Moment risk premia and the cross-section of stock returns in the European stock market

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Abstract

We investigate whether volatility, skewness, and kurtosis risks are priced in the European stock market and we assess the signs and the magnitudes of these higher order moment risk premia. To this end, we use estimates of the moments of the market returns extracted from index options. These estimates are forward-looking and represent the investors' forecast of the future realized moments in the next thirty days. We adopt two approaches to assess the pricing of moment risk: the model-free approach based on swap contracts (Zhao et al. (2013)), and the model-based approach built on portfolio-sorting techniques. The portfolio-sorting techniques used include multivariate sorting, four-way sorting and Fama-Macbeth regressions. We control for known risk factors such as market excess return, book-to-market, size and momentum.

Several results are obtained. First, stocks with high exposure to innovations in implied market volatility (skewness) exhibit low (high) returns on average. Second, the estimated premium for bearing market volatility (skewness) risk is negative (positive) and robust to the two methods employed. These

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premia are both statistically and economically significant and cannot be explained by common risk factors such as market excess return, book-to-market, firm size and momentum, which are at the core of the commonly used models. Third, unlike recent studies on the US market (Chang et al., 2013), there exists a premium on small-sized firms in the European stock market: small capitalization stocks earn significantly higher returns than high capitalization stocks. These results are important for investors and financial institutions who could take into account the variability in higher moments of the risk-neutral distribution in order to improve hedging and portfolio strategies. Measuring the portfolio exposure to market volatility and skewness is important in investment diversification decisions with respect to moment risk. This applies particularly for volatility, which is found to be positively priced during crisis periods, suggesting that portfolios with a negative exposure suffer from major losses during market turmoil periods. Regulators should take into account innovation not only in volatility, but also in skewness in order to promptly ease the market in case of large variation in higher order moments of the aggregate stock market.

Keywords: volatility risk; skewness risk; kurtosis risk; cross section; risk-neutral moments; risk premia

JEL classification: G12

1. **Introduction**

In the financial literature several approaches are proposed for the computation of risk premia on higher moments of stock return distribution. First, these premia can be computed as the difference between physical and risk-neutral moments where the former is a forecast computed from historical series of the underlying asset and the latter is the estimate obtained from option prices listed on that underlying asset (Zhao et al., 2013). The risk premium has a strong financial interpretation since it relies on a swap contract in which two parties agree to exchange, at maturity, a fixed swap rate for a floating realized rate. For instance, if investors are averse to increases in market variance, they are willing to pay a higher fixed rate relative to the floating rate in order to hedge against peaks of variance. The floating rate (i.e. subsequently realized variance) can be measured only at the maturity of the contract. The difference (negative in this case) is the variance risk premium.

Second, these premia can be assessed by using portfolio sorting techniques which rely on a two-step process. In the first step, stocks are clustered into different portfolios based on their exposure to a specific risk factor. In this way, each portfolio is composed of stocks with similar exposures to this risk factor. In the second step, out-of-sample returns (e.g. next-month returns) for different portfolios are collected, to avoid spurious effects (Agarwal et al., 2009). The rationale underlying this technique is that if a risk factor is priced, stocks with different sensitivities to innovations in the risk factor will show different future returns. Moreover, portfolio-sorting methods allow us to check the robustness of the results with respect to other factors affecting individual stock returns, e.g. market excess return, book-to-market, firm size, and momentum. This approach is based on an extension of the Merton (1973) Intertemporal Capital Asset Pricing Model (ICAPM), which treats the time-variation in the moments as risk factors.[1]

Empirical evidence on the existence and the signs of moment risk premia is mixed, depending on the estimation method used and the market under investigation. Moreover, most studies focus on the US market. Consequently, evidence on the European and other stock markets remains scant. The

[1] Other approaches have been proposed in the literature to estimate higher-order moment risk premia. Bali and Murray (2013) exploit portfolio strategies consisting of positions in individual options and in the underlying asset. Although this methodology represents an appealing method for assessing the existence and the signs of moment risk premia, it is not applicable to the European stock market. In fact, European options on individual stocks were introduced only recently and historical series are not long enough to perform this analysis.

majority of the studies that use the model-free approach (moment swap contracts) on time-series data (e.g. Elyasiani et al., 2016; Zhao et al., 2013) find a negative risk premium for variance and kurtosis and a positive risk premium for skewness. However, in studies based on cross-sectional data (portfolio-sorting techniques) the evidence is less clear. With regard to volatility risk, Ang et al. (2006) and Adrian and Rosenberg (2008) find a negative price for market volatility risk, while Chang et al. (2013) find an insignificant volatility risk premium. For skewness risk, Chang et al. (2013), Bali and Murray (2013), and Conrad et al. (2013) find a negative risk premium, while Kozhan et al. (2013), Xing et al. (2010) and Elyasiani et al. (2016) report evidence of a positive skewness risk premium.

The aim of this paper is to investigate whether volatility, skewness and kurtosis risks are priced in the European stock market and to assess the sign and the magnitude of the risk premia in the period 2008-2015. Our contribution is threefold. First, we check the estimates for robustness by using two different approaches in order to investigate moment risk premia (model-free and model-based). Second, we provide evidence about the existence of moment risk premia both in the European aggregate market, which is investigated to a limited extent in the literature and in the cross-section of European stock returns. Third, while most studies (especially papers focused on the cross-section of stock returns) are limited to the sample period prior to the crisis, we include in our dataset both the financial crisis and the European debt crisis. This allows us to assess the behaviour of moment risk premia in both calm and market turmoil periods.

We obtain several results. First, volatility is a priced factor in the cross-section of stock returns in the European stock market, and the volatility risk premium is negative. This is in line with some previous studies on the US market (e.g., Adrian and Rosenberg, 2008; Ang et al., 2006). A negative volatility risk premium indicates that a long position in volatility risk (i.e. an insurance-buying strategy with respect to volatility risk) yields on average a negative return. Second, unlike Chang et al. (2013) and Bali and Murray (2013), but consistent with Kozhan et al. (2013), and Elyasiani et al. (2016), the skewness risk premium was found to be positive. This indicates that skewness risk is also priced in the European stock market: investors are averse to negative changes in market skewness, and accept a lower future return for stocks that serve as a hedge against skewness risk.

Third, kurtosis risk is not priced, suggesting that the skewness risk premium accounts for the entire tail risk. The results for the signs of the volatility and the skewness risk premia are robust to the two methods employed (model-free and ICAPM based). These premia are both statistically and economically significant (the premia are equal to -0.51% and 0.58% on a monthly basis for volatility and skewness, respectively) and could not be explained by common risk factors such as market excess return, book-to-market, firm size and momentum. Therefore, these results are important for conservative investors, because they indicate that it is sufficient to hedge exposures to volatility and skewness of the risk-neutral distribution, ignoring the kurtosis risk.

