtosis risk to be *negative*, because higher market kurtosis today can be associated with a deterioration of the future investment opportunity set. Stocks that are positively correlated with changes in market kurtosis provide a hedge against this unfavorable scenario. Because of this desirable feature, risk-averse investors would require lower returns. The difference between the expected return of a high kurtosis exposure portfolio and a low kurtosis exposure portfolio should be negative. Alternatively, following the same reasoning, when investors are risk-neutral (risk-seeking), we expect the price of kurtosis risk to be zero (positive).

Empirically, researchers find negative prices of risk for market volatility and market skewness in the cross-section of stocks. Especially Ang, Hodrick, Xing and Zhang (2006) take the innovations in the market volatility index (VIX), as a state variable in the pricing kernel, and find that on average the stocks with positive correlation with the innovations in VIX have lower return. Adrian and Rosenberg (2008) decompose the market volatility into short-term and long-term components, and observe that they are both negatively priced. They argue that the short-term volatility captures the skewness risk of the market. Chang, Christoffersen and Jacobs (2012) extend the analysis of Ang, Hodrick, Xing and Zhang

(2006) to the skewness and the kurtosis of the market, in addition to its volatility, and show that assets with higher exposure to the innovations in the market skewness have significantly lower expected return.[3] Obviously, this finding about the price of market skewness is in contradiction to economic intuition.

There is a separate strand in the literature that explores the impact of noise traders and investors' sentiment on stocks returns. In an efficient market, when noise traders tend to deviate prices from their fundamentals, well-informed rational investors (arbitragers) are supposed to trade against them and bring prices back to fundamentals. However due to the limits to arbitrage (Shleifer and Vishny 1997), arbitragers cannot fully compensate these deviations. Moreover if the behavior of each noise traders was random, the risk of their sentiments fluctuations would diversify away and their mispricing would be corrected by rational investors (Fama and French 2007). However sentiments fluctuations follow systematic trends across all noise traders, and therefore assets, which are negatively affected by this risk factor must be compensated with higher expected returns.

Behavioral studies show that investors' sentiment can be the reason of many phenomena in finance. For example the closed-end fund discount (Lee, Shleifer and Thaler 1991), the number of IPO and the average return of the first day after IPO (Ibbotson, Sindelar and Ritter 1994), the share of equity issues in total equity and debt issues (Baker and Wurgler 2000), the NYSE share turnover (Baker and Stein 2004) and the dividend premium (Baker and Wurgler 2004) can be affected positively or negatively by the investors' sentiment. Baker and Wurgler (2006) take the changes in these variables as proxies of investors' sentiment. Moreover to

[3] In addition Chabi-Yo (2012) and Kozhan, Neuberger, Schneider (2013) find negative risk premia for market volatility and market skewness.

only capture the common variations of these proxies, they compute their first principal component and construct an investor sentiment index. However, quantities such as the number of IPOs or the equity share in new issues are likely to be high when risk premia are low. In fact, there exist well-known perfectly rational models showing that it makes sense for firms to go public / issue equity when risk premia are low. Therefore, an index measuring IPOs or equity issues is likely to pick up risk premia. Indeed, Brealey, Cooper and Kaplanis (2014) find evidence that contrary to the sentiment hypothesis, the Baker-Wurgler sentiment affects returns principally through their fundamentals rather than through deviations from fundamentals.

Behavioral researcher would argue that high sentiment periods are characterized as periods when stocks are overvalued and their expected returns are lower; investors are less risk averse and they are optimistic about the market prospect. As opposed to the high sentiment period, in the low sentiment periods investors are more risk averse, the future of the market is gloomy, stock are undervalued and they are excepted to have higher future returns. In high sentiment periods, noise traders are more active in the market and therefore the risk-return tradeoff is less significant. In particular, among others Yu and Yuan (2011) demonstrate that in high sentiment periods market risk is not priced, and the active participation of sentiment (noise) traders distorts the mean-variance tradeoff and consequently undermines the market volatility risk premium. In contrast, in low sentiment periods the positive tradeoff between the market variance and the market expected return is significant. In a related study, Lehnert, Lin and Wolff (2013) solve for the equity risk premium in a general equilibrium framework with a CRRA representative investor. They find that the equilibrium risk premium is a function greatly determined by representative investor's risk-aversion, which is found to be time-varying. In their empirical analysis, they show that the time-variation in investor sentiment can be associated with time-varying risk-aversion. During down-markets, e.g. times of low investor sentiment, the risk-aversion is high; when investors demand for equity increases in up-markets, where sentiment is high, risk-aversion decreases significantly. They show that time-variation in risk aversion directly relates to time-variation in investors demand for higher moment risk compensation.

In light of previous empirical evidence, we argue that the compensation of higher moments risk in the cross-section depend on market conditions, because risk aversion and, therefore, risk premia are known to be time-varying. It is well understood that in up-markets (high sentiment) market risk premia are low[4], and we should not detect a significant mean-variance in such periods. In down-markets (low sentiment) market risk premia are high and the mean-variance relationship is significant. This would also affect the exposure of stock returns to market risk captured by higher risk-neutral moments. Therefore, we expect the results to be different in up- and in down-markets, while the results in the low sentiment periods would reflect the rationally expected relationship, where investors exhibit the assumed risk-averse behavior.

In this paper, we compute the market volatility, skewness and kurtosis using the Bakshi, Kapadia and Madan (2003) model free characterization (hereinafter BKM), and investigate the relation between the stocks cross-sectional exposure to the innovations in these moments and their subsequent returns. For each day, the BKM methodology allows us to calculate the risk-neutral moments implied by out of money (OTM) S&P500 index options traded on that specific day, therefore, the computed moments are strictly conditional. Moreover as

[4] (e.g.) Rosenberg and Engle (2002) find that risk-aversion increase during recession and drops during expansion.

investors' expectations about market future conditions impact the options prices, the option implied moments are forward-looking. In empirical design, our research is very similar to Ang, Hodrick, Xing and Zhang (2006) and Chang, Christoffersen and Jacobs (2013), as they also study the market moments risk premia in stocks cross-section. We can also replicate their results for a longer period of time. In a subsample analysis, we compare the market volatility, skewness and kurtosis risk premia in up-markets (high sentiment periods) and down-markets (low sentiment periods). Hence, independently for each of the moments at the end of each month, we form five value-weighted portfolios from all of the stocks in NYSE, AMEX and NASDAQ, based on their exposure to the market moments; such that the first portfolio is made up of stocks with the lowest exposure to that moment and the fifth one is constituted of the stocks with the highest exposure. Then we record the return of these portfolios over the subsequent month, and observe the price of risk with respect to the particular market moments. Particularly, we find that the market volatility premium is negative, the market kurtosis premium is positive, and the market skewness is priced significantly negative. The results for the market skewness and kurtosis seem counterintuitive, as we expected the opposite signs for each of them. However, once we segregate the results for up- and down-markets (high and low sentiment periods), we observe that:

(1) Due to investors' stronger risk-aversion, the price of market volatility risk is significantly negative in the low sentiment periods, while in the high sentiment periods, it is not statistically and economically significant. This finding is in line with previous research and an extension of Yu and Yuan (2011) and Lehnert, Lin and Wolff (2013) for the cross-section of stocks. The lower risk-aversion in up-markets lowers the otherwise significantly negative price of market volatility risk. One can use efficient-market arguments and interpret

the evidence as suggesting that the Baker-Wurgler type sentiment indices do not really measure investor sentiment, but instead simply measure time variation in risk-aversion, and, therefore, pick up risk premia.

(2) Following the reasoning regarding the price of market volatility risk, we expect the price of market skewness risk to be positive in down-markets (high risk aversion or low sentiment periods) and insignificant in up-markets (low risk aversion or high sentiment periods). However, the price of market skewness risk is found to be insignificant in down-markets, but significantly negative in up-markets (high sentiment periods), which is a results of the substantially lower risk aversion in that period. When investors are more risk-seeking, the hedge against the negative skewness scenario provided by the stock is not necessarily desirable. This property is not attractive and decreases its current price and increases its future expected return. Therefore, the difference between the expected return of a high (positive) skewness exposure portfolio and a low (negative) skewness exposure portfolio would be negative. Again, sentiment seems to pick up time variation in risk-aversion.

(3) In line with intuition, the price of market kurtosis is negative, but insignificant in the low sentiment period. In contrast, it is significantly positive in the high sentiment periods, which is in line with the results for volatility and skewness. More risk seeking investors find the hedge against the unfavorable scenario (negative skewness) provided by the stock not desirable, which decreases its current price and increases its future expected return. Therefore, the difference between the expected return of a high kurtosis exposure portfolio and a low kurtosis exposure portfolio would be positive. Hence, sentiment seems to pick up time variation in risk-aversion.

These results are robust, even after controlling for the Fama-French (1993) and the Carhart (1997) factors or orthogonalizing the sentiment measure with macroeconomic variables.

Our paper is also related to several other studies. Baker and Wurgler (2006) find that the investor sentiment has a larger impact on stocks with highly subjective valuations. Moreover, Stambaugh, Yu and Yuan (2012) argue that due to short-selling impediment, overpricing is more prevalent than underpricing, and empirically show that exploiting many of the market anomalies are only profitable during the high sentiment periods, when noise traders irrationally overvalue certain stocks. Our results support this line of argumentation.

The rest of this paper is structured as follows: In section 2, we explain about our data and the methodology that we use to extract the market moments. In section 3, we calculate the market moments risk premia in stocks cross-section, and compare these premia in the high sentiment and the low sentiment periods. Finally in section 4 we draw our conclusion, and provide our trading suggestion for the high sentiment and the low sentiment periods.

2. Data and Methodology

In this paper our main goal is to compare the market moments risk premia in the cross-section of the stocks, when the investor sentiment is high and low. Hence to begin with, we need to clarify what we exactly mean by stocks cross-section, the high sentiment and the low sentiment periods and the market moments. We conduct all our analysis on the largest common interval between our data sets, from January 1996 to June 2010.

Stocks Cross-Section

To compare the market moments risk premia in the cross-section of stocks, we obtain the daily return time series of all actively traded[5] ordinary common shares, transacted at NYSE,

[5] As it does not affect our conclusion, we omit an ignorable portion of stocks with *Halted*, *Suspended* or *Unknown* trading status.

AMEX and NASDAQ, from the database of the Center for Research in Security Prices (CRSP). In each month, we omit the stocks with missing observations. Table (1) describes some information about this dataset.

