Risk Aversion, Sentiment and the Cross Section of Stock Returns

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June 2017

Abstract

Previous research suggests that the cross section of stock returns has substantial exposure to risk captured by higher moments of market returns, implied by S&P500 index option prices. 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 a measure of investors' risk aversion. In particular, our results suggest that only in down-markets (high risk aversion periods), the exposure to the market volatility innovations is priced significantly negative in the cross-section of stocks, while it is not priced in up-markets (low risk aversion periods). 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. Furthermore, we find that an index of investor sentiment is strongly negatively affected by past realizations (6-12 months) of our proxy of investors' risk aversion. As a result, our empirical results can be replicated by analyzing periods of high and low sentiment, separately. Our results shed some light on how risk aversion and sentiment covary over time.

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1. Introduction

Assets that pay off well in bearish markets are more desirable than assets with a high payoff in bullish markets. Merton (1973) introduced the intertemporal capital asset pricing model [ICAPM] to address the static drawback in CAPM (Sharpe 1964; Lintner 1965) and argued 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 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. Negative shifts in the investment opportunity set reduce the consumption for a given level of future wealth. Intuitively, we can 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.

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[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).

[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).

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 exhibit lower risk aversion (e.g. risk-seeking behavior), we expect the price of volatility risk to be 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 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 exhibit lower risk aversion (e.g. risk-seeking behavior), we expect the price of skewness risk to be 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 exhibit lower risk aversion (e.g. risk-seeking behavior), we expect the price of

kurtosis risk to be 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 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 (2013) 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 risk is in contradiction to economic intuition that we developed earlier, assuming risk averse investors.

It is broadly believed that risk aversion fluctuates over the business cycle, rising in recessions and dropping in expansions (e.g. Rosenberg and Engle (2002)). We argue that the compensation of higher moment risks in the stock cross-section also depend on market conditions. As in up-markets the relative risk aversion is low, we do not expect to detect e.g. a significant mean-variance relationship in such periods. However, in down-markets, the relative risk aversion is high and the mean-variance relationship is expected to be significant. This would also affect the exposure of stock returns to market risks captured by higher risk-neutral moments. Therefore, we expect results to be different in up- and in down-markets,

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

which might shed some light on the previously found counterintuitive results for market skewness.

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 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 in periods of low risk aversion, 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. In our empirical analysis, we test the validity of this hypothesis, and find that the Baker-Wurgler investor sentiment index, which is a composition of risk premium sensitive proxies, is strongly negatively affected by past realizations (6-12 months) in the investors' relative risk aversion.

Behavioral researchers would argue that high sentiment periods are characterized as periods when stocks are overvalued, investors are optimistic about the market prospect and stocks expected returns are low. 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.

In this paper, we aim to investigate the relationship between risk aversion and sentiment. We compute risk-neutral 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 investors' expectations about market future conditions impact the options prices, the option implied moments are strictly forward-looking. Our empirical design 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 the cross-section of expected stock returns. Indeed, we can 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, characterized by periods of low risk aversion, and down-markets, characterized by high risk aversion periods in the market. We compute the investor relative risk aversion time series, using the methodology of Campbell and Cochrane (1999) and Brandt and Wang (2003). Hence, independently for each of the moments at the end of each month, we form five value-weighted portfolios from all stocks in the CRSP database, according to their exposure to the market moments; such that the first portfolio includes the 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 specific 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 conduct the sub-sample analysis based on periods of low and high risk aversion, we observe that:

(1) The price of market volatility risk is significantly negative in down-markets, periods of high risk aversion, while in the low risk aversion periods, it is not statistically and economically significant. The lower risk-aversion in up-markets lowers the otherwise significantly negative price of market volatility risk.

(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 and insignificant in up-markets. However, the price of market skewness risk is found to be insignificant in down-markets, but significantly negative in up-markets, 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.

(3) In line with intuition, we expect the price of market kurtosis risk to be negative in down-markets, and insignificant in up-markets. In contrast, it is insignificant periods of high risk aversion, and, partly significantly, positive in low risk aversion periods, which is in line with the results for market skewness. More risk seeking investors find the hedge against the unfavorable scenario (positive kurtosis) 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.

These results are robust, even after controlling for the Fama-French (1993) and the Carhart (1997) factors. Furthermore, we investigate the relationship between investors' risk aversion and an investor sentiment index. We find that sentiment is strongly negatively affected by past realizations (6-12 months) in the investors' relative risk aversion. In other words, periods of low (high) sentiment are typically preceded by periods of increased (decreased) risk aversion in the market. Our findings further suggest that our previous results can be replicated by analyzing periods of high and low sentiment, separately. 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, only pick up risk premia.

The rest of this paper is structured as follows: In section 2, we discuss the data and derive the main variables for our analysis. In section 3, we present the empirical results of the study and section 4 concludes.

2. Data and Methodology

Stocks Cross-Section

In order to compare the market moment prices of risk in the cross-section of stocks, we obtain the daily return time series of all actively traded[4] ordinary common shares, transacted at NYSE, AMEX and NASDAQ, from the database of the Center for Research in Security Prices (CRSP). The raw data is filtered in the usual way (e.g. see Chang, Christoffersen and Jacobs (2013)). In each month, we omit the stocks with missing observations. In addition, to calculate the market capitalization of each stock at the end of each month, we obtain the

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

monthly time series of the stock prices and the numbers of shares outstanding from CRSP. We conduct our asset pricing analysis on the largest common interval between our data sets, from January 1996 to June 2010.

Risk-Neutral 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 (OTM) European call and put options. Accordingly, Bakshi, Kapadia and Madan (2003) 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 in that day (e.g. Bollerslev, Tauchen and Zhou 2009). However since high-frequency returns are affiliated with microstructure frictions and the sampling properties of high frequency returns do not necessarily reflect the statistical characteristics of 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.

We use the methodology of Bakshi, Kapadia, Madan (2003) to calculate the risk neutral market moments time series. A detailed explanation about our implementation is provided in the appendix. As near-to-maturity options reflect investors' short-term expectations more clearly, for each day we calculate the risk-neutral moments for the horizon of the-next-30-

days. We obtain the daily prices of the European options written on the S&P 500 index from the Ivy DB of OptionMetrics. Since our option data is limited to January 1996 to June 2010, we conduct the rest of our analysis on this interval. Fortunately this interval covers mild and harsh, expansion and recession periods. Figure (1) exhibits the daily time series of the risk-neutral market volatility, market skewness and market kurtosis.

[PLEASE INSERT FIGURE 1 ABOUT HERE]

Figure (1) 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 to the market volatility, skewness and kurtosis, independently. The dynamics of the innovations in the market moments, named as ΔVol^{τ}, $\Delta Skew^{\tau}$ and $\Delta Kurt^{\tau}$, are shown in Equations (11) to (13), respectively.[5]

$$\Delta Vol_t^{\tau} = 0.1261 * \Delta Vol_{t-1}^{\tau} + (Vol_t^{\tau} - 0.9856 * Vol_{t-1}^{\tau}) \quad (11)$$

$$\Delta Skew_t^{\tau} = 0.4043 * \Delta Skew_{t-1}^{\tau} + (Skew_t^{\tau} - 0.9614 * Skew_{t-1}^{\tau}) \quad (12)$$

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

$$\Delta Kurt_t^{\tau} = 0.4280 * \Delta Kurt_{t-1}^{\tau} + (Kurt_t^{\tau} - 0.9458 * Kurt_{t-1}^{\tau}) \qquad (13)$$

Obviously the three AR (1) coefficients are extremely close to one, showing that the moment processes are highly autoregressive. Table (1) provides some descriptive statistics about these time series.