Fourth, in the European market we find evidence of a positive risk premium for firm size: stocks with low capitalization in general earned higher returns than stocks with high capitalization. This result is in contrast with recent evidence in the US market (Chang et al., 2013), indicating that investors perceive European stocks with low capitalization levels as riskier and as a result require higher future returns on these stocks.

Fifth, the explanatory power of Fama-MacBeth regressions greatly improves when accounting for innovations in implied moments as risk factors, in addition to the standard four-factor Carhart model. This indicates that volatility and skewness are priced risk factors that play an important role in asset pricing. This result is important for investors and financial institutions: they can improve the performance of their portfolios by taking the variability in higher moments of the risk-neutral distribution into account in their portfolio choices. Risk-tolerant investors can speculate on volatility and skewness with short positions on volatility and long positions on skewness and long positions on small capitalization stocks.

The paper proceeds as follows. In section 2, we provide a description of the dataset and the methods used to obtain the risk-neutral moments and the other risk factors. In section 3, we present the theoretical motivation and the two approaches used to investigate the existence and the sign of higher moment risk premia. Section 4 examines the empirical application of the two methods to the European stock market. The last section concludes.

2. Data and methodology

This is the first study to investigate the pricing of volatility and higher moment risk in the European stock market. The data set used to compute the implied moments consists of closing prices on EURO STOXX 50-index options (OESX), recorded from 02 January 2008 to 30 December 2015. OESX are European options on the EURO STOXX 50, a capital-weighted index composed of fifty of the largest and most liquid stocks in the Eurozone. The index was introduced on 26 February 1998 and its composition is reviewed annually in September. As for the underlying asset, closing prices of the EURO STOXX 50 index recorded in the same time-period are used. Following Muzzioli (2013), the EURO STOXX 50 index is adjusted for dividends according to equation (1):

$$\hat{S}_t = S_t e^{-\delta_t \Delta t} \tag{1}$$

In this specification, S_t is the EURO STOXX 50 index value at time t, δ_t is the dividend yield at time t and Δt is the time to maturity of the option. As a proxy for the risk-free rate, Euribor rates with maturities of one week, one month, two months, and three months are used: the appropriate yield to maturity is computed by linear interpolation. We also collect the closing prices of individual stocks listed on the STOXX Europe 600 Index from 02 January 2008 to 30 December 2015. We use the STOXX Europe 600 stocks data in order to have a wider basket of shares for implementing the portfolio sorting techniques. The data set for the OESX is obtained from IVolatility;[2] the time series of the EURO STOXX 50 index and the STOXX Europe 600 individual stocks, the dividend yield and the Euribor rates are obtained from Datastream. A graphical comparison between the EURO STOXX 50 index and STOXX Europe 600 index is presented in Figure 1, showing that the two market indices display similar patterns in the period under investigation. The correlation coefficient between EURO STOXX 50 and STOXX Europe 600 market returns is about 96% pointing to an almost perfect co-movement between the two markets. This allows us to use the innovations in the risk-neutral moments of the EURO STOXX 50 as risk factors priced in the STOXX Europe 600 stocks.

To compute risk-neutral moments of the EURO STOXX 50 return distribution, following Muzzioli (2013), we apply several filters to the option data set in order to eliminate arbitrage opportunities and other irregularities in the prices. First, we eliminate the options close to expiry (options with time to maturity of less than eight days) because they may suffer from pricing anomalies that occur close to expiration. Second, following Ait-Sahalia and Lo (1998) only at-the-money options and out-of-the-money options are retained. These include put options with moneyness lower than 1.03 ($K/S < 1.03$, where K is the strike price and S is the index value), and call options with moneyness higher than 0.97 ($K/S > 0.97$). Third, we eliminate the option prices violating the standard no-arbitrage constraints. Finally, in line with Carr and Madan (2005), we check that butterfly spread strategies are non-negatively priced, in order to avoid arbitrage opportunities.

We compute the risk-neutral variance, skewness, and kurtosis for the EURO STOXX 50 index by using the Bakshi et al. (2003) method. The results are interpolated in order to obtain a 30-day forward-looking measure and subsequently annualized. Model-free measures of the three implied higher moments: volatility (VOL) computed as the square root of model-free variance, skewness ($SKEW$), and

[2] IVolatility.com is a data service that provides detailed information about options traded on US, European and Asian markets.

kurtosis ($KURT$) for the EURO STOXX 50 index return distribution are presented in Figure 2. It is evident from this figure that implied volatility is in general high in the period 2008-2012, a period characterized by a sharp decline in the EURO STOXX 50 level, due to both the Financial Crisis of 2008-2009 and the European Debt Crisis of 2011-2012. On the other hand, both risk-neutral skewness and kurtosis present a larger number of peaks in the last part of our dataset when market volatility is low.

In line with Chang et al. (2013), we fit an autoregressive moving average (ARMA) model to the time series of variance, skewness and kurtosis in order to remove autocorrelation in the data. The autocorrelation functions indicate that the ARMA (1,1) models are needed to remove the autocorrelation in the series for the innovations in skewness and kurtosis, but not for volatility. As a result, we compute daily innovations for volatility by using the first differences. In this way, we can also easily compare our results with those of the previous studies, such as Ang et al. (2006).

We derive the market excess return ($R_m - R_f$) as the difference between the daily performance of STOXX Europe 600 index and daily risk-free rate. We also compute other commonly used risk factors that account for the characteristics of the firm such as size and book-to-market proposed by Fama and French (1993, 1996), and momentum introduced by Carhart (1997). The size factor "small-minus-big" (SMB) aims to capture the return compensation for additional risk attached to stocks characterized by low capitalization levels and for this reason more exposed to economic and financial shocks. The book-to-market factor (or values factor) "high-minus-low" (HML) measures the difference in return between stocks with high book-to-market (value stocks) and low book-to-market (growth stocks). Last, the momentum factor "up-minus-down" (UMD) accounts for the momentum of the stock prices, as proposed by Jegadeesh and Titman (1993). To elaborate, stocks characterized by high past returns (winners) tend to have a better future performance, compared to stocks that have low past returns (losers). Hereafter, we will refer to these factors as Carhart's (1997) four risk factors.

2.1 Descriptive analysis

In Table 1, we report the average values of the factors, the parameters for the ARMA (1,1) model describing the factor used to obtain the $\Delta SKEW$ and $\Delta KURT$ residuals, the correlation coefficients among innovations in market implied moments, and Carhart (1997) four risk factors: market excess return (MKT), size (SMB), book-to-market (HML) and momentum (UMD).