[PLEASE INSERT TABLE 1 ABOUT HERE]

In addition, to calculate the market capitalization of each stock at the end of each month, we obtain the monthly time series of the stock prices and the numbers of shares outstanding from CRSP.

Investor Sentiment

Delong, Shleifer, Summers, Waldmann (1990a, 1990b) argue that rational investors risk-aversion and noise traders unpredictability does not allow the rational investors to fully compensate for noise traders irrationality. In a theoretical setup, Delong, Shleifer, Summers, Waldmann (1990a) show that in the short-term, rational investors imitate the behaviors of noise traders[6] and thereby intensify the stock market anomalies induced by noise traders. Delong, Shleifer, Summers, Waldmann (1990b) find a systematic relation between the fluctuations in the close-end mutual fund discount and the variations in noise traders' opinion. Accordingly, Lee, Shleifer and Thaler (1991) introduce the close-end mutual fund discount as proxy for systematic investor sentiment.

Moreover, previous literature shows that waves of investors' sentiment impact the number of IPOs and the average returns of the first day after IPOs (Ibbotson, Sindelar and Ritter 1994), the share of equity issues in total equity and debt issues (Baker and Wurgler 2000), the NYSE

[6] Rational investors buy an asset, once noise traders are also speculatively buying that asset, and sell the asset at its peak.

share turnover (Baker and Stein 2004), the dividend premium (Baker and Wurgler 2004).[7] Some of these proxies reflect the variations in investors' sentiment more rapidly than the others. Hence to compute their common variations and formulate an investor sentiment index, Baker and Wurgler (2006) adjust these time series according to their lead-lag relationships, and find their first principal component. Furthermore, to remove the impact of the economic fundamentals on these sentiment proxies, Baker and Wurgler (2006 and 2007) take the regression residuals of each proxy on certain macroeconomic indicators[8], as cleaned proxies. Then they take the first principal component of these cleaned proxies as the orthogonalized sentiment index. We obtain the monthly time series of the investor sentiment index and the investor orthogonalized sentiment index from the personal website of Jeffrey Wurgler. Figure (1) exhibits these two time series.

[PLEASE INSERT FIGURE 1 ABOUT HERE]

As Figure (1) shows, the sentiment and the orthogonalized sentiment indexes are very similar and they are strongly mean-reverting. Table (1) summarizes some of the statistical properties of these two time series.

Market Moments

Bakshi and Madan (2000) showed that any claim payoff with finite expectation can be spanned by a continuum of out of the money (hereinafter OTM) European call and put

[7] Studies on the impact of investor sentiment are not limited to the equity markets and are stretched to various asset classes. For instance, Han (2007) investigates the effect of investors' sentiment on option prices.

[8] The Growth in industrial production, the real growth in durable, nondurable, and services consumption, the growth in employment, and the NBER recession indicator.

options. Accordingly, Bakshi, Kapadia and Madan (2003) [hereinafter BKM] set up a model free framework to exploit the conditional time series of the risk-neutral moments.

For each day, the BKM methodology allows us to calculate the risk-neutral moments implied by the S&P500 index options traded on that specific day. Therefore the computed moments are strictly conditional and forward-looking, as opposed to the traditional techniques, which use a rolling-window of daily market returns and consequently to increase the accuracy, they sacrifice conditionality and vice versa. Alternatively one can use high-frequency market returns of a single day to compute the market moments of that day (e.g. Bollerslev, Tauchen and Zhou 2009). However since the high-frequency returns are affiliated with microstructure frictions and the sampling properties of the high frequency returns do not necessarily reflect the statistical characteristics of the daily returns (Brenner, Pasquariello and Subrahmanyam 2009), using intraday data is not the best choice for estimating the higher moments, namely skewness and kurtosis. Moreover the moments computed using rolling-windows or high-frequency data do not reflect investors' anticipation about the future market conditions.

Based on the BKM, one can measure the volatility, the skewness and the kurtosis of S&P500 index return, using the prices of the European options written on the S&P500 index as:

$$Vol_t^{\tau} = \sqrt{e^{r\tau}\, V(t,\tau)\ -\ \mu(t,\tau)^2} \tag{1}$$

$$Skew_t^{\tau} = \frac{e^{r\tau}W(t,\tau) - 3\mu(t,\tau)e^{r\tau}V(t,\tau) + 2\mu(t,\tau)^3}{[Vol_t^{\tau}]^{\frac{3}{2}}} \tag{2}$$

and

$$Kurt_t^{\tau} = \frac{e^{r\tau}X(t,\tau) - 4\mu(t,\tau)e^{r\tau}W(t,\tau) + 6\, e^{r\tau}\mu(t,\tau)^2V(t,\tau) - 3\mu(t,\tau)^4}{[Vol_t^{\tau}]^2} \tag{3}$$

where,

$$\mu(t,\tau) = e^{r\tau} - 1 - \frac{e^{r\tau}}{2}V(t,\tau) - \frac{e^{r\tau}}{6}W(t,\tau) - \frac{e^{r\tau}}{24}X(t,\tau) \tag{4}$$

$$V(t,\tau) = \int_{S(t)}^{\infty} \frac{2\left(1 - ln\left[\frac{K}{S(t)}\right]\right)}{K^2} C(t,\tau;K)\, dK + \int_{0}^{S(t)} \frac{2\left(1 + ln\left[\frac{S(t)}{K}\right]\right)}{K^2} P(t,\tau;K)\, dK \tag{5}$$

$$W(t,\tau) = \int_{S(t)}^{\infty} \frac{6\, ln\left[\frac{K}{S(t)}\right] - 3\left(ln\left[\frac{K}{S(t)}\right]\right)^2}{K^2} C(t,\tau;K)\, dK - \int_{0}^{S(t)} \frac{6\, ln\left[\frac{S(t)}{K}\right] + 3\left(ln\left[\frac{S(t)}{K}\right]\right)^2}{K^2} P(t,\tau;K)\, dK \tag{6}$$

and

$$X(t,\tau) = \int_{S(t)}^{\infty} \frac{12\left(ln\left[\frac{K}{S(t)}\right]\right)^2 - 4\left(ln\left[\frac{K}{S(t)}\right]\right)^3}{K^2} C(t,\tau;K)\, dK + \int_{0}^{S(t)} \frac{12\left(ln\left[\frac{S(t)}{K}\right]\right)^2 + 4\left(ln\left[\frac{S(t)}{K}\right]\right)^3}{K^2} P(t,\tau;K)\, dK \tag{7}$$

In these formulas, τ is the time-to-maturity of the options used for calculating the market moments, which can also be interpreted as the horizon over which we compute the moments. Also, r is the risk-free rate and $S(t)$ is the price of the option underlying (here the S&P500 index value) at day t. $C(t,\tau;K)$ and $P(t,\tau;K)$ represent the prices of the European call and put options (written on the S&P500 index), with strike price K and time-to-maturity of τ.

Options with near maturity reflect investors' short-term expectations more clearly, therefore for each day we calculate the risk-neutral moments for the horizon of the-next-30-calendardays. For this purpose, we obtain the daily prices of the European options written on the S&P 500 index from the Ivy DB of OptionMetrics. For each option, this database provides us with various information, such as transaction date, bid and ask prices, time-to-maturity, strike price, underlying asset value (S&P 500 index), dividend yield and the Black and Scholes (1973) implied volatility. Due to illiquidity and microstructural limitations, we eliminate the options with less than six days-to-maturity and cheaper than $\$3/8$.

On each day, we want to calculate the risk-neutral moments for the horizon of the-next-30-days. However options with exactly 30 days-to-maturity are not traded in all days, therefore for these days we calculate the market moments for the two closest available maturities, smaller and bigger than 30 days, and then use linear interpolation to find estimations of the market moments for the horizon of the-next-30-days.

In order to calculate the integrals in Equations (5) to (7) accurately, we need to have a fine continuum of OTM options for every strike price. However options are not written on every strike price. Therefore following Chang, Christoffersen and Jacobs (2013) on each day, we fit a natural cubic spline[9] to the volatility smile of the OTM options with a specific time-to-maturity, so that we can find an estimation of the implied volatility and thereby the option price ($C(t,\tau;K)$ or $P(t,\tau;K)$) for every moneyness ratio ($\frac{K}{S(t)}$), using the Black and Scholes (1973) formula. To do so we take the put options, whose moneyness ratios are less than 1.03 and the call options whose moneyness ratios are more than 0.97 as OTM options, and fit a

[9] If only two maturities are available, we linearly interpolate between the implied volatilities.

cubic spline to them.[10] Using this spline, we can find an estimation of the implied volatility for every moneyness level between 0.01 and 2. We break this interval to 1000 equal slices and compute the integrals in Equations (5) to (7).

To make it more comparable to other studies, we report the annualized volatility as:

$$Annualized\ Vol_t^{\tau} = Vol_t^{\tau} \times \sqrt{\frac{365}{\tau}} \tag{8}$$

Figure (2) exhibits the daily time series of the risk-neutral market volatility, market skewness and market kurtosis that we exploit out of the S&P500 index options.

[PLEASE INSERT FIGURE 2 ABOUT HERE]

Figure (2) reveals many stylized facts about the market moments. Panel (a) shows that the market volatility varies over time and big sudden spikes in this moment decline very slowly. The market skewness is always negative, and in investors' perception the likelihood of huge negative shocks is higher than the same-size positive shocks. The market kurtosis is always more than 3, showing that the investors' risk-neutral expectation about the market return distribution is more fat-tailed than the normal distribution.

Since we want to investigate the comovement of stocks cross-sectional returns with continuous deterioration or improvement in the future investment opportunity set, we capture the innovations in the market moments as the residuals of the ARMA (1, 1) processes fitted

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[10] For the moneyness values above the maximum available moneyness and below the minimum available moneyness, we assume the implied volatility is constant and equal to the implied volatility of the highest and the lowest available moneyness values, respectively.

to the market volatility, skewness and kurtosis, independently. These innovation processes are shown in Figure (3).

[PLEASE INSERT FIGURE 3 ABOUT HERE]

The dynamics of the innovations in the market moments, named as ΔVol^{τ}, $\Delta Skew^{\tau}$ and $\Delta Kurt^{\tau}$, are shown in Equations (9) to (11), respectively.[11]

$$\Delta Vol_t^{\tau} = 0.1261 * \Delta Vol_{t-1}^{\tau} + (Vol_t^{\tau} - 0.9856 * Vol_{t-1}^{\tau}) \tag{9}$$

$$\Delta Skew_t^{\tau} = 0.4043 * \Delta Skew_{t-1}^{\tau} + (Skew_t^{\tau} - 0.9614 * Skew_{t-1}^{\tau}) \tag{10}$$

$$\Delta Kurt_t^{\tau} = 0.4280 * \Delta Kurt_{t-1}^{\tau} + (Kurt_t^{\tau} - 0.9458 * Kurt_{t-1}^{\tau}) \tag{11}$$

Obviously the three AR (1) coefficients are very close to one, which show that the moments processes are extremely autoregressive. Table (3) provides some descriptive statistics about these time series.