[PLEASE INSERT TABLE 1 ABOUT HERE]

As it is clear from Panel (B) in Table (1), the correlation coefficient between $\Delta Skew_t^{\tau}$ and $\Delta Kurt_t^{\tau}$ is -0.88. Following Chang, Christoffersen and Jacobs (2013), 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 $\Delta Skew_t^{\tau}$.

$$\Delta Kurt_t^{\tau} = a + b\, \Delta Skew_t^{\tau} + \Delta^{\perp} Kurt_t^{\tau} \qquad (14)$$

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

Relative Risk Aversion

Based on the habit formation idea, Cochrane and Campbell (1999) setup a framework to exploit the time variation in investors risk aversion. Brandt and Wang (2003) improve this model by adding the impact of inflation uncertainty to risk aversion. They find investor risk aversion is influenced by release of bad news in the consumption growth and inflation. We mainly focus on the implementation of Brandt and Wang (2003) to exploit the time varying risk aversion, however since we work with real consumption growth and real stock prices (as opposed to their nominal values), we omit the impact of inflation and assume that the investor risk aversion is only influenced by news in real consumption growth. We assume a representative agent maximizes her life time utility function

$$U(C_0, C_1, C_2, \dots, C_\infty) = \sum_{t=0}^{\infty} \delta^t u(C_t - X_t) \tag{1}$$

where

$$u(C_t - X_t) = \begin{cases} \ln(C_t - X_t) & if\ \alpha = 1 \\ \dfrac{(C_t - X_t)^{1-\alpha} - 1}{1-\alpha} & if\ \alpha > 0\ and\ \alpha \neq 1 \end{cases} \tag{2}$$

Here δ is a subjective discount factor, and α shows the curvature of the utility function. Also, C_t and X_t are the level of consumption and habit at time t.

In this setup a few points are crucial. Firstly, at any point in time the consumption must be higher than the habit level, so that $C_t - X_t > 0$, and the utility function is measurable. Secondly, at the steady state the habit is not affected by consumption $\left(\frac{dX_t}{dC_t} = 0\right)$. And finally, except in the steady state, with any increase in the consumption the habit should increase $\left(\frac{dX_t}{dC_t} > 0\right)$. In this case, the Relative Risk Aversion at time t (RRA_t) will be

$$RRA_t = -\frac{C_t\, u''^{(C_t - X_t)}}{u'(C_t - X_t)} = \alpha \frac{C_t}{C_t - X_t} \tag{3}$$

Hence following Brandt and Wang (2003), we define the dynamic of log relative risk aversion $\gamma_t = \ln(RRA_t)$ as

$$\gamma_{t+1} = \bar{\gamma} + \emptyset(\gamma_t - \bar{\gamma}) - e_{t+1} \tag{4}$$

where

$$e_{t+1} = \lambda(\gamma_t)(g_{t+1} - E_t[g_{t+1}]) \tag{5}$$

The investor risk aversion is mean-reverting if $\emptyset < 1$. In equation (5), $g_{t+1} = ln(C_{t+1}) - ln(C_t)$ is the consumption growth rate between time t and $t+1$. Furthermore $\lambda(\gamma_t)$ reflects the sensitivity of relative risk aversion to news about consumption growth, and following Brandt and Wang (2003) we set it as

$$\lambda(\gamma_t) = \frac{1}{\alpha}\exp(\gamma_t) - 1 \tag{6}$$

From the sensitivity function in equation (6), it is clear that once the risk aversion increase, the investor becomes more sensitive to news in the consumption growth.

Based on the fundamental equation of asset pricing, for every asset with the payoff of P_{t+1} and the standardized payoff of $R_{t+1} = \frac{P_{t+1}}{P_t}$, we have

$$1 = E_t\left[m_{t,t+1}\, R_{t+1}\right] \tag{7}$$

Where $m_{t,t+1}$ is the pricing kernel between time t and $t+1$. In our setup, instead of using the nominal prices, we execute the computations on the real price values. Therefore, the real pricing kernel in our setup will be

$$m_{t,t+1} = \delta \exp\big(\alpha(\gamma_{t+1} - \gamma_t - g_{t+1})\big) \tag{8}$$

In order to estimate the values of our unknown parameters $\theta = \{\alpha, \delta, \bar{\gamma}, \emptyset\}$, we use the Generalized Method of Moments (GMM). For this purpose, first to obtain an estimation of $E_t[g_{t+1}]$ in equation (5), we fit an ARMA (1, 1) process[6] to the consumption growth time

[6] Although our result is not sensitive to the choice of p and q in ARMA (p, q) model, ARMA (1, 1) process provides us the best Akaike Information Criterion (AIC), among the models that we tested. The detailed analysis is available upon request.

series, and take the fitted value at $t + 1$ as our estimation for $E_t[g_{t+1}]$. Then we minimize the sum of squares of deviations from equation (7) using certain conditioning variables Z_t. In order words, we define h_{t+1} as

$$h_{t+1} = (m_{t,t+1} R_{t+1} - 1) \otimes Z_t \tag{9}$$

Obviously $E_t[h_{t+1}] = 0$. Thus based on the idea of GMM and law of iterated expectations, we find θ that minimize the norm of $h_{t+1}(\theta)$

$$\left[\frac{1}{T}\sum_{t=1}^{T} h_{t+1}(\theta)\right] W_T \left[\frac{1}{T}\sum_{t=1}^{T} h_{t+1}(\theta)\right] \tag{10}$$

W_T is the optimal weight matrix that we update based on Hansen (1982) in each iteration of the optimization process.

We obtain the Personal Consumption Expenditure data from website of the Federal Reserve Bank of Saint Louis. We select the dividend yield, term spread and 1-month US Treasury yield as the conditioning variables, and fit the model to the monthly time series of 25 Fama and French stock portfolios. We calculate the investor risk aversion for a period from 1965 to 2010. The huge dispersion between the 25 Fama and French stock portfolios and our long study period, with several economic expansions and recessions, enables us to compute the relative risk aversion time series accurately. Figure (2) shows the relative risk aversion time series over a period from 1965 until 2010.

[PLEASE INSERT FIGURE 2 ABOUT HERE]

As can be seen from the figure, risk aversion fluctuates over the business cycle, rising in recessions and dropping in expansions. Table (2) provides some basic statistics about the relative risk aversion time series. Our estimation of θ is also reported in this Table. The relative risk aversion time series ranges from 4.411 to 5.224, which is a very legitimate interval based on the past literature.

[PLEASE INSERT TABLE 2 ABOUT HERE]

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 mimic the behaviors of noise traders[7] 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 share turnover (Baker and Stein 2004), the dividend premium (Baker and Wurgler 2004).[8] 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,

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

[8] 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.

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[9], 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. Table (2) provides some basic statistics.

3. Empirical Analysis

Asset Pricing Tests

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 ($\Delta\mathrm{Vol}$) should have different expected returns in the subsequent periods. Motivated by this fact, they measure and compare the stocks cross-sectional exposure to the market volatility innovations ($\Delta\mathrm{Vol_t} = \mathrm{Vol_t} - \mathrm{Vol_{t-1}}$), using the market volatility index (VIX) of the Chicago Board of Options Exchange (CBOE). Chang, Christoffersen and Jacobs (2013) extend this analysis for the market skewness innovations ($\Delta\mathrm{Skew}$) and the market kurtosis innovations ($\Delta\mathrm{Kurt}$). We carry out the same analysis for a longer time interval, but additionally we investigate the effect of these cross-sectional exposures in up- and down-markets, characterized by low and high risk aversion, respectively.

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

Results presented in Table (3) reveal that there exists a significantly negative correlation of -0.78, between $\Delta\mathrm{Vol}$ and the concurrent market excess return $(\mathrm{R_m} - \mathrm{R_f})$. 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 $\Delta\mathrm{Vol}$, starting from January 1996, we take one-month daily returns[10] of each stock and run the following regression

$$\mathrm{r}_t^i - \mathrm{r}_{f,t} = \beta_0^i + \beta_{MKT}^i\, \mathrm{MKT}_t + \beta_{\Delta Vol}^i\, \Delta\mathrm{Vol}_t + \beta_{\Delta Skew}^i\, \Delta\mathrm{Skew}_t + \beta_{\Delta Kurt}^i\, \Delta\mathrm{Kurt}_t + \varepsilon_t^i \tag{15}$$

Where $\mathrm{MKT}(= \mathrm{R_m} - \mathrm{R_f})$ 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

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[10] 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.