Several observations are in order at this point. First, innovations in volatility are strongly and negatively related to market excess return (correlation = -0.69, significant at the 1% level). Second, innovations in market skewness are negatively and significantly related to market excess return (MKT) (correlation = -0.20, significant at 1%), while those of market kurtosis display a positive relation with MKT factor (correlation = 0.07, significant at 1%). It is notable that these findings are similar both in terms of sign and magnitude to those obtained by Chang et al. (2013) for the US market, for the 1996-2007 period. The correlation coefficient between the moments and market returns could be useful for formulation of an a-priori expectations about the sign of moment risk premia (Chang et al., 2013) and will be further discussed in the following section.

Third, the relation between innovations in skewness and kurtosis is strongly negative (correlation = -0.85, significant at 1%). This result is as expected: a low value in risk-neutral skewness points to a pronounced left tail and is therefore reflected in a high value of kurtosis. The high correlation between innovations in the third- and fourth-order moments may make it hard to distinguish between the effects of innovations in skewness and those in kurtosis. To address this issue, following Chang et al. (2013), we orthogonalize the innovations in kurtosis against those of the skewness as follows:

$$\Delta KURT_t = \beta_0 + \beta_1 \Delta SKEW_t + \varepsilon_t \tag{2}$$

In this specification, $\Delta KURT_t$ and $\Delta SKEW$ are the innovations in risk-neutral kurtosis and skewness, respectively. Throughout the paper, we use the residuals of regression (2) as the innovations in kurtosis.

This allows us to eliminate most of the correlation between the two measures. The post-orthogonalization correlations, reported on the right-hand side of Table 1 confirm this point. Innovations in kurtosis continue to be negatively related with those of market volatility. Innovations in implied volatility, skewness, and kurtosis are shown in Figure 3, indicating that, unlike volatility, innovations in higher order moments present greater changes in the last years of the sample, a period characterized by lower values of volatility and its innovations.

3. Theoretical motivation

Our objective is to investigate the higher moment risk premia in the European market. To this end, we exploit two main approaches. The first approach is model-free in nature and relies on the moment swap contract. In this approach the risk premia are computed as the difference between the physical forecast and the risk-neutral forecast for volatility, skewness, and kurtosis of EURO STOXX 50 returns (Zhao et al., 2013). This method is totally model-free and relies on a swap contract in which two parties agree to exchange, at maturity, a fixed swap rate for a floating realized rate. As a consequence, it has a straightforward financial interpretation. For instance, the long side in a variance swap pays a fixed rate (the variance swap rate which is equal to the risk-neutral expectation of variance) and receives a floating rate (the realized or physical variance). If investors are averse to increases in market variance, they are willing to pay a fixed rate which is higher than the floating rate (which is measured at the maturity of the contract), in order to hedge against peaks of variance; the difference is the variance risk premium.

Previous studies on European markets, e.g. Elyasiani et al. (2016) investigating the Italian market in the period 2005-2014, point to a negative risk premium for variance and kurtosis, and a positive risk premium for skewness. This result suggests that investors are averse to positive (negative) peaks in market variance and kurtosis (skewness), i.e. they are willing to pay a premium in order to hedge against increases (decreases) in variance and kurtosis (skewness). As a result, in line with Elyasiani et al. (2016), we expect to find the risk-neutral distribution to be more volatile, left-skewed and fat-tailed than the subsequently realized one.

In the second part of the analysis discussed in section 4.2, we aim to obtain a robust estimate for the moment risk premia exploiting a portfolio-based approach in the cross-section of STOXX Europe 600 stock returns. Using the cross-section of stock returns, rather than realized moments of the market index, allows us to create portfolios of stocks characterized by different sensitivities to the risk factors under investigation. Moreover, it allows us to check for cross-sectional effects, such as size and value factors introduced by Fama and French (1993) and the momentum effect proposed by Jegadeesh and Titman (1993).

The approach adopted in the second part of the analysis is model-based, relying on an extension of the Merton (1973) and Campbell (1993, 1996) intertemporal capital asset pricing model (ICAPM). The innovation introduced in these multifactor models is that investment opportunities are allowed to vary over time. As a result, the risk premia are associated with the conditional covariance between asset returns and innovations in the state variables, which act as a proxy for the time-variation of the investment opportunity set. In particular, Campbell (1993, 1996) show that if the representative agent is more risk averse than an agent with log utility, assets that co-vary positively (i.e. their price increases) with good news about the quality of the future investment opportunity set (future expected returns for the aggregate stock market) earn higher returns on average. Chen (2002), who proposes an extension of Campbell's model allowing for time-varying covariance and stochastic market volatility, suggests that risk-averse investors seek to hedge against changes in future market volatility. As a result, an asset that acts as a hedge against volatility risk earns a lower expected return. The economic rationale underlying this model is that with an increase in uncertainty about future market returns (i.e. when volatility increases), risk-averse investors reduce current consumption and increase cautionary savings. The pricing of stochastic time-varying volatility is investigated in Ang et al. (2006), who provide an empirical application of the Chen (2002) model, and find the volatility risk premium to be negative and significant.

Chang et al. (2013) show that for higher-order moments, the price of market skewness and kurtosis risks depends on the fourth and the fifth derivative of the utility function, which are hard to assess. Therefore, all the contributions in the literature adopt an empirical approach to evaluate the signs of the risk premia. Chang et al. (2013) extend the Ang et al. (2006) analysis in order to account not only for time-variation in market volatility, but also for time-varying higher-order moments of the aggregate market stock returns as a proxy for the quality of the future investment opportunity set. They find evidence of a negative, statistically and economically significant, skewness risk premium for the US stock market in the period 1996-2007. Also Chabi-Yo (2012), who proposes an intertemporal extension of the three-moment and the four-moment CAPM, finds the price of market skewness risk to be negative.

These results cast light on an important and debated question in the literature: the sign of the skewness risk premium. In fact, while Chabi-Yo (2012) and Chang et al. (2013) find a negative risk premium, many others (e.g. Elyasiani et al., 2016; Kozhan et al., 2013) find a positive one. In particular, the positive risk premium is consistent with the investors' preference for assets with high (positive) odd moments and low even moments, a well-documented phenomenon in the literature (see e.g. Arditti, 1967; Kraus and Litzenberger, 1976; Scott and Horvath, 1980). This rationale is consistent with a negative risk premium for volatility and kurtosis and a positive one for skewness. If investors prefer low even moments, they are willing to pay a high fixed rate in order to hedge against increases in both time-varying volatility and kurtosis. As a result, the payoff for a long position in both volatility and kurtosis swaps (equal to the difference between the floating and the fixed swap rate) is negative. The opposite is true for skewness.