[PLEASE INSERT TABLE 3 ABOUT HERE]

As it is clear from Panel (b) in Table (3), the correlation coefficient between $\Delta Skew_t^{\tau}$ and $\Delta Kurt_t^{\tau}$ is -0.88. Following Chang, Christoffersen and Jacobs (2012), to avoid multicolinearity and to be able to differentiate the impact of $\Delta Skew_t^{\tau}$ from $\Delta Kurt_t^{\tau}$, we orthogonalize $\Delta Kurt_t^{\tau}$ with respect to $\Delta Skew_t^{\tau}$, such that $\Delta^{\perp} Kurt_t^{\tau}$ is the residuals time series of the linear regression of $\Delta Kurt_t^{\tau}$ on $\Delta Skew_t^{\tau}$.

$$\Delta Kurt_t^{\tau} = a + b\, \Delta Skew_t^{\tau} + \Delta^{\perp} Kurt_t^{\tau} \tag{12}$$

[11] As it does not change our interpretations but simplifies our computations, we divide $\Delta Skew$ and $\Delta Kurt$ time series by 100.

For simplicity of the notations, from here on ΔVol shows the innovations in the annualized market volatility, $\Delta Skew$ shows the innovations in the market skewness and $\Delta Kurt$ shows the innovations in the orthogonalized market kurtosis.

3. Empirical Analysis

Ang, Hodrick, Xing and Zhang (2006) argue that based on the arbitrage pricing theory, if the market volatility is a priced risk factor, it should also be a priced in stocks cross-section and thereby assets with different sensitivities to the market volatility innovations (ΔVol) should have different expected returns for the subsequent periods. Motivated by this fact, they measure and compare the stocks cross-sectional exposure to the market volatility innovations ($\Delta Vol_t = Vol_t - Vol_{t-1}$), using the market volatility index (VIX) of the Chicago Board of Options Exchange (CBOE). Also Chang, Christoffersen and Jacobs (2013) extend this analysis for the market skewness innovations ($\Delta Skew$) and the market kurtosis innovations ($\Delta Kurt$). We carry out the same analysis for a different (longer) time series of data, but additionally we investigate the effect of these cross-sectional exposures in up- and down-markets (high sentiment and low sentiment periods).

Results presented in Table (3) reveal that there exists a significantly negative correlation of -0.78, between ΔVol and the concurrent market excess return $(R_m - R_f)$. Thus usually positive shocks in the market volatility and the deterioration of the investment opportunity set are contemporaneously accompanied by negative market excess returns. Therefore according to the ICAPM of Merton, everything else being equal, a stock that pays off well when the market volatility rises (and the investment opportunities gets worse) must be more expensive than a stock that yields positively when the market volatility declines.

In order to capture the stocks conditional exposure to ΔVol, starting from January 1996, we take one-month daily returns[12] of each stock and run the following regression

$$r_t^i - r_{f,t} = \beta_0^i + \beta_{MKT}^i \, MKT_t + \beta_{\Delta Vol}^i \, \Delta Vol_t + \beta_{\Delta Skew}^i \, \Delta Skew_t + \beta_{\Delta Kurt}^i \, \Delta Kurt_t + \varepsilon_t^i \tag{13}$$

Where $MKT(= R_m - R_f)$ represents the excess return of the market over the risk-free asset. Hence for each stock (i) in each month, we obtain a set of β_{MKT}^i, $\beta_{\Delta Vol}^i$, $\beta_{\Delta Skew}^i$ and $\beta_{\Delta Kurt}^i$. A positive $\beta_{\Delta Vol}^i$ shows that the daily excess returns of asset (i) typically commoves in the same direction as the innovations in the market volatility. One can use the same interpretation for $\beta_{\Delta Skew}^i$ and $\beta_{\Delta Kurt}^i$.

In order to evaluate the tradeoff between the stocks exposure to the market moments innovations and their future expected return, at the end of each month, we rank all the stocks three times independently based on their $\beta_{\Delta Vol}$, $\beta_{\Delta Skew}$ and $\beta_{\Delta Kurt}$. In each time, we form five value-weighted exposure portfolios such that the first portfolios is composed of one-fifth of the stocks with the lowest exposures to each moment innovations (the stocks with the smallest $\beta_{\Delta Vol}$, $\beta_{\Delta Skew}$ or $\beta_{\Delta Kurt}$) and the last portfolio includes one-fifth of the stocks with the highest loadings on each moment innovations (the stocks with the largest $\beta_{\Delta Vol}$, $\beta_{\Delta Skew}$ or $\beta_{\Delta Kurt}$). Then we record the daily returns of these fifteen portfolios over the month after the betas calculation period, to construct the post-ranking returns time series.

We continue by rolling the window one month forward and repeat the same algorithm up until the end of our data sample in June 2010. Therefore we will obtain the daily time series

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[12] Among many others, Pastor and Stambaugh (2003), Ang, Hodrick, Xing and Zhang (2006) and Chang Christoffersen and Jacobs (2013) use one-month daily returns in the same setup, as it creates a good balance between the precision and the conditionality of the estimated betas.

of five volatility exposure portfolios (hereinafter: VEP1 to VEP5), five skewness exposure portfolios (hereinafter: SEP1 to SEP5) and five kurtosis exposure portfolios (hereinafter: KEP1 to KEP5), from January 1996 to June 2010. By construction VEP1, SEP1 and KEP1 are the post-ranking daily time series of the most negatively exposed portfolios to ΔVol, $\Delta Skew$ and $\Delta Kurt$, respectively and VEP5, SEP5 and KEP5 are the post-ranking daily time series of the most positively exposed portfolios to ΔVol, $\Delta Skew$ and $\Delta Kurt$, correspondingly[13].

Table (4) displays the average betas of the constructed exposure portfolios versus their corresponding average monthly returns. In addition, the alpha coefficients of each exposure portfolio based on the CAPM, the Fama-French Model and the Carhart Model are reported.

[PLEASE INSERT TABLE 4 ABOUT HERE]

Panel (a) is dedicated to the market volatility. In this panel, VEP5-1 represents a self-financing portfolio that goes long on VEP5 and short sales VEP1. SEP5-1 and KEP5-1, in Panel (b) and (c), represent similar portfolios for the market skewness and the market kurtosis.[14] Figure (4) pictures the information in Table (4).

[PLEASE INSERT FIGURE 4 ABOUT HERE]

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[13] Here, we focus on standard portfolio sorts on exposure to market moments. We also conduct the sorting approach used in e.g. Chang, Christoffersen and Jacobs (2013) to overcome the problem of correlation between different market moments (results not reported). We find that our results are robust to variations in the empirical setup.

[14] Thus: VEP5-1 = VEP5 – VEP1, SEP5-1 = SEP5 – SEP1, and KEP5-1 = KEP5 – KEP1.

The average monthly returns and the Carhart alphas of the volatility exposure portfolios follow a strictly declining pattern. In fact, as we move from VEP1 towards VEP5, by construction the average beta of the exposure portfolios increases, and as we intuitively expected, their average monthly returns and the alpha values decline. This result is in line with the findings of Ang, Hodrick, Xing and Zhang (2006). However it is crucial to notice that the average monthly return of VEP5-1 is oftentimes not statistically and economically significant, only marginally significant for the Carhart alpha. This can be inferred from the t-statistics that we measure using the Newey-West technique with 5 day lags.

Similarly in Panel (b) of Figure (4), we can observe strictly declining patterns for the average monthly returns and the Carhart alphas of the skewness exposure portfolios. This finding is exactly in line with the results of Chang, Christoffersen and Jacobs (2013). Stocks with positive exposure to the market skewness innovations (positive $\beta_{\Delta Skew}$) have lower returns and alphas over the subsequent period. Even though the average monthly return and the Carhart alpha of the SEP5-1 portfolio are statistically significant, this result does seem counterintuitive. Particularly, the stocks with positive exposure to the market skewness (stocks with positive $\beta_{\Delta Skew}$) pay off poorly when the market skewness decreases, the negative jump risk increases and investment opportunities are shrinking. Thus, since they cannot provide a good hedge when the market is falling, they should be cheaper and have higher expected return over the subsequent periods.

Also when we move from KEP1 toward KEP5, Panel (c) of Figure (4) shows mildly increasing patterns for the average monthly returns and the Carhart alphas of the kurtosis exposure portfolios. The patterns are not monotonically increasing, and the average monthly returns and the different alpha values of KEP5-1 are not statistically significant. Nevertheless, with a similar line of reasoning as what we had for the exposure to the market volatility and the market skewness, the results are counterintuitive, since we would expect a downward sloping pattern.

Down- vs. Up-Markets

As mentioned earlier, up-markets (high sentiment periods) are characterized by an overvaluation in the market, investors are more risk-seeking and, therefore, risk premia are assumed to be low. Conversely, in down-markets (low sentiment periods) stocks are undervalued, investors are more risk-averse and market risk is priced. In order to distinguish between up- and down markets, we use the monthly time series of investor sentiment index computed by Baker and Wurgler (2006). We refer to the months with the sentiment index above its median as the high sentiment periods and the months with the sentiment index below its median as the low sentiment periods. Table (5) and Figure (5) summarize our results for the high sentiment periods.

[PLEASE INSERT TABLE 5 ABOUT HERE]

[PLEASE INSERT FIGURE 5 ABOUT HERE]

By looking at the first panels in Table (5) and Figure (5), we cannot observe an increasing or decreasing pattern in the average monthly returns of the volatility exposure portfolios or their corresponding alpha values. In other words in up-markets, market volatility is not priced in the cross-section and higher or lower exposure to the market volatility innovations does not result in higher or lower expected returns. However this result seems counterintuitive, because a stock with positive exposure to the market volatility innovations, (a stock with positive $\beta_{\Delta Vol}$) is very desirable as it pays off well when the investment opportunities are shrinking. Hence, compared to a stock with negative exposure to the market volatility innovations, this stock should be more expensive and have a smaller expected return. In conclusion, the absence of a downward sloping pattern in Panel (a) of Figure (5) indicates that in high sentiment periods, when the market is overvalued, the price of market volatility risk is not priced in the cross-section of stocks. The observed pattern suggests that investors appear to be more risk-seeking in that period.