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 return 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 of the five volatility exposure portfolios (VEP1 to VEP5), the five skewness exposure portfolios (SEP1 to SEP5) and the five kurtosis exposure portfolios (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[11].

Table (3) displays alpha values of each exposure portfolio based on the CAPM, the Fama-French Model and the Carhart Model.

[PLEASE INSERT TABLE 3 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.[12] Figure (3) pictures the information in Table (3).

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[11] 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.

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

[PLEASE INSERT FIGURE 3 ABOUT HERE]

The average monthly returns and the alpha values of the volatility exposure portfolios follow a 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 mention that the average monthly return of VEP5-1 is not statistically and economically significant. This can be inferred from the t-statistics, adjusted with the Newey-West technique.

Similarly in Panel (B) of Figure (3), we can observe strictly declining patterns for the average monthly returns and the alpha values 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 (3) 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, Risk Aversion

As expleined earlier, due to lower risk aversion, up-markets 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, due to higher levels of risk aversion, stocks are undervalued, investors are more risk-averse and market risk is priced. In order to distinguish between up- and down markets, we use our estimated coefficient of the relative risk aversion of the representative investor. We refer to the months with the relative risk aversion coefficient above its median as the high risk aversion periods and the months with the relative risk aversion coefficient below its median as the low risk aversion periods.

[PLEASE INSERT TABLE 4 ABOUT HERE]

[PLEASE INSERT FIGURE 4 ABOUT HERE]

By looking at Panel (A.L) in Table (4) and Figure (4), 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 low risk aversion periods, 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.L) of Figure (4) indicates that in low risk aversion periods, when the market is overvalued, the market volatility risk is not priced in the cross-section of stocks.

Similarly, 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.L) of Figure (4), are a 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 $\beta_{\Delta \mathrm{Skew}}$) 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 the low risk aversion periods. Similarly, in Panel (C.L) of Figure (4), 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 (low risk aversion 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.

In contrast, the sharply declining patterns of the average monthly returns and the alpha values of the market volatility exposure portfolios, shown in Panel (A.H) of Table (4) and Figure (4), show that in high risk aversion periods, investors demand a premium for market volatility risk. Comparing with up-markets, in high risk aversion 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. 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 low risk aversion periods, when they price the market skewness risk negatively and the market kurtosis risk positively, these moments are not significantly priced in the high risk aversion periods. In particular, as shown in Panel (B.H) and (C.H) of this table, in the high risk aversion 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 Carhart alpha of the KEP5-1 in the low risk aversion periods are now contrasted with insignificant values, suggesting that market skewness and kurtosis risk are not priced in the cross-section of stock.

Risk Aversion versus Sentiment

In order to understand the relationship between risk aversion and sentiment we subsequently relate our time series of risk aversion to the index of investor sentiment. We expect to see that once investors become more risk averse, sentiment declines and vice versa, because the sentiment index is composed of proxies, such as the number of IPOs and the NYSE share turnover, which are greatly influenced by the time variation in the risk aversion. To test this hypothesis, we first fit two independent AR (1) processes to the three time series. The residuals of the AR (1) processes in each period show us the unexpected increase or decrease in the relative risk aversion and the sentiment indices. Then we regress the values of the sentiment indices innovations on the 1-Month, 3-Month and 6-Month and 12-Month lagged values of the relative risk aversion time series, independently and jointly. The results for the sentiment and orthogonalized sentiment indices are reported in Panel (A) and (B) of Table (5), respectively.

[PLEASE INSERT TABLE 5 ABOUT HERE]

The results in Table (5) confirm our expectation. The rise of the relative risk aversion negatively affects the investor sentiment. Nevertheless this influence is not immediate. As Table (5) shows innovations in the relative risk aversion does not have any predictive power for the investor sentiment in the subsequent month. However the significant values of the coefficients in Regression (2) to (5) suggest that as the time passes, the sentiment index start to be negatively affected. We find it as an evidence that once an economic crisis starts and the risk aversion increases, the financial activities, such as the number of IPOs and the NYSE share turnover, gradually slow down. As a result the Baker and Wurgler sentiment indices, which capture the common variations of such financial activity proxies, decline over the subsequent periods, around 6-12 months after. In the following section, we repeat our asset pricing analysis using sentiment to distinguish between market conditions.

Down- vs. Up-Markets, Sentiment

We repeat exactly the same analysis, however, this time we split our analysis interval into high versus low sentiment periods. Table (6) and Figure (5) summarize our results with this setup.

[PLEASE INSERT TABLE 6 ABOUT HERE]

[PLEASE INSERT FIGURE 5 ABOUT HERE]

As expected, the results in Table (6) and Figure (5) are very similar to our finding in Table (4) and Figure (4). With the same line of reasoning as we had for high risk aversion periods, the volatility is priced in low sentiment periods, while this is not the case in high sentiment periods. The conclusions for the market skewness and market kurtosis are also very similar.

Overall, our findings suggest that investors are highly risk-averse in down-markets, which is picked up by a low sentiment index, where only market volatility risk is priced. Investors are more risk-seeking in up-markets, which is picked up by a high sentiment proxy, where predominately market skewness risk is priced. We interpret this as an empirical implication of the fact 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. In a related study, Lehnert, Lin and Wolff (2013) show that investors are more risk-averse in down-markets, proxied by low sentiment periods.

Robustness Tests

So far, we used the median of the risk aversion coefficient and investor sentiment index to distinguish between up- and down-markets. However our further analysis, shown in Panel (A) of Table (7) and (8)[13], demonstrates that splitting the sample using the mean does not change our results and interpretation.

[PLEASE INSERT TABLE 7 ABOUT HERE]

[PLEASE INSERT TABLE 8 ABOUT HERE]

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[13] For the sake of brevity, 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.

By splitting the sample between high and low risk aversion periods or high and low sentiment periods, we ignore the continuous nature of the variables. To be able to analyze the impact of the changes in the investor sentiment or risk aversion 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 or risk aversion time series, the contemporaneous changes in the market return, the Fama-French and the Carhart factors.

$$\mathrm{XEP}_t^{5-1} = \alpha + \beta_{\mathrm{Sent}}\Delta\mathrm{Sent}_{t-1} + \beta_{\mathrm{MKT}}\mathrm{MKT}_t \tag{16}$$

$$\mathrm{XEP}_t^{5-1} = \alpha + \beta_{\mathrm{Sent}}\Delta\mathrm{Sent}_{t-1} + \beta_{\mathrm{MKT}}\mathrm{MKT}_t + \beta_{\mathrm{SMB}}\mathrm{SMB}_t + \beta_{\mathrm{HML}}\mathrm{HML}_t \tag{17}$$

$$\mathrm{XEP}_t^{5-1} = \alpha + \beta_{\mathrm{Sent}}\Delta\mathrm{Sent}_{t-1} + \beta_{\mathrm{MKT}}\mathrm{MKT}_t + \beta_{\mathrm{SMB}}\mathrm{SMB}_t + \beta_{\mathrm{HML}}\mathrm{HML}_t + \beta_{\mathrm{Mom}}\mathrm{Mom}_t \tag{18}$$

and

$$\mathrm{XEP}_t^{5-1} = \alpha + \beta_{\mathrm{RRA}}\Delta\mathrm{RRA}_{t-1} + \beta_{\mathrm{MKT}}\mathrm{MKT}_t \tag{19}$$

$$\mathrm{XEP}_t^{5-1} = \alpha + \beta_{\mathrm{RRA}}\Delta\mathrm{RRA}_{t-1} + \beta_{\mathrm{MKT}}\mathrm{MKT}_t + \beta_{\mathrm{SMB}}\mathrm{SMB}_t + \beta_{\mathrm{HML}}\mathrm{HML}_t \tag{20}$$

$$\mathrm{XEP}_t^{5-1} = \alpha + \beta_{\mathrm{RRA}}\Delta\mathrm{RRA}_{t-1} + \beta_{\mathrm{MKT}}\mathrm{MKT}_t + \beta_{\mathrm{SMB}}\mathrm{SMB}_t + \beta_{\mathrm{HML}}\mathrm{HML}_t + \beta_{\mathrm{Mom}}\mathrm{Mom}_t \tag{21}$$

In these Equations XEP5-1 represents VEP5-1, SEP5-1 or KEP5-1. Table (8) reports the results of Regression Equations (16) to (21). The t-statistics are adjusted using the Newey-West technique.