To provide further arguments to support our *a priori* expectation about the signs of the moment risk premia and their empirical implications, we use the model adopted in Chang et al. (2013) for the US market, in which the market excess return and the innovations in volatility, skewness and kurtosis represent the risk factors:

$$R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i (R_{m,t} - R_{f,t}) + \beta_{\Delta VOL}^i \Delta VOL_t + \beta_{\Delta SKEW}^i \Delta SKEW_t + \beta_{\Delta KURT}^i \Delta KURT_t + \varepsilon_{i,t} \tag{3}$$

On day *t*, $R_{i,t}$, $R_{f,t}$ and $R_{m,t}$ are the returns on the i-th stock, the risk-free asset and the market portfolio, respectively, and ΔVOL_t, $\Delta SKEW_t$ and $\Delta KURT_t$ are the innovations in the first, the second, and the third moment, respectively. The regression coefficients ($\beta_{\Delta VOL}$, $\beta_{\Delta SKEW}$, $\beta_{\Delta KURT}$) capture the exposure of the *i*-th stock to volatility, skewness and kurtosis risks. For instance, stocks with positive $\beta_{\Delta VOL}$ react positively to an increase in market volatility and, as a result, they act as a hedge against volatility risk. Conversely, stocks characterized by negative $\beta_{\Delta VOL}$, react negatively when the market volatility increases. In the extension of the ICAPM model proposed in Chang et al. (2013), the total risk premium, i.e. the excess return of stock *i*, can be decomposed into the sum of the market, volatility, skewness and kurtosis risk premia, as described by equation (4):

$$E[R_i] - R_f = \lambda_0 + \lambda_{MKT}\beta_{MKT}^i + \lambda_{\Delta VOL}\beta_{\Delta VOL}^i + \lambda_{\Delta SKEW}\beta_{\Delta SKEW}^i + \lambda_{\Delta KURT}\beta_{\Delta KURT}^i \tag{4}$$

where $E[R_i] - R_f$ is the expected excess return of the *i*-th stock and λ_{MKT}, $\lambda_{\Delta VOL}$, $\lambda_{\Delta SKEW}$ and $\lambda_{\Delta KURT}$ are the price of market, volatility, skewness and kurtosis risk, respectively, which are multiplied by the respective quantities of risk β_{MKT}, $\beta_{\Delta VOL}$, $\beta_{\Delta SKEW}$, $\beta_{\Delta KURT}$. Note that in the empirical application proposed in Section 4.2, $E[R_i] - R_f$ is proxied by the next-month return of each portfolio.

In order to form an *a priori* expectation about the sign of the lambda coefficients, we point out that in the ICAPM model, the risk prices depend on whether the risk is perceived by investors as good or bad news about the quality of the future investment opportunity set. For instance, volatility matters in the cross-section of stock returns since an increase in market volatility is perceived as a deterioration in the investment opportunity set, and stocks that react positively to an increase in volatility are desirable for investors' hedging purposes. According to Chen (2002), when market implied volatility increases, investors hedge against volatility risk by selling (buying) stocks with negative (positive) $\beta_{\Delta VOL}$. As a result, the price of stocks with negative $\beta_{\Delta VOL}$ decreases and their future expected return increases, while the price of stocks whose return is positively related with market volatility increases and their expected return decreases. Therefore, we expect the price of volatility risk ($\lambda_{\Delta VOL}$) to be negative. According to the model in equation (4), given a negative price for volatility risk, we expect the excess stock return to decrease when $\beta_{\Delta VOL}$ increases. Stocks with the lowest (highest) $\beta_{\Delta VOL}$, are expected to achieve the highest (lowest) future return.

In order to form an *a priori* expectation about the price of skewness risk ($\lambda_{\Delta SKEW}$), Chang et al. (2013) argue that option implied (risk-neutral) skewness can be considered as a measure of downside jump risk. Therefore, a positive innovation in skewness (risk-neutral skewness increases or becomes less negative) indicates a lower probability of realizations in the left tail of the distribution. To elaborate, an increase in market skewness is associated with a lower downturn risk for the stock market and this could be interpreted as a positive shock to the investment opportunity set. On the other hand, negative innovations in market skewness are related to an increase in the downside jump risk and, as a result, they are perceived as a negative shock to the investment opportunity set.

When market skewness decreases, i.e. left-tail risk increases, investors hedge against skewness risk by selling (buying) stocks with positive (negative) $\beta_{\Delta SKEW}$, the price of stocks with a positive $\beta_{\Delta SKEW}$ decreases and their future expected return increases. On the other hand, the price of stocks with negative $\beta_{\Delta SKEW}$ increases and, as a result, their future return decreases. It follows that the price of stocks with a positive $\beta_{\Delta SKEW}$ reacts negatively to a decrease in risk-neutral skewness and, therefore, the expected return is positive in order to compensate their riskiness. Conversely, the price of stocks with negative $\beta_{\Delta SKEW}$ react positively and, therefore, these stocks act as a hedge against market skewness risk. Following this rationale, we can expect the market price of skewness risk to be positive.

Last, the rationale for kurtosis risk is similar to that for volatility risk. In fact, an increase in kurtosis means that the risk-neutral distribution becomes more fat-tailed and, as a result, the probability of extreme events increases. If the investors are risk-averse, we can suppose that they consider an increase in market kurtosis as an unfavorable shock to the investment opportunity set. Therefore, similar to volatility, we expect a negative price of kurtosis risk.

4. Empirical analysis

In this section, we conduct an empirical analysis of the two approaches presented in Section 3 for estimation of market volatility, skewness and kurtosis risk premia in the European stock market. First, following Zhao et al. (2013), we use the model-free method to compute volatility, skewness, and kurtosis risk premia by means of the moment swap contracts (section 4.1). Second, we investigate the pricing of the moment risk by using the model-based portfolio analysis (section 4.2). In line with Chang et al. (2013), in this latter analysis, we exploit three different methods including multivariate sorting, four-way sorting and Fama-Macbeth (1973) regressions to determine the risk premia. This allows us to check the robustness of our estimates of the risk premia.

4.1 The model-free method: moment swap contracts

In a variance swap, at maturity, the long side pays a fixed rate (the variance swap rate) and receives a floating rate (the realized or physical variance). The payoff, at maturity, for the long side can be presented as equation (5):

$$N(\sigma_R^2 - VRS) \quad (5)$$

where N is a notional Euro amount, σ_R^2 is the realized variance (computed at maturity), VRS is the fix variance swap rate, which is equal to the implied variance at the beginning of the contract. The payoff of the swap is equal to the variance risk premium, i.e. the amount that investors are willing to pay in order to be hedged against peaks of variance. Zhao et al. (2013) extend the variance swap to higher order moments and propose two new types of contracts: the skewness and the kurtosis swap. In both the skewness and the kurtosis swap contracts, the option-implied moment and the realized moment are, respectively, the fixed leg and the floating leg of the moment swap contract.