Likewise, the monotonic downward slopping patterns of the average monthly returns and the different alpha values of the five skewness exposure portfolios, displayed in Panel (b) of Figure (5), are another sign of investors' increased risk-seeking behavior in that period. Economic intuition would tell us that for risk-averse investors, a stock with low exposure to market skewness innovations, (a stock with negative $\beta_{\Delta Skew}$) provides a good hedge when the market skewness is becoming more negative and the investment opportunities are shrinking. Thus, it should be more expensive and have a smaller expected return. With a similar line of reasoning, a stock with positive exposure to the market skewness innovations should have a higher expected return. Hence, we should observe a strictly upward sloping pattern for the average monthly returns and the different alpha values of the five skewness exposure portfolios. This is not the case, which is counterintuitive. Remarkably, the price of markets skewness risk is negative and the average monthly return and the different alpha values of SEP5-1 are statistically and economically significant. In line with the results for market volatility, the observed pattern suggests that investors appear to be more risk-seeking in up-markets. Similarly, in Panel (c) of Figure (5), we would expect to see descending patterns in the average monthly returns and the different alpha values of the market kurtosis exposure portfolios. But in contrast, these patterns are ascending, which, again, is in line with our risk-aversion-based explanation.

In summary, in up-markets (high sentiment periods), the observed cross-sectional patterns for market volatility, skewness and kurtosis risk suggest that investors are temporally more risk-seeking. This is in line e.g. Rosenberg and Engle (2002), who find that risk-aversion increases during recession and drops during expansion, but also in line with Yu and Yuan (2010) and Lehnert, Lin and Wolff (2013), who show that investors are more risk-seeking in up-markets.

In the following, we study the characteristics of the moment's exposure portfolios only in down-markets, characterized by low sentiment. Table (6) and Figure (6) report the average monthly returns and the alpha values of the various exposure portfolios.

[PLEASE INSERT TABLE 6 ABOUT HERE]

[PLEASE INSERT FIGURE 6 ABOUT HERE]

The sharply declining patterns of the average monthly returns and the alpha values of the market volatility exposure portfolios, shown in Panel (a) of Table (6) and Figure (6), show that in down-markets (low sentiment periods) risk-averse investors demand a premium for market volatility risk. Comparing with up-markets, in low sentiment periods the VEP5-1 yields a negative average monthly return and statistically significant alpha values, in other words, market volatility risk is priced in the cross-section. This finding extends the conclusion of Yu and Yuan (2010) for the cross-section of stocks. With a time series approach, they show that the positive trade-off between the market variance and the market expected return is much stronger in the low sentiment periods. In a related study, Lehnert, Lin and Wolff (2013) show that investors are more risk-averse in down-markets, proxied by low sentiment periods. Furthermore, our result also corresponds to the arguments by Bakshi and Mandan (2006) and Chabi-Yo (2012) that high risk aversion implies a high volatility premium.

Moreover, in contrast to investors' risk-seeking behavior in the high sentiment periods, when they price the market skewness risk negatively and the market kurtosis risk positively, these moments are not significantly priced in the low sentiment periods. In particular, as shown in Panel (b) and (c) of Table (6), in the low sentiment periods the average monthly returns and the alpha values of the skewness exposure portfolios do not follow any particular pattern and SEP5-1 does not yield a significant average monthly return or alpha. In addition the positive average monthly return and the significant Carhart alpha of the KEP5-1 in the high sentiment periods are now contrasted with insignificant values, suggesting that market skewness and kurtosis risk is not priced in the cross-section of stock.

Overall, our findings suggest that investors are risk-averse in down-markets, proxied by low sentiment, where only market volatility risk is priced and more risk-seeking in up-markets (high sentiment periods), where predominately market skewness risk is priced. We interpret the evidence as suggesting that the Baker-Wurgler type sentiment indices do not really measure investor sentiment, but instead simply measure time-variation in investors' risk aversion and, therefore, pick up risk premia.

When is investor sentiment high? When is it low?

So far, we used the median of the investor sentiment index to distinguish between the high sentiment and low sentiment periods. Every month with index value above the median was considered as a high sentiment period and every month with index value below the median was regarded as a low sentiment period. However our further analysis, shown in Table (7)[15],

[15] To save space, we only report the statistics for VEP5-1, SEP5-1 and KEP5-1. The detailed statistics for all of the moments exposure portfolios are available upon request.

demonstrates that splitting the sample using the mean of the investor sentiment index does not change our results and interpretation.

[PLEASE INSERT FIGURE 7 ABOUT HERE]

[PLEASE INSERT FIGURE 8 ABOUT HERE]

Similarly, as we display in Table (8), using the investor orthogonalized sentiment index of Baker and Wurgler (2006) will let us derive the same conclusions.

Sentiment Level

By splitting the sample between the high sentiment and the low sentiment periods, we ignore the continuous nature of the investor sentiment index. For instance, we consider both months with investor sentiment values one-standard-deviation or three-standard-deviation above the median as the high sentiment periods. However, obviously in the latter case, the sentiment level is higher. To be able to analyze the impact of the changes in the investor sentiment level, for our whole data sample from January 1996 to June 2010, we regress the monthly time series of VEP5-1, SEP5-1 and KEP5-1 on the incremental lagged changes in the sentiment index, the contemporaneous changes in the market return, the Fama-French and the Carhart factors.

$$XEP_t^{5-1} = \alpha + \beta_{Sent}\Delta Sent_{t-1} + \beta_{MKT}MKT_t \tag{14}$$

$$XEP_t^{5-1} = \alpha + \beta_{Sent}\Delta Sent_{t-1} + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{HML}HML_t \tag{15}$$

$$XEP_t^{5-1} = \alpha + \beta_{Sent}\Delta Sent_{t-1} + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{Mom}Mom_t \tag{16}$$

In these Equations XEP5-1 represents VEP5-1, SEP5-1 or KEP5-1. Table (9) reports the results of Regression Equations (14) to (16). The t-statistics are computed using the Newey-West technique with 12 month lags.

[PLEASE INSERT FIGURE 9 ABOUT HERE]

As shown in Table (9), β_{Sent} is significantly positive, negative and positive for VEP5-1, SEP5-1 and KEP5-1, respectively. The results are in line with our earlier results. For example, for market volatility, the negative slope of the market volatility exposure portfolios shown in e.g. Figure (6), Panel (a), is significantly reduced once sentiment increases or risk-aversion decreases. Therefore, the impact of changes in sentiment on the VEP5-1 portfolio is found to be positive; in other words, higher sentiment or more risk-seeking behavior improves the returns of the high minus low market volatility exposure portfolio. The results for market skewness risk suggest that the relationship of changes in sentiment and the SEP5-1 portfolio is negative. The slightly negative slope of the market skewness exposure portfolios shown in e.g. Figure (6), Panel (b), becomes significantly more negative once sentiment increases or investors become more risk-seeking, in other words, the performance of the SEP5-1 portfolio deteriorates. In line with the results for market volatility risk, the relationship of changes in sentiment and the KEP5-1 portfolio is positive. The insignificant slope of the market skewness exposure portfolios shown in e.g. Figure (6), Panel (c), becomes significantly positive once sentiment increases (investors become more risk-seeking). The results for alpha suggest that our previous results are robust. In line with intuition, the alpha of the VEP5-1 portfolio is significantly negative, suggesting a negative price of market volatility risk. In contrast, the alpha of the SEP5-1 portfolio is also significantly negative, suggesting a negative price of market skewness risk, which we found to only be present in up-markets, and, which can be explained by risk-seeking behavior.

4. Conclusion

Previous research suggests that the cross-section of stock returns has exposure to market risk captured by higher moments. Intuitively, if a stock has positive (negative, positive) exposure to the market volatility (skewness, kurtosis) innovations, it is expected to have higher price and lower expected return. However, empirical studies show that stocks have low expected returns if they are substantially exposed to market volatility and skewness risk, while they have higher returns if they are exposed to market kurtosis risk. Using higher risk-neutral moments implied by S&P500 index option prices, we study this puzzling behavior and find that higher moments price of risk is time-varying and has significantly different patterns under different market conditions, proxied by investor sentiment. In particular, our results suggest that only in down-markets, when investors are more risk-averse, the exposure to the market volatility innovations is priced significantly negative, while this significance disappears in up-markets, when investors become more risk-seeking. In contradiction to some recent empirical studies, we find that the price of the innovations in the market skewness is significantly negative, only when the investor sentiment is high and investors are more risk-seeking, while it is not priced in down-markets. Similarly our findings further suggest that the price of kurtosis risk is positive in high sentiment periods, while it is not priced in low sentiment periods. Importantly, our findings confirm the previous results for volatility in the cross-section of stocks, but suggest that the previously counter-intuitive reported result for skewness is mainly a feature of the data in up-markets, caused by investors' risk-seeking behavior. Our results persist even after controlling for the Fama-French and Carhart factors, or orthogonalizing the investor sentiment index with macroeconomic variables. We interpret the evidence as suggesting that the Baker-Wurgler type sentiment index do not really measure investor sentiment, but instead simply measure time variation in risk-aversion and, therefore, picks up risk-premia.