[PLEASE INSERT TABLE 9 ABOUT HERE]

As shown in Panel (A) of 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 (4), Panel (A.L), 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 (4), Panel (B.L), 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 (4), Panel (C.L), 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.

Similar line of reasoning follows for the interpretation of the results in Panel (B) of Table (9), regarding the coefficients found for β_{RRA}.

3. 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 feature of the data and find that higher moments price of risk is time-varying and has significantly different patterns under different market conditions, proxied by investors' risk aversion. 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 investors exhibit low risk aversion, while it is not priced in down-markets. Similarly, our findings further suggest that the price of kurtosis risk is positive in low risk aversion periods, while it is not priced in periods of high risk aversion. Importantly, our findings confirm the previous results for volatility in the cross-section of stocks, but suggest that the previously counter-intuitive results for skewness are mainly a feature of the data in up-markets, caused by investors' more risk-seeking behavior. Our results persist even after controlling for the Fama-French and Carhart factors.

Furthermore, we investigate the relationship between investors' risk aversion and an investor sentiment proxy. Investor sentiment indices are typically composed of risk premium sensitive proxies, such as the number of IPOs or the equity share in new issues, which are likely to be high in periods of low risk aversion. Along this line of reasoning, we find that our proxy of investors' risk aversion affects an index of investor sentiment with a 6-12 months lag. In other words, periods of low (high) sentiment are typically preceded by periods of increased (decreased) risk aversion in the market. As a result, our previous results can be replicated by analyzing periods of high and low sentiment, separately. This is in line with previous evidence, which suggest that mean-variance relationship only holds in low sentiment periods. We interpret these results as descriptive of how risk aversion and sentiment covary over time.

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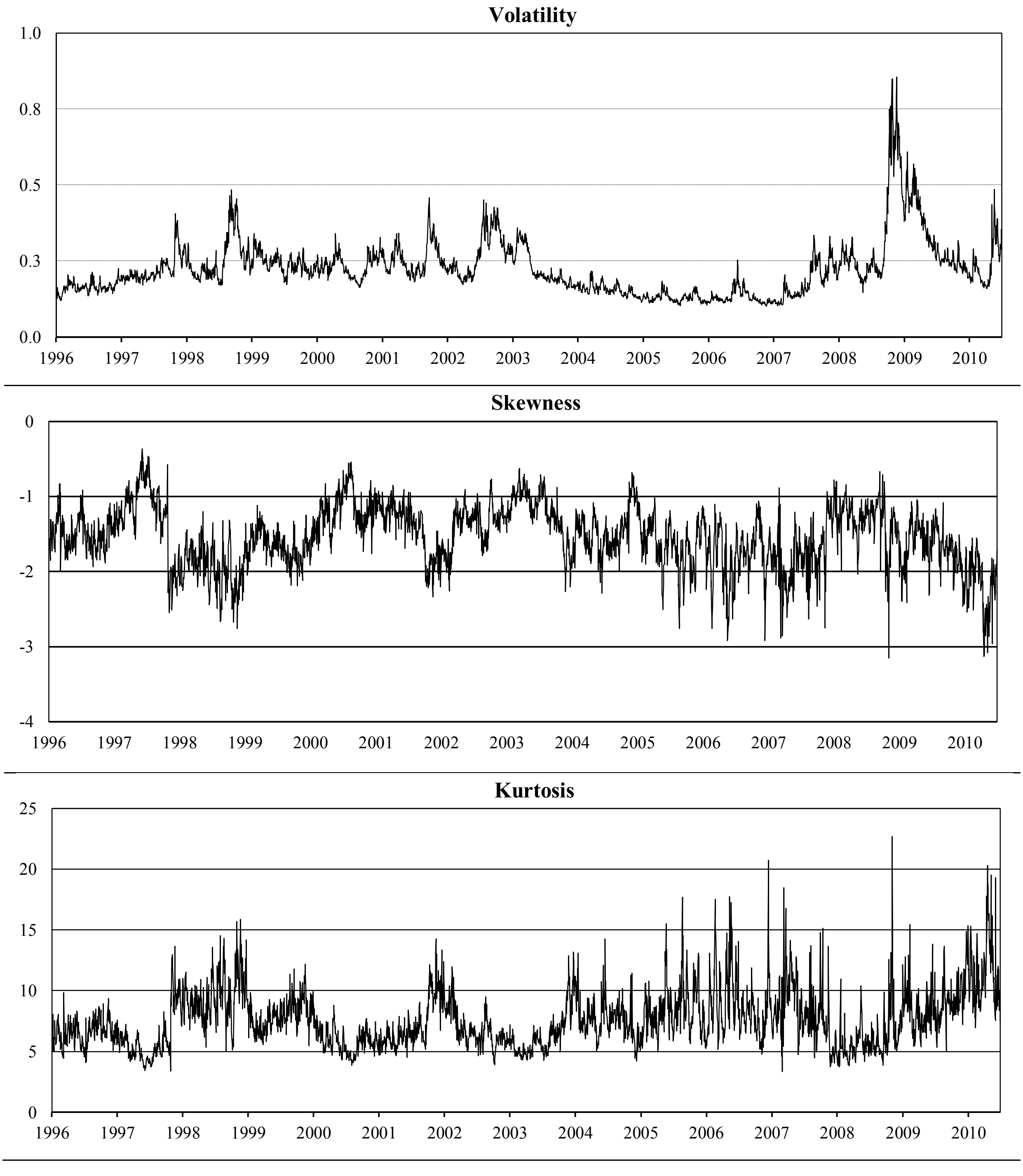
Figure 1 - The Volatility, Skewness and Kurtosis of the S&P 500 Index Return



Notes: We implement the Bakshi, Kapadia, 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.

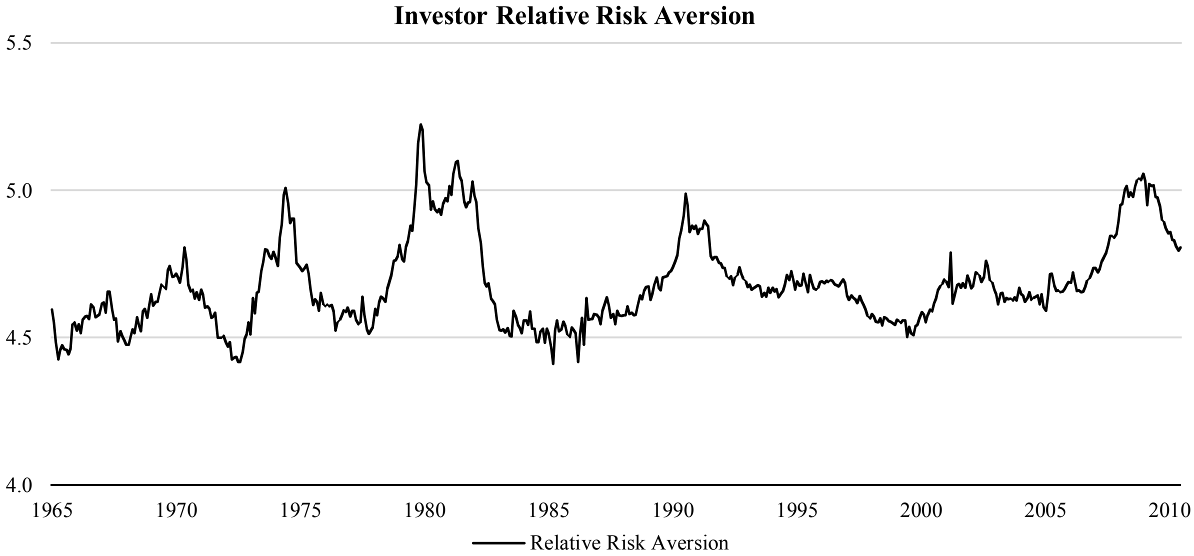
Table 1 - Factors Dynamics and Correlations

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 report the correlations of the market moment innovations with the Fama-French factors.