In order to compute variance, skewness, and kurtosis risk premia, each day we compute the implied moment from EURO STOXX 50 option prices and the realized moments from daily EURO STOXX 50 log-returns by using a rolling window of 30 calendar days. In this way, the realized moments refer to the same time-period covered by the risk-neutral counterparts. For greater clarity and in line with the analysis in the next sections, we report results for volatility (VOL), defined as the square root of the model-free implied variance, instead of variance. The average values for risk-neutral and realized (physical) moments are reported in Table 2. From this table, we observe that the risk-neutral distribution of market returns is more volatile, more negatively skewed, and more fat-tailed than its corresponding realized distribution, which is almost symmetrical. The evidence in Table 2 points to the existence of a risk premium for each of the three higher moments of the return distribution. In particular, both the volatility and the kurtosis risk premia are negative and statistically significant (at 1%). On the other hand, the skewness risk premium is positive and statistically significant (at the 1% level). This suggests that investors are willing to pay a premium in order to be hedged against peaks of volatility and kurtosis or against negative peaks (drops) in skewness. In Table 2, we present also the correlation coefficients between moment risk premia. We can see from the correlation values that while the volatility and skewness risk premia are uncorrelated, kurtosis and skewness risk premia are strongly and significantly correlated (-0.902, significant at the 1% level). Moreover, skewness and kurtosis are also strongly correlated, because fat tails are normally associated with asymmetry in the distribution. This suggests that higher-order moments are driven by a common source of risk. This issue will be discussed in the next section. It is notable that correlations do not capture the non-linearities possibly present between moments.

4.2 Model-based portfolio sorting analysis of risk premia

In section 4.1 we investigated the existence, significance, and the magnitude of risk premia for the EURO STOXX 50 index option market by means of the moment swap contracts. Significance of risk premia in this framework indicates that higher moment risks are priced in the market. In this section we use portfolio sorting to determine whether innovations in implied-option market volatility, skewness and kurtosis are priced risk factors in the sense that they matter in explaining individual stock returns. Since we need a large number of stocks to be able to implement the portfolio sorting strategies, in this section, we use the STOXX Europe 600 index data, instead of the EURO STOXX 50, used in section 4.1. Our cross-sectional analysis will be conducted using three different methods: multivariate sorting, four-way sorting and Fama-Macbeth (1973) regressions, described next.

4.2.1 Multivariate sorting

The objective is to test the relation between stock exposure to innovations in option-implied volatility, skewness, and kurtosis and its future returns in an out-of-sample framework. The use of out-of-sample returns allows us to avoid spurious effects (correlation between the estimated exposures and returns). This is in line with previous studies such as Ang et al. (2006), Agarwal et al. (2009) and Chang et al. (2013). The rationale underlying the cross-sectional analysis is that if a risk factor is priced in the market, stocks with different sensitivities to different risk factors will show different future returns. Following Ang et al. (2006) and Chang et al. (2013), our analysis is based on a two-step process. In the first step, we use daily data on a one-month window in order to estimate the model described by equation (3), (presented in Section 3), using the Ordinary Least Squares (OLS). This step produces estimates of the beta coefficients for the risk factors considered for each individual stock. In the second step, we perform a cross-sectional analysis by creating five equally-weighted portfolios based on quintiles of the sensitivity to each risk factor: $\beta^i_{\Delta VOL}$, $\beta^i_{\Delta SKEW}$ and $\beta^i_{\Delta KURT}$.

The first (fifth) portfolio holds the stocks with the lowest (highest) value of the beta. We compute the return on each portfolio in the subsequent month as a proxy for its expected return. The use of equally-weighted portfolio is motivated by the features of the market under investigation. Specifically, one drawback of the value-weighting procedure is that it gives more weight to the information regarding returns of large-cap stocks (Plyakha et al., 2014). As a significant part of the STOXX Europe 600 index focus on a limited number of stocks (mainly financial and energy stocks), especially during the financial crisis, we prefer equally-weighted sorting to isolate the results of the analysis from individual firms' events. Moreover, the equally-weighted portfolio, relative to the value- and price-weighted portfolios, is relatively more highly exposed to the value, size, and market factors (Plyakha et al., 2014). As a result, it is better suited to our analysis aimed at detecting market risk premia.

In order to assess whether the effects of innovations in implied moments on stock returns sustain themselves after controlling for the Carhart (1997) risk factors, we compute the four-factor alpha for each of the five portfolios (Q1, Q2, Q3, Q4, Q5) plus the long-short portfolio (Q5-Q1) by estimating the following equation:

$$R_{j,t} = \alpha^j + \beta^j_{MKT} MKT_t + \beta^j_{SMB} SMB_t + \beta^j_{HML} HML_t + \beta^j_{UMD} UMD_t + \varepsilon_{j,t} \tag{6}$$

where $R_{j,t}$ is the portfolio return (post-ranking) in day *t*, for $j=1,\ldots,6$ and MKT_t, SMB_t, HML_t and UMD_t are the factors used in order to evaluate the robustness of the intercept. The intercept is referred to as the "four-factor alpha" by Carhart (1997). It represents the amount of portfolio return not explained by

Carhart (1997) risk factors, and, as a result, it is attributable to the risk factor under investigation (volatility, skewness or kurtosis). The long-short portfolio (Q5-Q1) is computed as the difference between the return of the portfolio characterized by the highest exposure to the risk factor (Q5) and the one characterized by the lowest exposure (Q1). We repeat the procedure each month, by rolling the estimation window over to the next month. We report the results for portfolios sorted by exposure to innovations in volatility, skewness, and kurtosis in Table 3, Panel A, Panel B and Panel C, respectively.

4.2.1.1 Portfolios sorted by exposure to innovations in market volatility

Starting from volatility exposure, if a positive innovation in market volatility (an increase in volatility) is perceived by the investors as a deterioration of the investment opportunity set, stocks with positive exposure (positive $\beta^{i}_{\Delta VOL}$) to innovations in market volatility act as a hedge against volatility risk. As a result, they are desirable for investors since they provide positive returns when market volatility increases (which is usually associated to a decrease in market returns), resulting in a lower expected future return for such assets. On the other hand, stocks with negative exposure to innovations in volatility (negative $\beta^{i}_{\Delta VOL}$, i.e. stocks that suffer from major declines when volatility increases) should earn high future returns in order to compensate investors for the higher risk. Therefore, we expect the average returns on portfolios sorted by exposure to innovations in market volatility to have a decreasing pattern from the first quintile (Q1), characterized by the lowest exposure (negative beta), to volatility to the fifth quintile (Q5), characterized by the highest exposure (positive beta) to volatility. As a result, we expect a negative return and a negative alpha for the high-low portfolio (Q5-Q1) and a monotonic pattern in both the average returns and the alphas for portfolios sorted based on their exposure to volatility risk.