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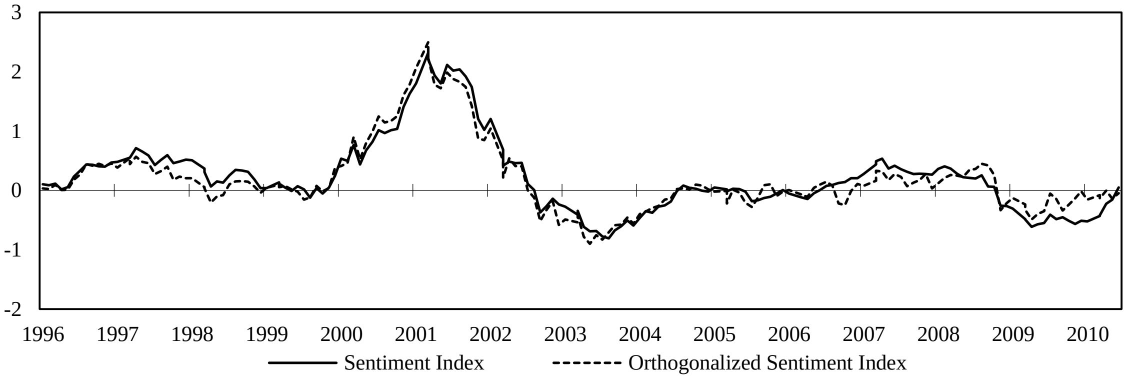
Figure 1 - The Investor Sentiment Index and the Orthogonalized Investor Sentiment Index



Notes: *Baker and Wurgler (2006) measure the investor sentiment index as the first principal component of the close-end fund discount, the IPO volume, the average return of the first day after IPO, the share of equity issues in total equity and debt issues, the NYSE share turnover and the dividend premium time series. To remove the impact of the macroeconomic factors, they also orthogonalized the sentiment index using certain macroeconomic variables, namely the growth in industrial production, the real growth in durable, nondurable, and services consumption, the growth in employment, and the NBER recession indicator.*

Table 1 - The Investor Sentiment Index and the Orthogonalized Investor Sentiment Index

Statistics	Investor Sentiment Index	Orthogonalized Investor Sentiment Index
Number of Periods (Month)	174	
Mean	0.222	0.195
Standard Deviation	0.614	0.596
Percentiles		
5th Percentile	-0.596	-0.566
25th Percentile	-0.141	-0.129
Median	0.113	0.070
75th Percentile	0.444	0.383
95 Percentile	1.805	1.752
Correlation	0.961	
Innovations Correlation	0.821	

Notes: *Baker and Wurgler (2006) measure the investor sentiment index as the first principal component of the close-end fund discount, the IPO volume, the average return of the first day after IPO, the share of equity issues in total equity and debt issues, the NYSE share turnover and the dividend premium time series. To remove the impact of the macroeconomic factors, they also orthogonalized the sentiment index using certain macroeconomic variables, namely the growth in industrial production, the real growth in durable, nondurable, and services consumption, the growth in employment, and the NBER recession indicator.*

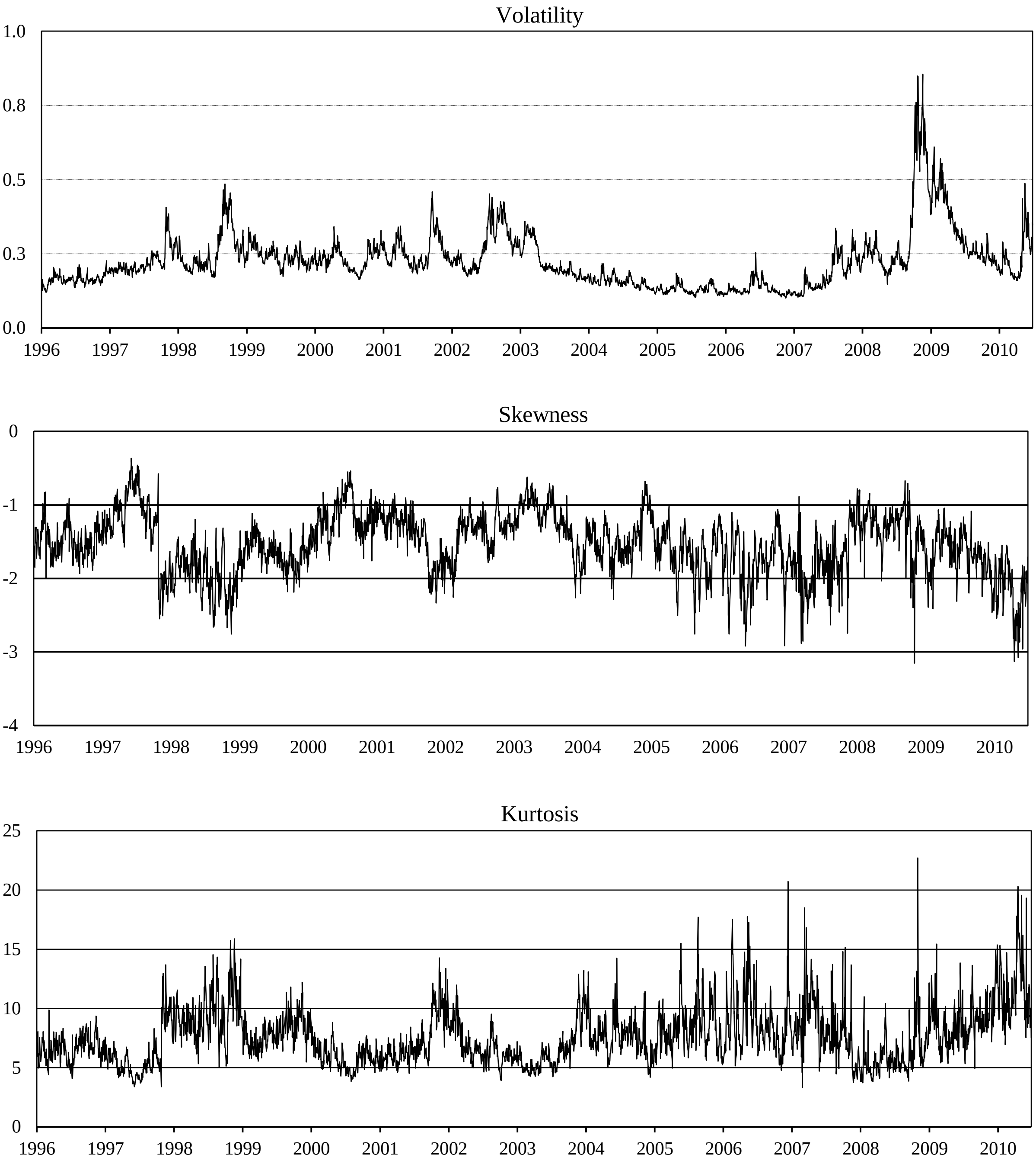
Table 2 - Stock Return Daily

Panel (a): Before Cleaning the Data			
Number of Stocks per Month		Number of Observations per Month	
Maximum	9,306	Maximum	211,234
Median	7,118.5	Median	153,947
Minimum	6,634	Minimum	116,115
Total Number of Stocks	17 083	Total Number of Observations	27,950,063

Panel (b): After Cleaning the Data			
Number of Stocks per Month		Number of Observations per Month	
Maximum	9,042	Maximum	207,000
Median	6,931	Median	150,851
Minimum	6,496	Minimum	112,815
Total Number of Stocks	16,988	Total Number of Observations	27,302,012

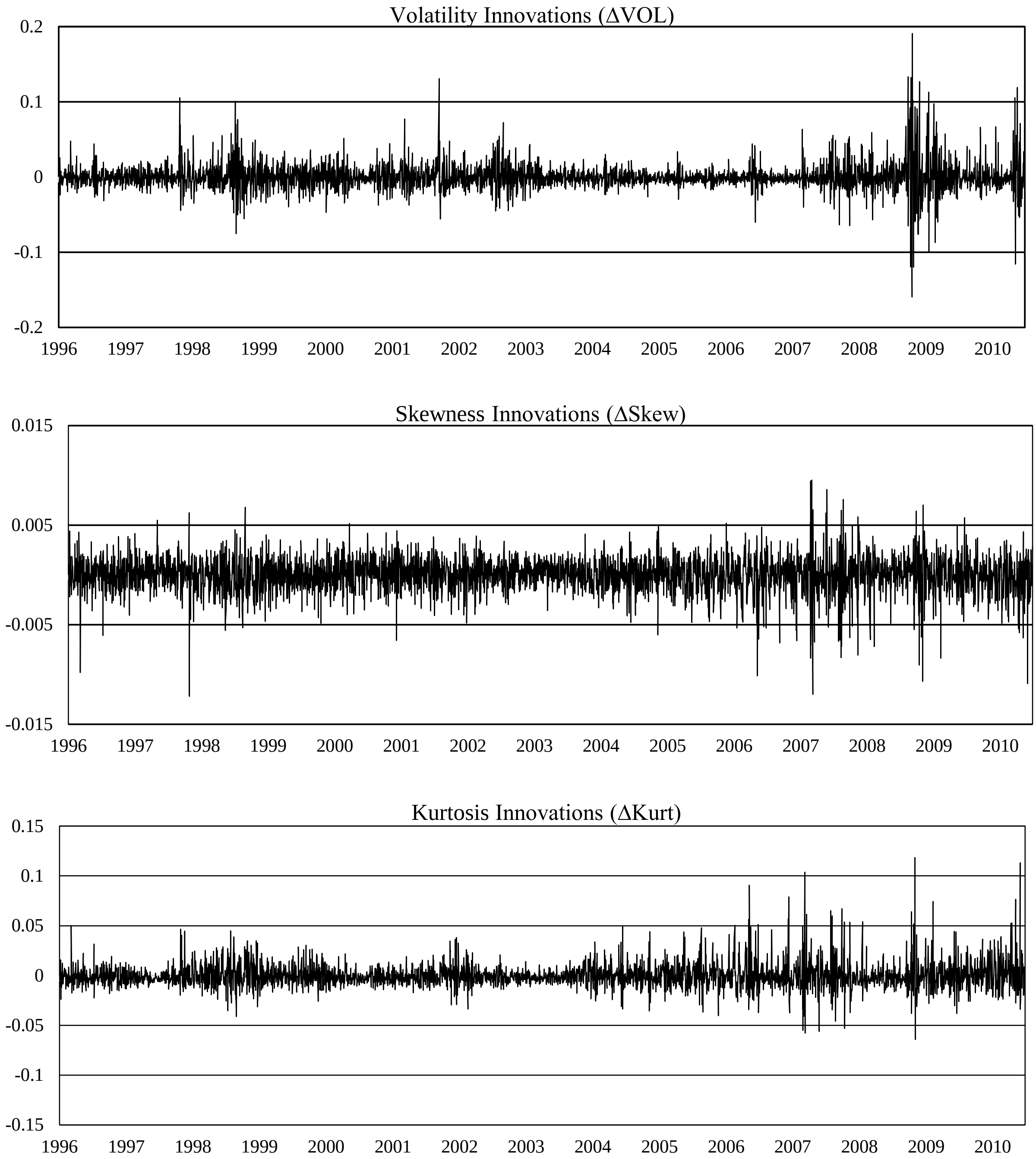
Notes: *We download the daily return time series of all the common stocks, listed in NYSE, AMEX and NASDAQ from the database of the Center for Research in Security Prices (CRSP) from January 1996 to June 2010. Panel (a) shows the size of this data. To have more accurate regressions in each month, we remove the stocks that have missing observations. Panel (b) shows the size of our data after removing these stocks.*

Figure 2 - The Volatility, Skewness and Kurtosis of the S&P 500 Index Return



Notes: *We implement the Bakshi, Kapadia, and Madan (2003) methodology to compute the risk-neutral market moments using the synthetic out of money options written on the S&P 500 index, obtained from the Ivy Database OptionMetrics.*