Figure 2 - Relative Risk Aversion



Notes: The figure shows the relative risk aversion of a representative investor over time. We measure the investor relative risk aversion time series, using the methodology of Campbell and Cochrane (1999) and Brandt and Wang (2003).

Table 2 - The Investor Sentiment Index and the Orthogonalized Investor Sentiment Index

Statistics	Relative Risk Aversion	Investor Sentiment Index	Orthogonalized Investor Sentiment Index
Number of Periods (Month)	546	546	546
Mean	4.680	0.000	0.000
Standard Deviation	0.148	1.000	1.000
Percentiles			
Minimum	4.411	-2.548	-2.578
5th Percentile	4.489	-1.736	-1.751
25th Percentile	4.573	-0.506	-0.464
Median	4.656	0.015	-0.014
75th Percentile	4.738	0.548	0.448
95 Percentile	4.992	1.888	1.787
Maximum	5.224	2.422	2.691
Correlations			
Investor Sentiment Index	-0.040		
Orthogonalized Investor Sentiment Index	0.069	0.970	
Model Calibration			
α	1.954		
$\bar{\gamma}$	1.532		
$\emptyset$	0.938		
δ	0.991		

Notes: We measure the investor relative risk aversion time series, using the methodology of Campbell and Cochrane (1999) and Brandt and Wang (2003). 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 3 - Exposure Portfolios Over All Periods

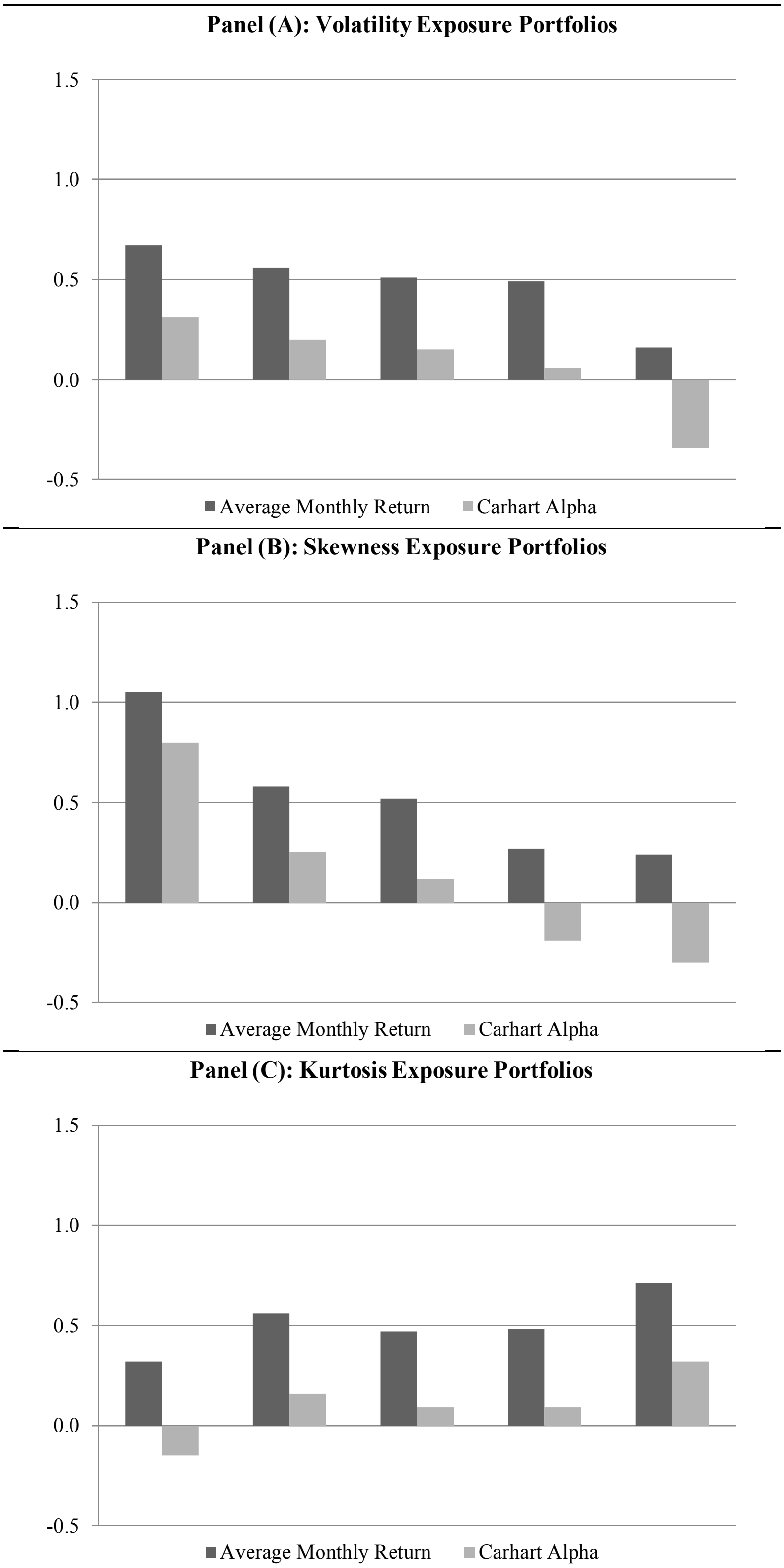
		Average Monthly Return	Alpha		
			CAPM	Fama-French	Carhart
Panel (A): Volatility Exposure Portfolios	VEP1	0.67	0.21	0.15	0.31
		(1.18)	(0.81)	(0.58)	(1.25)
	VEP2	0.56	0.19	0.19	0.20
		(1.40)	(1.56)	(1.64)	(1.73)
	VEP3	0.51	0.17	0.17	0.15
		(1.41)	(2.17)	(2.34)	(2.02)
	VEP4	0.49	0.12	0.09	0.06
		(1.17)	(1.07)	(0.80)	(0.49)
	VEP5	0.16	-0.31	-0.40	-0.34
		(0.26)	(-1.17)	(-1.81)	(-1.51)
	VEP5-1	-0.51	-0.52	-0.55	-0.65
		(-1.25)	(-1.27)	(-1.41)	(-1.63)
Panel (B): Skewness Exposure Portfolios	SEP1	1.05	0.61	0.64	0.80
		(1.88)	(2.53)	(2.69)	(3.31)
	SEP2	0.58	0.22	0.23	0.25
		(1.45)	(1.94)	(2.21)	(2.22)
	SEP3	0.52	0.17	0.15	0.12
		(1.37)	(2.12)	(1.92)	(1.60)
	SEP4	0.27	-0.10	-0.16	-0.19
		(0.66)	(-0.86)	(-1.36)	(-1.50)
	SEP5	0.24	-0.23	-0.36	-0.30
		(0.41)	(-0.96)	(-1.73)	(-1.41)
	SEP5-1	**-0.81**	**-0.84**	**-1.00**	**-1.10**
		(-2.32)	**(-2.42)**	**(-2.88)**	**(-2.97)**
Panel (C): Kurtosis Exposure Portfolios	KEP1	0.32	-0.13	-0.22	-0.15
		(0.56)	(-0.57)	(-1.01)	(-0.72)
	KEP2	0.56	0.20	0.19	0.16
		(1.45)	(1.84)	(1.71)	(1.38)
	KEP3	0.47	0.12	0.12	0.09
		(1.26)	(1.30)	(1.50)	(1.03)
	KEP4	0.48	0.10	0.07	0.09
		(1.11)	(0.86)	(0.61)	(0.82)
	KEP5	0.71	0.24	0.17	0.32
		(1.23)	(0.98)	(0.73)	(1.35)
	KEP5-1	0.40	0.38	0.39	0.47
		(1.12)	(1.08)	(1.12)	(1.30)

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 section (A). For sections (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 21 day lags.