The results, reported in Table 3, Panel A, show that both the average return and the alpha for the long-short portfolio (Q5-Q1) are negative and significant. Moreover, both the average returns of the equally weighted portfolios and the associated four-factor alphas present a monotonically decreasing pattern from the portfolio with the lowest exposure (Q1) to the one with the highest exposure (Q5). This pattern is also detectable in Figure 4, where the relation between average returns, Carhart four-factor alphas, and the portfolio exposures to the risk factor, are depicted. This evidence points to a significant negative volatility risk premium, which is priced in the cross-section of stocks returns. This is in line with previous findings in Ang et al. (2006), but it is different from Chang et at. (2013), where the volatility risk premium is negative, but not significant: both studies investigated the US market. In particular, we find that stocks with negative exposure ($\beta^{i}_{\Delta VOL}$) to innovations in market volatility earn higher future returns than stocks with positive exposure to volatility risk. The latter act as a hedge (i.e. they increase in value when volatility increases). The higher return on the former compensates investors for the higher level of risk. Moreover, this result is also consistent with the negative sign for the volatility risk premium obtained in Section 4.1 by using the volatility swap contract, suggesting that investors are averse to increases in market volatility and are willing to pay a premium reflected in a lower return for stocks that act as a hedge against market volatility risk.

4.2.1.2 Portfolios sorted by exposure to innovations in market skewness

The results for portfolios sorted with respect to exposure to innovations in market skewness are reported in Table 3, Panel B. It may be seen that the average return and the alphas of the different portfolios present a monotonically increasing pattern with the sole exception of the third quintile portfolio. Moreover, the four-factor alpha for the long-short portfolio (Q5-Q1) is positive and statistically significant, suggesting a positive skewness risk premium, in line with the evidence obtained in the previous section. Therefore, we conclude that also market skewness risk is a priced factor in the cross-section of stock returns: investors are averse to negative changes in market skewness, and accept a lower future return for stocks that act as a hedge against skewness risk (stocks with negative $\beta^{i}_{\Delta SKEW}$).

This result stands in contrast with the findings of Chang et al. (2013) who report a robust negative skewness risk premium for the US, reflected in a decreasing pattern in average returns and alphas from Q1 to Q5. The reasons for the dissimilarity in finding are twofold. First, the difference in institutional features between the European markets studied here and the US market studied by Chang et al. (2013). This includes e.g., dissimilarity in market depth (US markets are deeper) and in sectoral diversification (European markets are concentrated on financial stocks). Second, dissimilarity in the sample period. Specifically, we investigate the European market over the period 2008-2015, which was heavily influenced by the financial crisis and the European debt crisis and therefore is characterized by a greater volatility, compared to the US market in the period 1996-2007.

In Figure 4 we can see that the alpha and the average return generally increases when the exposure (beta) to skewness risk increases, suggesting that stocks with negative exposure ($\beta^{i}_{\Delta SKEW}$) to skewness innovations earn lower future returns than stocks with positive exposure to skewness risk. The latter act as a hedge against skewness risk.

4.2.1.3 Portfolios sorted by exposure to innovations in market kurtosis

Finally, we report the cumulative return for portfolios with different exposure to innovations in kurtosis in Table 3, Panel C. According to the figures in this table, the return and the Carhart four-factor alpha for the Q5-Q1 portfolios are not statistically different from zero. Moreover, we cannot detect any monotonic patterns in the average returns and the alpha statistics (see Figure 4). Therefore, we conclude that kurtosis risk is not priced in the cross-section of stock returns. This stands in contrast to our previous findings based on the kurtosis swap contract reported in Table 2. It should be noted that we have orthogonalized innovations in kurtosis with respect to innovations in skewness in order to remove the high correlation between the two variables. This may be the reason why kurtosis risk is no longer significant in the portfolio analysis. Given the high correlation between skewness and kurtosis, the former may capture the effect of the latter to a large extent.

In Figure 5, we report the cumulative return for portfolios with different exposures to innovation in the risk factors. We can see that while the performance of the portfolios with different exposures to volatility risk displays a divergent pattern and a pronounced spread between VOL1 and VOL5 (portfolios with negative exposure to volatility display a higher return than those with positive exposure), we do not find any striking evidence for portfolios sorted with respect to exposure to kurtosis risk. On the other hand, portfolios sorted by exposure to skewness risk display a less evident pattern but a marked difference between SKEW1 and SKEW5. The evidence in Figure 5 supports the results obtained in the multivariate sorting analysis: volatility and skewness are priced factors in the cross-section of stocks returns, while the same is not true for kurtosis.

To sum up, the empirical evidence based on multivariate portfolio sorting confirms the results obtained in Section 4.1 for volatility and skewness, namely that the second- and the third-order moments matter in explaining individual stock returns. On the other hand, once orthogonalized against skewness, kurtosis risk is not priced in the cross-section of STOXX Europe 600 stock returns, namely that it does not show a marginal independent riskiness beyond that shown by skewness. We discuss this result further in the next section.

4.2.2 Four-way sorting

One drawback of the multivariate sorting analysis discussed in Section 4.2.1 is the difficulty in separating the effect of each risk factor because the exposures to the different factors introduced in equation (3) are correlated. In particular, market excess returns and innovations in volatility show a high degree of correlation (-0.71, significant at the 1% level) that has to be isolated. In order to address this issue, we follow the methodology proposed in Chang et al. (2013) for the US data. These authors perform a four-way sorting that allows them to isolate the pricing effects of the different risk factors. This procedure is superior to Agarwal et al. (2009) who use a three-way sorting.

The four-way sorting procedure is based on the following steps. First, each month we sort the stocks into three different sub-samples based on their exposure to the market excess return factor. The first (third) sub-sample is formed by the stocks with the lowest (highest) estimate of β^{i}_{MKT} in that period. Second, within each sub-sample, we again sort the stocks into three sub-samples; those characterized by a low, medium and high exposure to volatility risk, respectively. Third, we repeat the procedure within each of the previous nine groups by sorting again on the basis of the differences in exposure to innovations in skewness (high, medium or low). In this way we obtain 27 groups. As a fourth step, we sort again according to innovations in kurtosis (high, medium or low). We thus obtain 81 groups of stocks ranked by their high, medium or low exposure to market, volatility, skewness and kurtosis risk (see Figure 6 for a diagram of the procedure).