Figure 3 – The Innovations in the Volatility, Skewness and Kurtosis of the S&P 500 Index Return



Notes: *We fit an Auto-Regressive Moving Average (1, 1) process to the volatility, the skewness and the kurtosis time series of the market returns and take the residuals time series as the innovations processes.*

Table 3 - Factors Dynamics and Correlations

Panel (a): Factors Dynamics						
			Correlation		ARMA (1, 1) Parameters	
	Mean	Standard Deviation	Skewness	Kurtosis	AR(1)	MA(1)
Volatility	0.22	0.09	0.0085	-0.047	0.9856	-0.1261
Skewness	-1.54	0.41		-0.931	0.9614	-0.4043
Kurtosis	7.60	2.35			0.9458	-0.4280

Panel (b): Factors Correlations			
	Correlation		
	ΔVol	$\Delta Skew$	$\Delta Kurt$
ΔVol		0.06	-0.14
$\Delta Skew$			-0.88
$R_m - R_f$	-0.78	-0.24	0.27
SMB	0.09	0.02	-0.04
HML	0.06	0.02	-0.04

Notes: *In Panel (a), we report the correlations and the parameters of the ARMA (1, 1) process fitted to the daily time series of the volatility, the skewness and the kurtosis of the S&P500 index return. Furthermore, in Panel (b) we can see the correlations of the market moments innovations with the Fama-French factors, namely the market excess return (Rm-Rf) and the factors portfolios of market capitalization (SMB) and book to market ratio (HML).*

Table 4 - Exposure Portfolios over All Periods

		Average Monthly Return	Alpha		
			CAPM	Fama-French	Carhart
Panel (a): Volatility Exposure Portfolios	VEP1	0.67	0.21	0.15	0.31
		(1.15)	(0.85)	(0.62)	(1.32)
	VEP2	0.56	0.19	0.19	0.20
		(1.30)	(1.61)	(1.64)	(1.74)
	VEP3	0.51	0.17	0.17	0.15
		(1.31)	(1.95)	(2.00)	(1.75)
	VEP4	0.49	0.12	0.09	0.06
		(1.12)	(1.04)	(0.77)	(0.48)
	VEP5	0.16	-0.31	-0.40	-0.34
		(0.26)	(-1.18)	(-1.68)	(-1.42)
	VEP5-1	-0.51	-0.52	-0.55	**-0.65**
		(-1.31)	(-1.34)	(-1.44)	**(-1.69)**
Panel (b): Skewness Exposure Portfolios	SEP1	1.05	0.61	0.64	0.80
		(1.84)	(2.44)	(2.63)	(3.35)
	SEP2	0.58	0.22	0.23	0.25
		(1.37)	(1.95)	(2.18)	(2.24)
	SEP3	0.52	0.17	0.15	0.12
		(1.30)	(1.97)	(1.76)	(1.47)
	SEP4	0.27	-0.10	-0.16	-0.19
		(0.61)	(-0.83)	(-1.36)	(-1.52)
	SEP5	0.24	-0.23	-0.36	-0.30
		(0.39)	(-0.90)	(-1.55)	(-1.27)
	SEP5-1	**-0.81**	**-0.84**	**-1.00**	**-1.10**
		(-2.10)	**(-2.21)**	**(-2.70)**	**(-2.88)**
Panel (c): Kurtosis Exposure Portfolios	KEP1	0.32	-0.13	-0.22	-0.15
		(0.53)	(-0.53)	(-0.92)	(-0.65)
	KEP2	0.56	0.20	0.19	0.16
		(1.35)	(1.83)	(1.69)	(1.40)
	KEP3	0.47	0.12	0.12	0.09
		(1.18)	(1.34)	(1.44)	(1.01)
	KEP4	0.48	0.10	0.07	0.09
		(1.07)	(0.89)	(0.63)	(0.85)
	KEP5	0.71	0.24	0.17	0.32
		(1.18)	(0.97)	(0.70)	(1.35)
	KEP5-1	0.40	0.38	0.39	0.47
		(1.08)	(1.03)	(1.07)	(1.27)

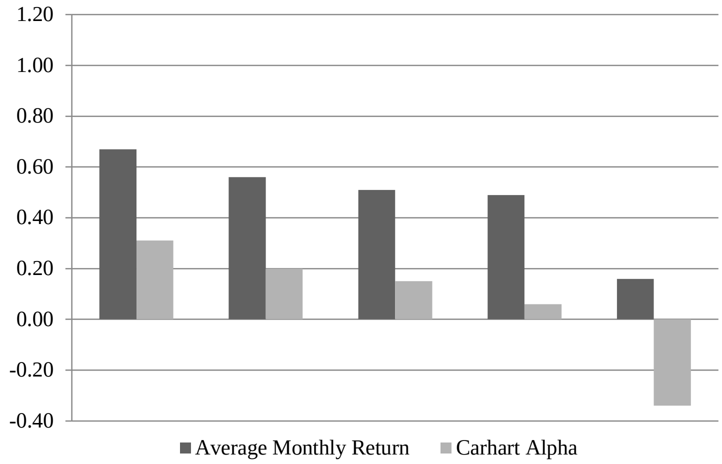
Notes: *For each stock at the end of each month, we run the following regression equation to obtain the conditional exposure of each stock to the market moments innovations.*

$$r_t^i - r_f = \beta_0^i + \beta_{MKT}^i\, MKT_t + \beta_{\Delta Vol}^i\, \Delta Vol_t + \beta_{\Delta Skew}^i\, \Delta Skew_t + \beta_{\Delta Kurt}^i\, \Delta^{\perp} Kurt\,_t + \varepsilon_t^i$$

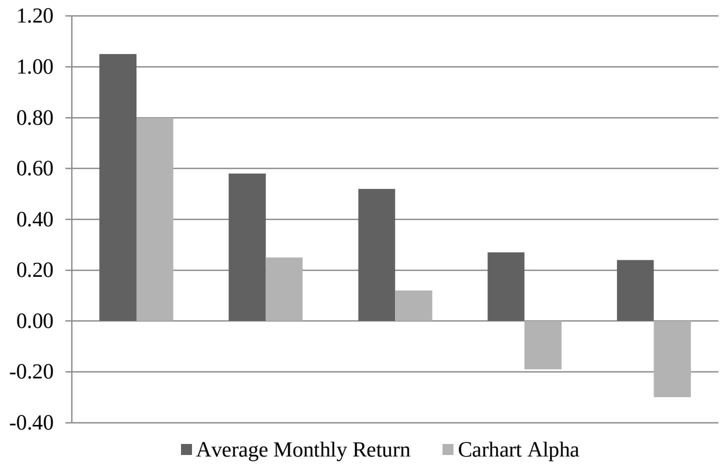
Then for Panel (a), at the end of each month, we sort the $\beta_{\Delta Vol}^i$s calculated for all of the stocks and form five value-weighted portfolios, such that the first volatility exposure portfolio, VEP(1), includes one-fifth of the stocks with the lowest exposures to ΔVol and the last volatility exposure portfolio, VEP(5), is constituted of one-fifth of the stocks with the highest exposures to ΔVol. We record the daily returns of these portfolios over the month after, as post-ranking daily time series, and roll the one-month window ahead. By repeating the same algorithm over all our data sample, we will achieve the five post-ranking portfolios returns time series, named as VEP(1) to VEP(5). We report the average pre-ranking betas, the average monthly returns and the alpha values of these portfolios in Panel (a). For Panel (b) and (c), we use the same regression equation however this time we will sort the stocks according to their $\beta_{\Delta Skew}^i$s, and $\beta_{\Delta kurt}^i$s form five SEPs and five KEPs. In order to obtain the monthly estimations for the alpha values, we multiply the daily alphas by 21. The t-stats that are significant at 90% confidence level are bold faced. We measure the t-statistics using the Newey-West technique with 5 day lags.

Figure 4 - Exposure Portfolios over All Periods

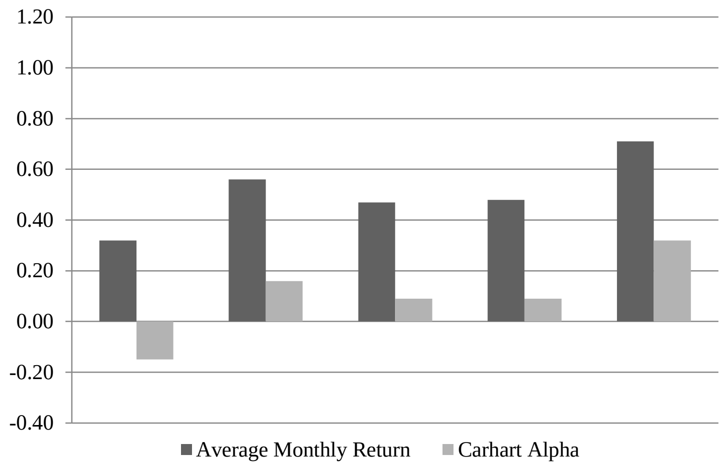
Panel (a): Volatility Exposure Portfolios over All Periods



Panel (b): Skewness Exposure Portfolios over All Periods



Panel (c): Kurtosis Exposure Portfolios over All Periods



Notes: *Panel (a) to (c) show the average monthly returns and the Carhart alphas of the constructed volatility, skewness and kurtosis exposure portfolios versus their corresponding $\beta_{\Delta Vol}$s, $\beta_{\Delta Skew}$s and $\beta_{\Delta Kurt}$s for all of the periods.*