Figure 3 - Exposure Portfolios over All Periods



Notes: Panel (A) to (C) show the average monthly returns and the alpha values 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 4 - Exposure Portfolios over Low Risk Aversion and High Risk Aversion Periods

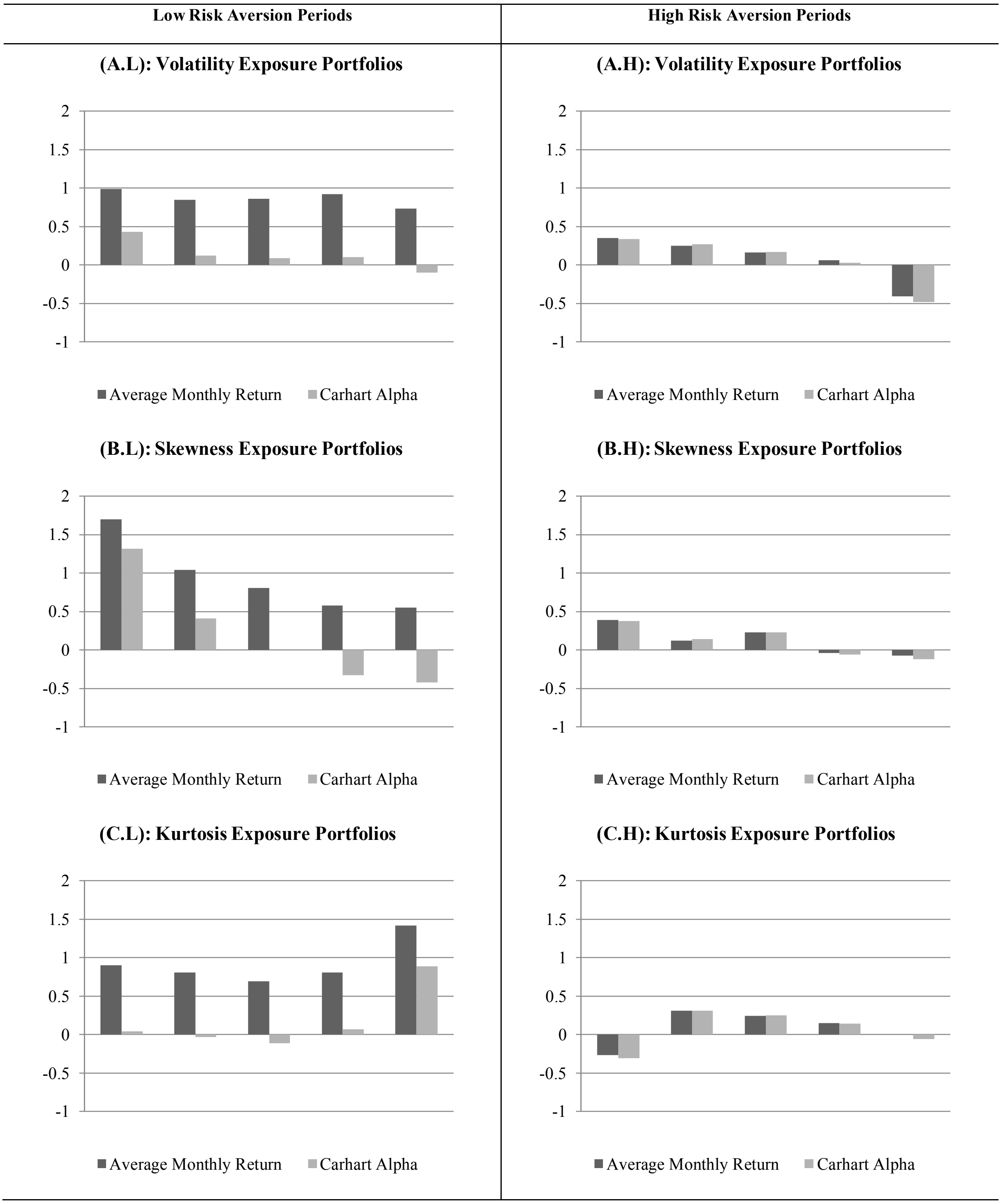
Low Risk Aversion Periods		Average Monthly Return	Alpha			**High Risk Aversion Periods**		Average Monthly Return	Alpha		
			CAPM	Fama-French	Carhart				CAPM	Fama-French	Carhart
(A.L): Volatility Exposure Portfolios	VEP1	0.99	0.12	0.24	0.43	(A.H): Volatility Exposure Portfolios	VEP1	0.35	0.35	0.31	0.34
		(1.34)	(0.28)	(0.57)	(1.06)			(0.40)	(1.11)	(0.96)	(1.07)
	VEP2	0.85	0.14	0.06	0.12		VEP2	0.25	0.26	0.27	0.27
		(1.82)	(0.73)	(0.34)	(0.67)			(0.39)	(1.83)	(1.96)	(1.91)
	VEP3	0.86	0.20	0.10	0.09		VEP3	0.16	0.17	0.18	0.17
		(2.11)	(1.64)	(0.98)	(0.90)			(0.27)	(1.74)	(1.84)	(1.78)
	VEP4	0.92	0.18	0.16	0.10		VEP4	0.06	0.06	0.03	0.03
		(1.81)	(1.01)	(0.89)	(0.56)			(0.09)	(0.45)	(0.24)	(0.22)
	VEP5	0.73	-0.26	-0.03	-0.10		VEP5	-0.41	-0.41	-0.51	-0.48
		(0.92)	(-0.65)	(-0.11)	(-0.29)			(-0.43)	(-1.11)	(-1.55)	(-1.62)
	VEP5-1	-0.26	-0.37	-0.27	-0.52		VEP5-1	-0.76	-0.76	**-0.83**	**-0.82**
		(-0.40)	(-0.56)	(-0.45)	(-0.82)			(-1.54)	(-1.52)	**(-1.70)**	**(-1.69)**
(B.L): Skewness Exposure Portfolios	SEP1	1.70	0.75	1.09	1.32	(B.H): Skewness Exposure Portfolios	SEP1	0.39	0.40	0.37	0.38
		(2.36)	(1.98)	(2.53)	(3.40)			(0.46)	(1.36)	(1.31)	(1.43)
	SEP2	1.04	0.33	0.37	0.41		SEP2	0.12	0.12	0.14	0.14
		(2.13)	(1.88)	(2.29)	(2.66)			(0.18)	(0.86)	(1.00)	(1.00)
	SEP3	0.81	0.15	0.01	-0.00		SEP3	0.23	0.24	0.24	0.23
		(1.88)	(1.13)	(0.11)	(-0.02)			(0.37)	(2.63)	(2.68)	(2.62)
	SEP4	0.58	-0.12	-0.27	-0.33		SEP4	-0.04	-0.03	-0.06	-0.06
		(1.19)	(-0.73)	(-1.62)	(-1.94)			(-0.06)	(-0.21)	(-0.37)	(-0.37)
	SEP5	0.55	-0.36	-0.36	-0.42		SEP5	-0.07	-0.06	-0.16	-0.12
		(0.79)	(-1.12)	(-1.49)	(-1.73)			(-0.07)	(-0.17)	(-0.45)	(-0.39)
	SEP5-1	**-1.15**	**-1.11**	**-1.45**	**-1.74**		SEP5-1	-0.46	-0.46	-0.52	-0.51
		(-2.24)	**(-2.10)**	**(-2.65)**	**(-3.43)**			(-0.99)	(-1.00)	(-1.16)	(-1.14)
(C.L): Kurtosis Exposure Portfolios	KEP1	0.90	-0.02	0.06	0.04	(C.H): Kurtosis Exposure Portfolios	KEP1	-0.27	-0.27	-0.34	-0.31
		(1.29)	(-0.06)	(0.24)	(0.16)			(-0.31)	(-0.78)	(-1.01)	(-0.97)
	KEP2	0.81	0.12	0.01	-0.03		KEP2	0.31	0.31	0.31	0.31
		(1.76)	(0.64)	(0.05)	(-0.15)			(0.49)	(2.51)	(2.60)	(2.52)
	KEP3	0.69	0.03	-0.07	-0.11		KEP3	0.24	0.25	0.26	0.25
		(1.66)	(0.18)	(-0.62)	(-0.89)			(0.39)	(2.52)	(2.70)	(2.70)
	KEP4	0.81	0.08	0.03	0.07		KEP4	0.15	0.15	0.14	0.14
		(1.54)	(0.45)	(0.16)	(0.40)			(0.22)	(1.04)	(0.96)	(0.96)
	KEP5	1.42	0.48	0.75	0.89		KEP5	-0.00	0.00	-0.09	-0.06
		(1.89)	(1.29)	(1.90)	(2.36)			(-0.00)	(0.01)	(-0.29)	(-0.20)
	KEP5-1	0.52	0.50	0.69	0.85		KEP5-1	0.27	0.27	0.25	0.25
		(1.05)	(1.00)	(1.30)	(1.62)			(0.53)	(0.53)	(0.51)	(0.51)

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 $\beta_{\Delta Vol}^i$ 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 and high risk aversion periods in Panel (A.H) and (A.L). For Panel (B.H), (B.L), (C.H) and (C.L) we use the same regression equation however this time we will sort the stocks according to their $\beta_{\Delta Skew}^i$, and $\beta_{\Delta kurt}^i$ 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. The t-statistics are adjusted using the Newey-West technique.