We compute the return on equally-weighted portfolios within each group over the next month. Finally, in order to have portfolios exposed to a single risk factor and neutral to the other risk factors, we take a long position on the 27 portfolios with the highest exposure to that factor and a short position in the 27 portfolios with the lowest exposure to the same risk factor. Neutrality over other risk factors is ensured by the fact that the 27 portfolios are well diversified with respect to them (e.g. the 27 portfolios with the highest exposure to market risk collect stocks with low, medium and high exposure to volatility, skewness and kurtosis risk). The average returns of factor portfolios exposed to excess return, volatility, skewness and kurtosis ($FMKT$, $FVOL$, $FSKEW$ and $FKURT$) are computed as:

$$
\begin{aligned}
FMKT &= (1/27)(R\beta_{\Delta MKT,H} - R\beta_{\Delta MKT,L}) \\
FVOL &= (1/27)(R\beta_{\Delta VOL,H} - R\beta_{\Delta VOL,L}) \\
FSKEW &= (1/27)(R\beta_{\Delta SKEW,H} - R\beta_{\Delta SKEW,L}) \\
FKURT &= (1/27)(R\beta_{\Delta KURT,H} - R\beta_{\Delta KURT,L})
\end{aligned}
\tag{7}
$$

where $R\beta_{\Delta MKT,H}$ $R\beta_{\Delta VOL,H}$, $R\beta_{\Delta SKEW,H}$ and $R\beta_{\Delta KURT,H}$ are the sum of the returns of the portfolios characterized by the highest exposure to the specific risk factor and $R\beta_{\Delta MKT,L}$, $R\beta_{\Delta VOL,L}$, $R\beta_{\Delta SKEW,L}$ and $R\beta_{\Delta KURT,L}$ are the sum of the returns of the portfolios characterized by the lowest exposure to the specific risk factor.

The average returns of the four-factor portfolios represent the investors' compensation for time-varying market excess return, volatility, skewness and kurtosis risks. For instance, the return of the $FVOL$ portfolio reflects the return of a zero-cost portfolio, which is exposed only to volatility risk and is neutral to the other risk factors. Therefore, each average return of the factors can be viewed as the risk premium for exposure to that risk factor.

The average returns and the Carhart alphas for the four-factor portfolios are reported in Table 4. We can see that the average monthly volatility risk premium is equal to -0.47% (-5.64% if annualized), which is statistically significant. This indicates that portfolios that take a long position on volatility (i.e. an insurance-buying strategy on volatility risk) earn on average a negative return. This result is consistent with our previous analysis based on the volatility swap and the multivariate portfolio sorting that reveal a negative risk premium for volatility (reported in Table 2 and in Table 3, Panel A).

The estimated risk premium for skewness risk, reported in Table 4, column 5-6, is positive and weakly significant (at the 10% level). In terms of magnitude, this risk premium stands at 0.16% on a monthly basis (1.92% if annualized). The results based on four-way sorting analysis confirm those based on multivariate sorting discussed in the previous sections, though weakly. The average return for the high-low portfolio sorted with respect to kurtosis risk and the Carhart alpha, reported in Table 4, columns 7-8, are not statistically different from zero. Again, the results show that kurtosis risk is not priced in the cross-section of stock returns.

The cumulative returns for the factor portfolios based on innovations in volatility, skewness and kurtosis are presented in Figure 7. Interestingly, we see that the return on the volatility factor portfolio ($FVOL$), that captures the volatility risk premium, is positive during the 2008 market decline, suggesting a positive risk premium on volatility in that specific period. The positive risk premium means that portfolios that take a long position on volatility (e.g. portfolio long on fifth-quintile and short on first-quintile stocks or simply a long position in a variance swap contract) yield positive returns during market stress periods. This evidence is consistent with a realized volatility higher than the implied one, during the market decline. It appears that in the critical phase of the financial crisis of 2007-2009, stocks that acted as a hedge against volatility risk (i.e., stocks with positive $\beta_{\Delta VOL}$) achieved a better performance than the ones negatively exposed to volatility risk (i.e. stocks with negative $\beta_{\Delta VOL}$). This confirms that being long on a variance swap is an insurance-buying strategy in the sense that the return of the position is on average negative (i.e. the investor pays the volatility risk-premium), but if the insured event (peak in volatility) occurs, the strategy realizes a significant return. This pattern, although less evident, can be detected also in the middle of Figure 7 during the European debt crisis (2011-2012). This result highlights the importance of portfolio diversification also with regard to volatility risk in order to avoid large losses during market turmoil periods. Specifically, investors could set a long position in a variance swap contract or increase the portfolio portion of stock characterized by positive volatility beta. Also a short position on stocks characterized by negative volatility beta would have significantly improved the portfolio performance. The skewness and the kurtosis risk premia do not vary significantly during the entire sample period: the skewness risk premium remains positive and the kurtosis risk premium remains close to zero throughout the sample period.

In Table 5, we report the average monthly returns for the factor portfolios *FVOL*, *FSKEW*, *FKURT*, the Carhart risk factors, and the correlation coefficients between the risk factors. In particular, we see that only the SMB factor, which captures the excess return of low capitalization firms relative to high capitalization firms, is statistically significant and equal to 0.49% on a monthly basis (5.88% annualized). The positive price of size risk suggests that stocks characterized by low capitalization levels earn higher returns than the ones characterized by high capitalization levels, pointing to the existence of a small-size premium. The cumulative returns for the Carhart (1997) four-factor portfolios based on market excess return, size, book-to-market and momentum are depicted in Figure 8. From this figure, we see that the size factor is the only factor that provides a constant positive performance over the entire sample period, highlighting the significant over-performance of small capitalizations stocks relative to the high capitalization ones. This finding is in contrast with results for the US stock market (Chang et al., 2013), where a size risk factor is not priced, highlighting the different structure of the two stock markets: in the European market, which is more concentrated than the US one, size matters.