Table 5 - Exposure Portfolios over High Sentiment Periods

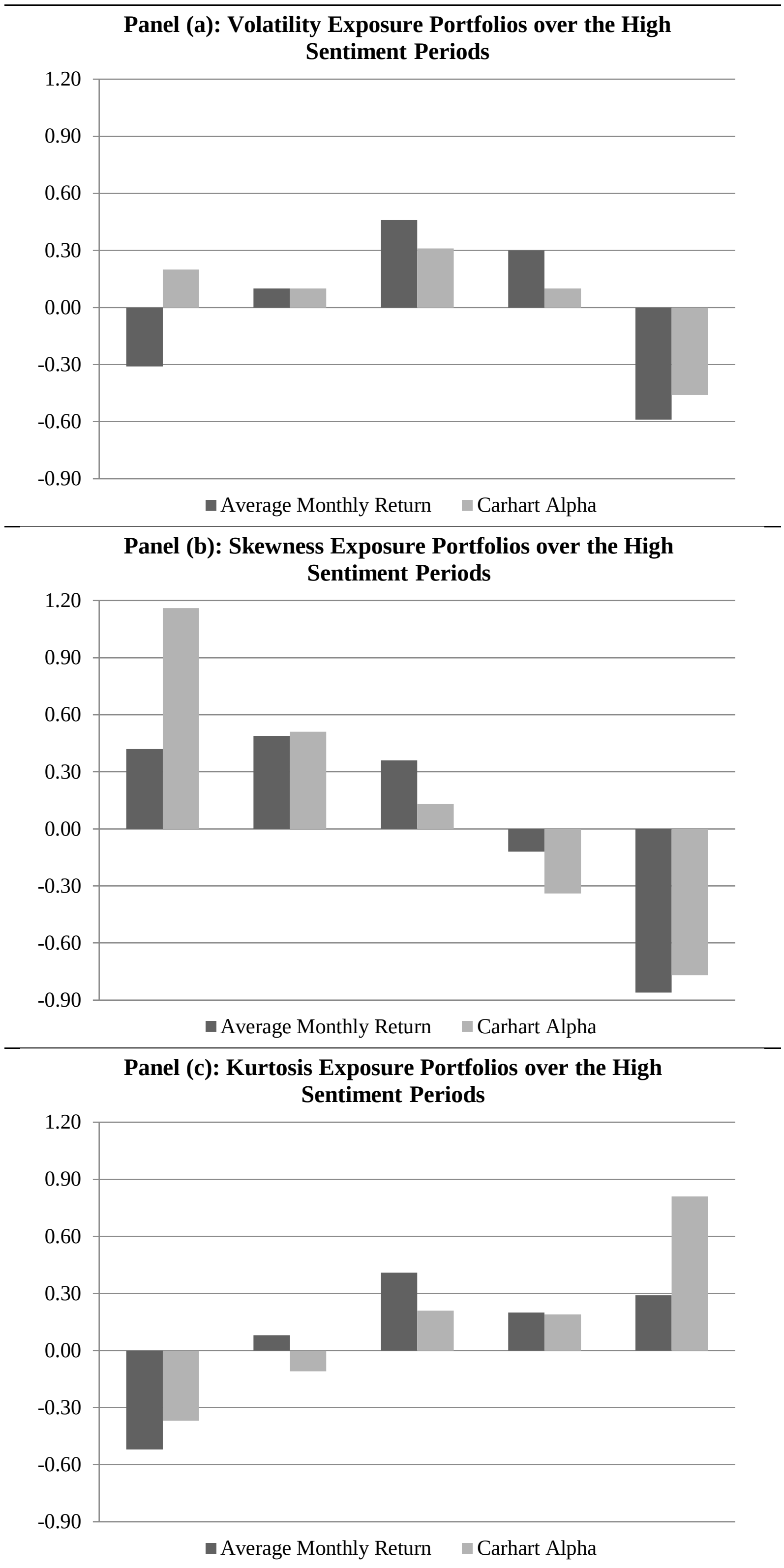
		Average Monthly Return	Alpha CAPM	Fama-French	Carhart
Panel (a): Volatility Exposure Portfolios	VEP1	-0.31 (-0.37)	-0.35 (-0.87)	-0.33 (-0.82)	0.20 (0.53)
	VEP2	0.10 (0.17)	0.07 (0.35)	0.02 (0.08)	0.10 (0.54)
	VEP3	0.46 (0.86)	0.43 (3.09)	0.37 (2.86)	0.31 (2.36)
	VEP4	0.30 (0.49)	0.26 (1.30)	0.26 (1.32)	0.10 (0.46)
	VEP5	-0.59 (-0.66)	-0.63 (-1.49)	-0.39 (-1.07)	-0.46 (-1.20)
	VEP5-1	-0.28 (-0.44)	-0.28 (-0.44)	-0.06 (-0.10)	-0.67 (-1.04)
Panel (b): Skewness Exposure Portfolios	SEP1	0.42 (0.49)	0.37 (0.89)	0.65 (1.62)	1.16 (2.98)
	SEP2	0.49 (0.82)	0.45 (2.63)	0.44 (2.73)	0.51 (2.95)
	SEP3	0.36 (0.67)	0.33 (2.31)	0.20 (1.57)	0.13 (0.93)
	SEP4	-0.12 (-0.19)	-0.15 (-0.83)	-0.23 (-1.25)	-0.34 (-1.80)
	SEP5	-0.86 (-1.03)	-0.91 (-2.33)	-0.78 (-2.28)	-0.77 (-2.19)
	SEP5-1	**-1.28** **(-2.13)**	**-1.28** **(-2.13)**	**-1.43** **(-2.45)**	**-1.93** **(-3.19)**
Panel (c): Kurtosis Exposure Portfolios	KEP1	-0.52 (-0.63)	-0.57 (-1.48)	-0.44 (-1.30)	-0.37 (-1.07)
	KEP2	0.08 (0.14)	0.05 (0.28)	-0.01 (-0.04)	-0.11 (-0.59)
	KEP3	0.41 (0.75)	0.38 (2.46)	0.32 (2.24)	0.21 (1.50)
	KEP4	0.20 (0.33)	0.17 (0.93)	0.12 (0.67)	0.19 (1.06)
	KEP5	0.29 (0.33)	0.24 (0.59)	0.43 (1.09)	0.81 (2.12)
	KEP5-1	0.81 (1.40)	0.81 (1.40)	0.86 (1.52)	**1.18** **(1.98)**

Notes: *For each stock at the end of each month, we run the following regression equation to obtain the conditional exposure of each stock to the market moments innovations.*

$$r_t^i - r_f = \beta_0^i + \beta_{MKT}^i\, MKT_t + \beta_{\Delta Vol}^i\, \Delta Vol_t + \beta_{\Delta Skew}^i\, \Delta Skew_t + \beta_{\Delta Kurt}^i\, \Delta^{\perp} Kurt_{\ t} + \varepsilon_t^i$$

Then for Panel (a), at the end of each month, we sort the $\beta_{\Delta Vol}^i$s calculated for all of the stocks and form five value-weighted portfolios, such that the first volatility exposure portfolio, VEP(1), includes one-fifth of the stocks with the lowest exposures to ΔVol and the last volatility exposure portfolio, VEP(5), is constituted of one-fifth of the stocks with the highest exposures to ΔVol. We record the daily returns of these portfolios over the month after, as post-ranking daily time series, and roll the one-month window ahead. By repeating the same algorithm over all our data sample, we will achieve the five post-ranking portfolios returns time series, named as VEP(1) to VEP(5). We report the average pre-ranking betas, the average monthly returns and the alpha values of these portfolios over the high sentiment periods in Panel (a). For Panel (b) and (c), we use the same regression equation however this time we will sort the stocks according to their $\beta_{\Delta Skew}^i$s, and $\beta_{\Delta kurt}^i$s form five SEPs and five KEPs. In order to obtain the monthly estimations for the alpha values, we multiply the daily alphas by 21. The t-stats that are significant at 90% confidence level are bold faced. We measure the t-statistics using the Newey-West technique with 5 day lags.

Figure 5 - Exposure Portfolios over the High Sentiment Periods



Notes: *Panel (a) to (c) show the average monthly returns and the Carhart alphas of the constructed volatility, skewness and kurtosis exposure portfolios versus their corresponding $\beta_{\Delta Vol}$s, $\beta_{\Delta Skew}$s and $\beta_{\Delta Kurt}$s over the high sentiment periods.*