Figure 4- Exposure Portfolios over Low Risk Aversion and High Risk Aversion Periods



Notes: Panel (A.L) to (C.H) show the average monthly returns and alpha values of the constructed volatility, skewness and kurtosis exposure portfolios versus their corresponding $\beta_{\Delta Vol}$, $\beta_{\Delta Skew}$ and $\beta_{\Delta Kurt}$ over the low risk aversion and high risk aversion periods.

Table 5 - The Impact of Risk Aversion on the Future Values of the Investor Sentiment Indices

Panel (A)		**Sentiment Index**				
		Regression (1)	Regression (2)	Regression (3)	Regression (4)	Regression (5)
Intercept		0.000	0.000	0.000	0.000	0.005
		(0.00)	(0.00)	(0.00)	(0.00)	(0.88)
Relative Risk Aversion	**1-Month Lagged**	0.131				0.164
		(0.86)				(1.08)
	3-Month Lagged		**-0.252**			-0.206
			(-1.66)			(-1.36)
	6-Month Lagged			**-0.326**		**-0.297**
				(-2.15)		**(-1.97)**
	12-Month Lagged				**-0.400**	**-0.390**
					(-2.67)	**(-2.59)**

Panel (B)		**Orthogonalized Sentiment Index**				
		Regression (1)	Regression (2)	Regression (3)	Regression (4)	Regression (5)
Intercept		0.000	0.000	0.000	0.000	0.005
		(0.00)	(0.00)	(0.00)	(0.00)	(0.79)
Relative Risk Aversion	**1-Month Lagged**	0.301				0.328
		(1.57)				(1.70)
	3-Month Lagged		-0.210			-0.172
			(-1.09)			(-0.90)
	6-Month Lagged			**-0.319**		-0.294
				(-1.67)		(-1.54)
	12-Month Lagged				-0.305	**-0.310**
					(-1.60)	**(-1.63)**

Table 6 - Exposure Portfolios over High Sentiment and Low Sentiment Periods

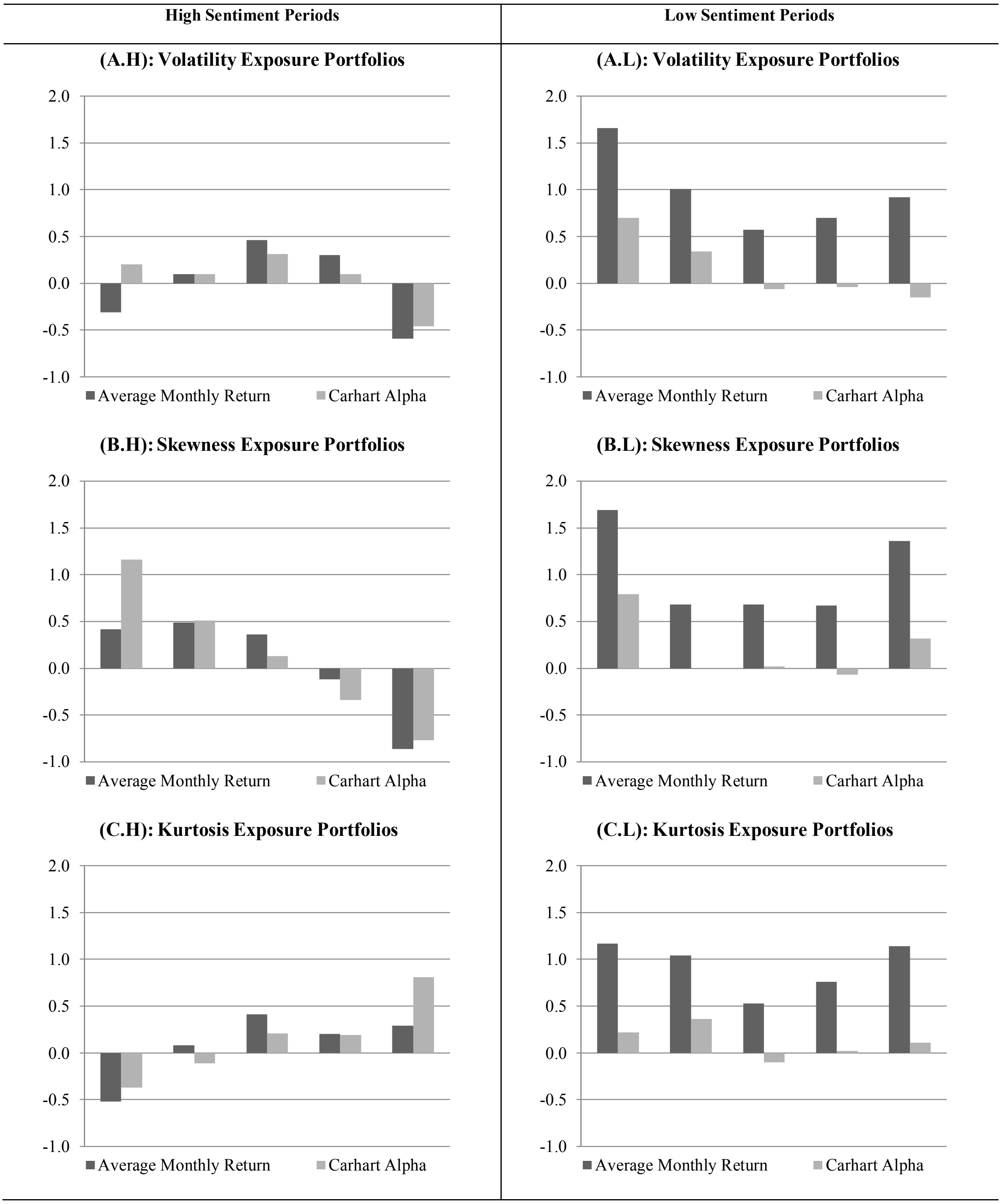
High Sentiment Periods		Average Monthly Return	Alpha			**Low Sentiment Periods**		Average Monthly Return	Alpha		
			CAPM	Fama-French	Carhart				CAPM	Fama-French	Carhart
(A.H): Volatility Exposure Portfolios	VEP1	-0.31	-0.35	-0.33	0.2	(A.L): Volatility Exposure Portfolios	VEP1	1.66	0.77	0.72	0.7
		(-0.37)	(-0.87)	(-0.82)	-0.53			-2.03	-2.81	-2.65	-2.62
	VEP2	0.1	0.07	0.02	0.1		VEP2	1.01	0.3	0.33	0.34
		-0.17	-0.35	-0.08	-0.54			-1.66	-2.41	-2.66	-2.74
	VEP3	0.46	0.43	0.37	0.31		VEP3	0.57	-0.1	-0.07	-0.06
		-0.86	-3.09	-2.86	-2.36			-0.98	(-0.98)	(-0.62)	(-0.59)
	VEP4	0.3	0.26	0.26	0.1		VEP4	0.7	-0.02	-0.03	-0.04
		-0.49	-1.3	-1.32	-0.46			-1.08	(-0.13)	(-0.27)	(-0.32)
	VEP5	-0.59	-0.63	-0.39	-0.46		VEP5	0.92	0.04	-0.1	-0.15
		(-0.66)	(-1.49)	(-1.07)	(-1.20)			-1.06	-0.12	(-0.34)	(-0.55)
	VEP5-1	-0.28	-0.28	-0.06	-0.67		VEP5-1	**-0.74**	**-0.73**	**-0.82**	**-0.85**
		(-0.44)	(-0.44)	(-0.10)	(-1.04)			**(-1.71)**	**(-1.72)**	**(-1.94)**	**(-2.04)**
(B.H): Skewness Exposure Portfolios	SEP1	0.42	0.37	0.65	1.16	(B.L): Skewness Exposure Portfolios	SEP1	1.69	0.89	0.81	0.79
		-0.49	-0.89	-1.62	-2.98			-2.2	-3.27	-3.05	-3.05
	SEP2	0.49	0.45	0.44	0.51		SEP2	0.68	-0.03	0	0
		-0.82	-2.63	-2.73	-2.95			-1.1	(-0.23)	(-0.01)	(-0.00)
	SEP3	0.36	0.33	0.2	0.13		SEP3	0.68	0	0.02	0.02
		-0.67	-2.31	-1.57	-0.93			-1.15	0	-0.18	-0.2
	SEP4	-0.12	-0.15	-0.23	-0.34		SEP4	0.67	-0.07	-0.07	-0.07
		(-0.19)	(-0.83)	(-1.25)	(-1.80)			-1.02	(-0.47)	(-0.44)	(-0.46)
	SEP5	-0.86	-0.91	-0.78	-0.77		SEP5	1.36	0.43	0.35	0.32
		(-1.03)	(-2.33)	(-2.28)	(-2.19)			-1.5	-1.3	-1.17	-1.08
	SEP5-1	**-1.28**	**-1.28**	**-1.43**	**-1.93**		SEP5-1	-0.33	-0.46	-0.46	-0.48
		(-2.13)	**(-2.13)**	**(-2.45)**	**(-3.19)**			(-0.70)	(-0.99)	(-1.02)	(-1.07)
(C.H): Kurtosis Exposure Portfolios	KEP1	-0.52	-0.57	-0.44	-0.37	(C.L): Kurtosis Exposure Portfolios	KEP1	1.17	0.33	0.25	0.22
		(-0.63)	(-1.48)	(-1.30)	(-1.07)			-1.38	-1	-0.82	-0.75
	KEP2	0.08	0.05	-0.01	-0.11		KEP2	1.04	0.35	0.36	0.36
		-0.14	-0.28	(-0.04)	(-0.59)			-1.75	-2.75	-2.77	-2.8
	KEP3	0.41	0.38	0.32	0.21		KEP3	0.53	-0.15	-0.11	-0.1
		-0.75	-2.46	-2.24	-1.5			-0.91	(-1.49)	(-1.15)	(-1.08)
	KEP4	0.2	0.17	0.12	0.19		KEP4	0.76	0.01	0.02	0.02
		-0.33	-0.93	-0.67	-1.06			-1.15	-0.04	-0.2	-0.16
	KEP5	0.29	0.24	0.43	0.81		KEP5	1.14	0.24	0.15	0.11
		-0.33	-0.59	-1.09	-2.12			-1.34	-0.87	-0.55	-0.43
	KEP5-1	0.81	0.81	0.86	**1.18**		KEP5-1	-0.02	-0.09	-0.11	-0.11
		-1.4	-1.4	-1.52	**-1.98**			(-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 $\beta_{\Delta Vol}^i$ 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 and low sentiment periods in Panel (A.H) and (A.L). For Panel (B.H), (B.L), (C.H) and (C.L) we use the same regression equation however this time we will sort the stocks according to their $\beta_{\Delta Skew}^i$, and $\beta_{\Delta kurt}^i$ 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. The t-statistics are adjusted using the Newey-West technique.

Figure 5 - Exposure Portfolios over High Sentiment and Low Sentiment Periods



Notes: Panel (A.H) to (C.L) show the average monthly returns and alpha values 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 and low sentiment periods.*

Table 7 - Exposure Portfolios over Low and High Risk Aversion Periods, Segregated with the Mean of the Risk Aversion Time Series

Exposure Portfolios over Low and High Risk Aversion Periods, Segregated with the Mean of the Risk Aversion Time Series					
		Average Monthly Return	Alpha		
			CAPM	Fama-French	Carhart
Low Risk Aversion Periods	VEP5-1	-0.27	-0.33	-0.18	-0.52
		(-0.56)	(-0.67)	(-0.39)	(-1.09)
	SEP5-1	**-1.02**	**-1.03**	**-1.30**	**-1.61**
		(-2.45)	**(-2.42)**	**(-2.95)**	**(-3.61)**
	KEP5-1	0.47	0.46	0.59	**0.77**
		(1.21)	(1.17)	(1.41)	**(1.77)**
High Risk Aversion Periods	VEP5-1	-1.09	-1.09	-1.17	**-1.27**
		(-1.46)	(-1.43)	(-1.59)	**(-1.84)**
	SEP5-1	-0.28	-0.28	-0.19	-0.30
		(-0.42)	(-0.43)	(-0.29)	(-0.50)
	KEP5-1	0.22	0.22	0.21	0.21
		(0.30)	(0.29)	(0.28)	(0.30)

Notes: In this table, in order to segregate the low and the high risk aversion periods, we use the mean of the risk aversion time series.

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

Panel (A): Exposure Portfolios over High and Low Sentiment Periods, Segregated with the Mean of the Sentiment Index

		Average Monthly Return	Alpha		
			CAPM	Fama-French	Carhart
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)**
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)

Panel (B): Exposure Portfolios over High and Low Sentiment Periods, Segregated with the Median of the Orthogonalized Sentiment Index

		Average Monthly Return	Alpha		
			CAPM	Fama-French	Carhart
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)**
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 Panel (A), in order to segregate the high and the low sentiment periods we use the mean of the sentiment index.
For Panel (B), 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.

Table 9 – The Impact Investor Sentiment Level

Panel (A): The Impact of Increase in The Sentiment Index

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)

Panel (B): The Impact of Increase in the Relative Risk Aversion

Portfolio	Alpha	Sent Beta	Market Beta	SMB Beta	HML Beta	Mom Beta
VEP5-1	-0.005	-0.056	0.092			
	(-1.468)	(-0.309)	(0.795)			
	-0.006	-0.064	0.058	0.323	0.100	
	(-1.732)	(-0.354)	(0.625)	(1.469)	(0.516)	
	-0.007	-0.065	0.082	0.316	0.113	0.046
	(-1.73)	(-0.369)	(0.744)	(1.505)	(0.616)	(0.364)
SEP5-1	-0.008	**0.230**	0.040			
	(-3.097)	**(2.024)**	(0.393)			
	-0.010	**0.242**	0.060	**0.168**	**0.219**	
	(-3.058)	**(2.286)**	(0.874)	**(2.248)**	**(1.83)**	
	-0.010	**0.239**	0.101	**0.155**	**0.241**	0.081
	(-2.8)	**(2.125)**	(1.841)	**(2.039)**	**(1.82)**	(0.781)
KEP5-1	0.004	-0.153	0.019			
	(1.322)	(-1.152)	(0.184)			
	0.004	**-0.159**	0.001	0.083	-0.014	
	(1.204)	**(-1.651)**	(0.019)	(1.138)	(-0.11)	
	0.005	-0.154	-0.075	0.107	-0.056	**-0.150**
	(1.428)	(-1.109)	(-1.04)	(1.187)	(-0.404)	**(-1.916)**

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 and relative risk aversion time series, the market return, the Fama-French and the Carhart factors. We adjust the t-statistics using the Newey-West technique with 12 month lags.

Appendix: Measuring the Risk Neutral Moments

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

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

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

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

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-calendar-days. 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[14] 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 cubic spline to them.[15] 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:

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

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

[15] 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.