Table 6 - Exposure Portfolios over Low Sentiment Periods

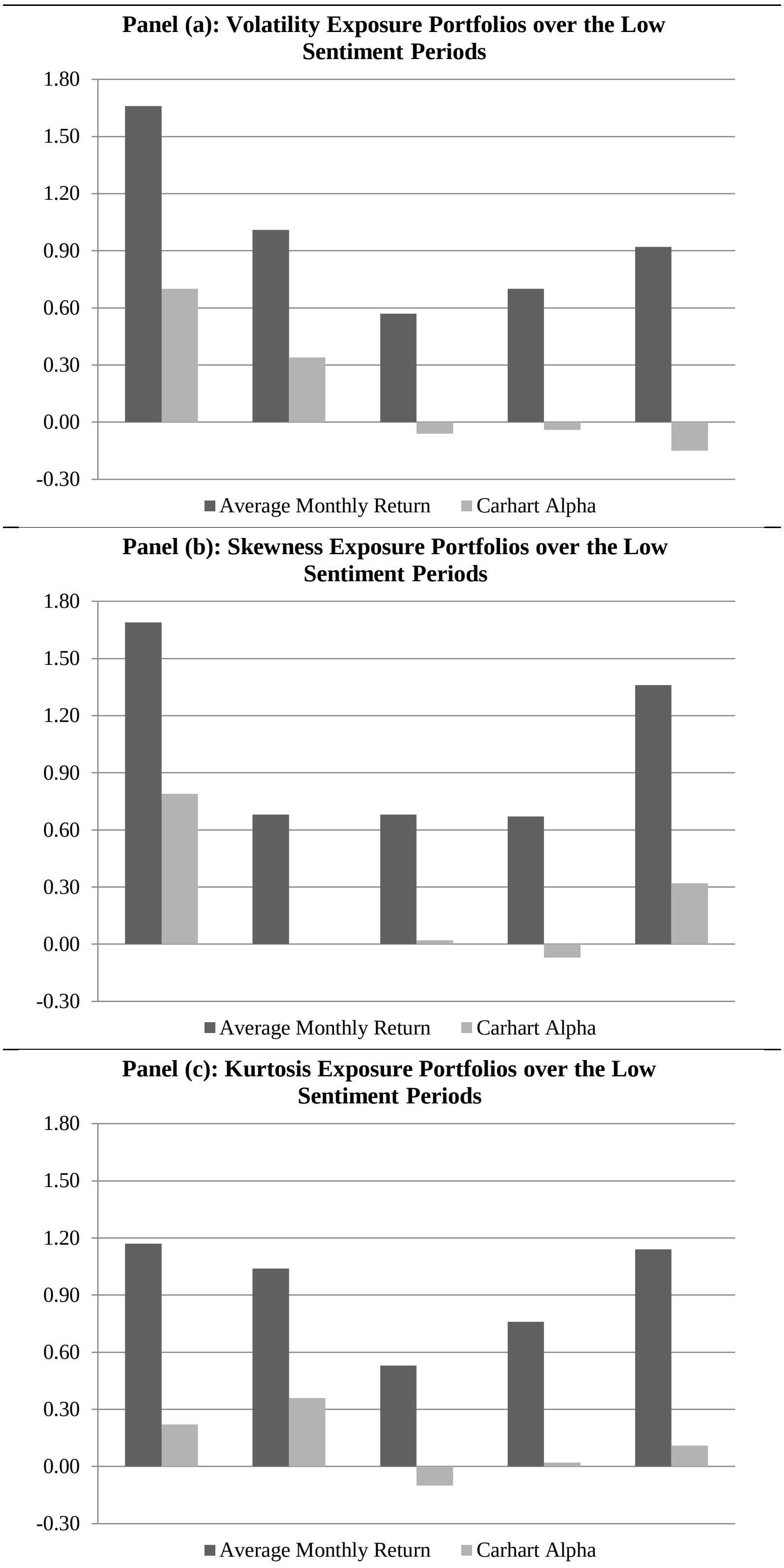
		Average Monthly Return	Alpha		
			CAPM	Fama-French	Carhart
Panel (a): Volatility Exposure Portfolios	VEP1	1.66	0.77	0.72	0.70
		(2.03)	(2.81)	(2.65)	(2.62)
	VEP2	1.01	0.30	0.33	0.34
		(1.66)	(2.41)	(2.66)	(2.74)
	VEP3	0.57	-0.10	-0.07	-0.06
		(0.98)	(-0.98)	(-0.62)	(-0.59)
	VEP4	0.70	-0.02	-0.03	-0.04
		(1.08)	(-0.13)	(-0.27)	(-0.32)
	VEP5	0.92	0.04	-0.10	-0.15
		(1.06)	(0.12)	(-0.34)	(-0.55)
	VEP5-1	**-0.74**	**-0.73**	**-0.82**	**-0.85**
		(-1.71)	**(-1.72)**	**(-1.94)**	**(-2.04)**
Panel (b): Skewness Exposure Portfolios	SEP1	1.69	0.89	0.81	0.79
		(2.20)	(3.27)	(3.05)	(3.05)
	SEP2	0.68	-0.03	-0.00	-0.00
		(1.10)	(-0.23)	(-0.01)	(-0.00)
	SEP3	0.68	0.00	0.02	0.02
		(1.15)	(0.00)	(0.18)	(0.20)
	SEP4	0.67	-0.07	-0.07	-0.07
		(1.02)	(-0.47)	(-0.44)	(-0.46)
	SEP5	1.36	0.43	0.35	0.32
		(1.50)	(1.30)	(1.17)	(1.08)
	SEP5-1	-0.33	-0.46	-0.46	-0.48
		(-0.70)	(-0.99)	(-1.02)	(-1.07)
Panel (c): Kurtosis Exposure Portfolios	KEP1	1.17	0.33	0.25	0.22
		(1.38)	(1.00)	(0.82)	(0.75)
	KEP2	1.04	0.35	0.36	0.36
		(1.75)	(2.75)	(2.77)	(2.80)
	KEP3	0.53	-0.15	-0.11	-0.10
		(0.91)	(-1.49)	(-1.15)	(-1.08)
	KEP4	0.76	0.01	0.02	0.02
		(1.15)	(0.04)	(0.20)	(0.16)
	KEP5	1.14	0.24	0.15	0.11
		(1.34)	(0.87)	(0.55)	(0.43)
	KEP5-1	-0.02	-0.09	-0.11	-0.11
		(-0.05)	(-0.20)	(-0.24)	(-0.26)

Notes: *For each stock at the end of each month, we run the following regression equation to obtain the conditional exposure of each stock to the market moments innovations.*

$$r_t^i - r_f = \beta_0^i + \beta_{MKT}^i\, MKT_t + \beta_{\Delta Vol}^i\, \Delta Vol_t + \beta_{\Delta Skew}^i\, \Delta Skew_t + \beta_{\Delta Kurt}^i\, \Delta^{\perp} Kurt_{\ t} + \varepsilon_t^i$$

Then for Panel (a), at the end of each month, we sort the $\beta_{\Delta Vol}^i$*s calculated for all of the stocks and form five value-weighted portfolios, such that the first volatility exposure portfolio, VEP(1), includes one-fifth of the stocks with the lowest exposures to* ΔVol *and the last volatility exposure portfolio, VEP(5), is constituted of one-fifth of the stocks with the highest exposures to* ΔVol*. We record the daily returns of these portfolios over the month after, as post-ranking daily time series, and roll the one-month window ahead. By repeating the same algorithm over all our data sample, we will achieve the five post-ranking portfolios returns time series, named as VEP(1) to VEP(5). We report the average pre-ranking betas, the average monthly returns and the alpha values of these portfolios over the low sentiment periods in Panel (a). For Panel (b) and (c), we use the same regression equation however this time we will sort the stocks according to their* $\beta_{\Delta Skew}^i$*s, and* $\beta_{\Delta kurt}^i$*s form five SEPs and five KEPs. In order to obtain the monthly estimations for the alpha values, we multiply the daily alphas by 21. The t-stats that are significant at 90% confidence level are bold faced. We measure the t-statistics using the Newey-West technique with 5 day lags.*

Figure 6 - Exposure Portfolios over Low Sentiment Periods



Notes: *Panel (a) to (c) show the average monthly returns and the Carhart alphas of the constructed volatility, skewness and kurtosis exposure portfolios versus their corresponding $\beta_{\Delta Vol}$s, $\beta_{\Delta Skew}$s and $\beta_{\Delta Kurt}$s over the low sentiment periods.*

Table 7 - Exposure Portfolios over High and Low Sentiment Periods, Segregated with the Mean of the Sentiment Index

		Average Monthly Return	Alpha		
			CAPM	Fama-French	Carhart
Over the High Sentiment Periods	VEP5-1	-0.21	-0.18	-0.02	-0.57
		(-0.28)	(-0.25)	(-0.03)	(-0.78)
	SEP5-1	**-1.44**	**-1.44**	**-1.51**	**-2.17**
		(-2.20)	**(-2.20)**	**(-2.30)**	**(-3.41)**
	KEP5-1	**1.13**	**1.13**	**1.08**	**1.54**
		(-1.79)	**(-1.79)**	**(-1.71)**	**(-2.41)**
Over the Low Sentiment Periods	VEP5-1	**-0.74**	**-0.71**	**-0.79**	**-0.79**
		(-1.86)	**(-1.82)**	**(-2.03)**	**(-2.04)**
	SEP5-1	-0.34	-0.46	-0.45	-0.46
		(-0.73)	(-1.03)	(-1.04)	(-1.07)
	KEP5-1	-0.15	-0.22	-0.24	-0.23
		(-0.35)	(-0.53)	(-0.56)	(-0.56)

Notes: *For this table, in order to segregate the high and the low sentiment periods we use the mean of the sentiment index, as opposed to Tables (5) and (6), for which we used the median for periods separation.*

Table 8 - Exposure Portfolios over High and Low Sentiment Periods, Segregated with the Median of the Investor Orthogonalized Sentiment Index

		Average Monthly Return	Alpha		
			CAPM	Fama-French	Carhart
Over the High Sentiment Periods	VEP5-1	-0.46	-0.46	-0.28	-0.81
		(-0.71)	(-0.71)	(-0.44)	(-1.29)
	SEP5-1	**-1.22**	**-1.21**	**-1.29**	**-1.70**
		(-1.93)	**(-1.92)**	**(-2.09)**	**(-2.63)**
	KEP5-1	0.88	0.88	**0.98**	**1.19**
		(-1.46)	(-1.46)	**(-1.65)**	**(-1.90)**
Over the Low Sentiment Periods	VEP5-1	-0.56	-0.65	-0.67	**-0.68**
		(-1.32)	(-1.57)	(-1.63)	**(-1.69)**
	SEP5-1	-0.39	-0.58	-0.58	-0.58
		(-0.91)	(-1.43)	(-1.46)	(-1.48)
	KEP5-1	-0.09	-0.22	-0.25	-0.26
		(-0.22)	(-0.54)	(-0.61)	(-0.64)

Notes: *For this table, in order to segregate the high and the low sentiment periods we use the median of the Investor Orthogonalized Sentiment Index, as opposed to Tables (5) and (6), for which we used the median of the Investor Sentiment Index.*

Figure 9 – The Impact Investor Sentiment Level

Portfolio	Alpha	Sent Beta	Market Beta	SMB Beta	HML Beta	Mom Beta
VEP5-1	-0.005	0.040	0.096			
	(-1.517)	(1.466)	(0.986)			
	-0.007	**0.040**	0.049	**0.327**	0.074	
	(-1.845)	**(1.891)**	(0.594)	**(1.789)**	(0.451)	
	-0.007	**0.037**	0.063	**0.322**	0.088	0.027
	(-1.768)	**(1.643)**	(0.709)	**(1.759)**	(0.573)	(0.242)
SEP5-1	**-0.008**	**-0.049**	0.002			
	(-3.268)	**(-2.855)**	(0.022)			
	-0.009	**-0.049**	-0.015	**0.169**	0.068	
	(-3.5)	**(-2.718)**	(-0.162)	**(2.246)**	(0.632)	
	-0.008	**-0.042**	-0.054	**0.184**	0.029	-0.076
	(-3.908)	**(-2.436)**	(-0.438)	**(2.099)**	(0.268)	(-0.913)
KEP5-1	0.004	0.038	0.056			
	(1.289)	(1.404)	(0.572)			
	0.003	0.036	0.061	**0.104**	0.110	
	(1.028)	(1.438)	(0.614)	**(1.853)**	(1.143)	
	0.003	**0.039**	0.045	**0.110**	0.094	-0.032
	(1.082)	**(1.711)**	(0.362)	**(1.914)**	(0.828)	(-0.418)

Notes: *To be able to analyze the impact of the changes in the investor sentiment level, for our whole data sample from January 1996 to June 2010, we regress the monthly time series of VEP5-1, SEP5-1 and KEP5-1 on the incremental changes in the sentiment index, the market return, the Fama-French and the Carhart factors.*

$$XEP_t^{5-1} = \alpha + \beta_{Sent}\Delta Sent_{t-1} + \beta_{MKT}MKT_t$$

$$XEP_t^{5-1} = \alpha + \beta_{Sent}\Delta Sent_{t-1} + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{HML}HML_t$$

$$XEP_t^{5-1} = \alpha + \beta_{Sent}\Delta Sent_{t-1} + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{Mom}Mom_t$$

In these Equations XEP5-1 can be VEP5-1, SEP5-1 or KEP5-1.

We measure the t-statistics using the Newey-West technique with 12 month lags.