4.2.3 Fama-MacBeth regressions

In order to evaluate the robustness of our results on pricing of higher moment risk based on cross-sectional analysis described in the earlier sections, we compute the price of market, volatility, skewness and kurtosis risks also by means of Fama and MacBeth (1973) regressions. In order to have a sufficient number of stocks in any sub-group we choose to use 25 Fama-French portfolios, formed each month based on Size and Book-to-Market values. Fama and Macbeth (1973) regressions are constructed in two steps. First, we estimate the betas on six month[3] daily returns by running the most general model, namely the Carhart model augmented with innovations in volatility, skewness and kurtosis as described by equation (8). Second, in order to compute the price of the risk factors, we use the estimated betas

[3] We found similar results when estimating betas by using 60- and 90-day portfolio returns.

from equation (8) as regressors in the model described by equation (9) and estimate equation (9) for the next month, where $E\left[R_i\right]$ is proxied by the next-month return of each of the 25 portfolios. The procedure is repeated by rolling the estimation window over to the next month.

$$\begin{aligned} R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i (R_{m,t} - R_{f,t}) + \beta_{\Delta VOL}^i \Delta VOL_t + \beta_{\Delta SKEW}^i \Delta SKEW_t + \\ \beta_{\Delta KURT}^i \Delta KURT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \beta_{UMD}^i UMD_t + \varepsilon_{i,t} \end{aligned} \quad (8)$$

$$\begin{aligned} E\left[R_i\right] - R_f = \lambda_0 + \lambda_{MKT} \beta_{MKT}^i + \lambda_{\Delta VOL} \beta_{\Delta VOL}^i + \lambda_{\Delta SKEW} \beta_{\Delta SKEW}^i \\ + \lambda_{\Delta KURT} \beta_{\Delta KURT}^i + \lambda_{SMB} \beta_{SMB}^i + \lambda_{HML} \beta_{HML}^i + \lambda_{UMD} \beta_{UMD}^i \end{aligned} \quad (9)$$

In order to compare the pricing performance of the most general model with one of the nested models, we also use Fama and Macbeth (1973) regressions in order to estimate the four-factor Carhart model described by equations (10-11), (the FFC4 model):

$$R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i (R_{m,t} - R_{f,t}) + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \beta_{UMD}^i UMD_t + \varepsilon_{i,t} \quad (10)$$

$$E\left[R_i\right] - R_f = \lambda_0 + \lambda_{MKT} \beta_{MKT}^i + \lambda_{SMB} \beta_{SMB}^i + \lambda_{HML} \beta_{HML}^i + \lambda_{UMD} \beta_{UMD}^i \quad (11)$$

and the Four-Moment CAPM model described by equations (12-13):

$$R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i (R_{m,t} - R_{f,t}) + \beta_{\Delta VOL}^i \Delta VOL_t + \beta_{\Delta SKEW}^i \Delta SKEW_t + \beta_{\Delta KURT}^i \Delta KURT_t + \varepsilon_{i,t} \quad (12)$$

$$E\left[R_i\right] - R_f = \lambda_0 + \lambda_{MKT} \beta_{MKT}^i + \lambda_{\Delta VOL} \beta_{\Delta VOL}^i + \lambda_{\Delta SKEW} \beta_{\Delta SKEW}^i + \lambda_{\Delta KURT} \beta_{\Delta KURT}^i \quad (13)$$

Table 6 reports the average of the monthly estimates of the price of risk (lambda) obtained by using the three different models described by equations (8)-(13). If the pricing model is correct, the value of the intercept should not be significantly different from zero. In the most general model, the Carhart model augmented with innovations in volatility, skewness and kurtosis (equations 8-9), last column of Table 6, we find that the lambda coefficients for volatility and skewness are both statistically significant, suggesting that volatility risk and skewness risk are priced factors in portfolio returns. Statistical significance of the prices of volatility risk (with a negative sign) and skewness risk (with a positive sign) supports the results obtained in previous sections about the sign of the risk premia on these higher moments of the return distribution. This indicates that investors are averse to increases in volatility and decreases in risk-neutral skewness and, consequently, they are willing to accept a lower return on stocks that serve as a hedge against their risks. On the other hand, the lambda coefficient for kurtosis risk is found to be statistically insignificant, suggesting that kurtosis risk is not a priced factor in the cross-section of stock returns. This finding is also in line with our earlier results (sections 4.2.1-4.2.2). Moreover, we find that lambda for the size factor is positive and statistically significant, in line with our results in Section 4.2.2. Investors require higher returns on small capitalization stocks relative to high capitalization stocks in order to be rewarded for the higher level of risk. Last, we see that the complete model described by equations (8) and (9) can explain a large part of the portfolio returns (80%), suggesting that the introduction of innovations in market volatility, skewness, and kurtosis greatly improves the explanatory power of the standard four-factor Carhart model (the Adjusted R^2 increases by 22.63% when we move from the four-factor Carhart model (equations 10-11) to the complete model (equations 8-9).

On the other hand, when we consider the Four-Moment CAPM model (equations 10-11, second column of Table 6) we obtain a worse fit compared to both the complete and the four-factor Carhart model, indicating that the Carhart factors are important in the explanation of the cross-section of future returns. This is evident also from the four-factor Carhart model (FFC4) described by equations (10-11) where size is the only significant factor.

To sum up, we investigated the pricing of volatility and higher moment risks in the European stock markets by using two different approaches: the model-free approach based on swap contracts, and the model-based approach based on multivariate sorting, four-way sorting and Fama and Macbeth regressions. We find robust evidence that volatility risk is priced both in the EURO STOXX 50 option market and in the cross-section of STOXX Europe 600 stock returns. In particular, the results point to a negative volatility risk premium, suggesting that investors are averse to increases in market volatility and are willing to pay a premium in order to be hedged against peaks of volatility in the market. This premium is manifested in a lower return for stocks that provide a hedge against volatility. This result is consistent with previous evidence on the subject in the US market (e.g. Ang et al., 2006; Carr and Wu, 2009). Furthermore, by investigating the skewness swap contract, we find strong evidence of a positive skewness risk premium in the EURO STOXX 50 option market, which is reflected, although weakly, in a positive skewness risk premium also in the cross-section of STOXX Europe 600 stock returns. This result stands in contrast to the findings by Chang et al. (2013) for the US market. We find that the results sustain themselves even when other common risk factors (market excess return, size, book-to-market and momentum) are included in the model.

Our results suggest that investors are averse to negative peaks (drops) in risk-neutral skewness and require a higher return for stocks characterized by positive exposure to skewness risk (positive $\beta^{i}_{\Delta SKEW}$). Finally, we find that the size factor is the only Carhart factor priced in the cross-section of stock returns, indicating that investors perceive stocks with low capitalization levels as riskier and require higher future returns on these stocks. On the other hand, excess market returns, book-to-market and momentum are not priced risk factors in our sample. A possible explanation for the finding on the excess market returns factor (MKT) is its high and significant correlation with innovations in volatility, reported in Table 1 (-0.69). The strong co-movement between the two suggests that volatility risk may also capture a large part of the risk associated with variations in market return. On the other hand, by looking at Figure 8, momentum appears to be priced positively in the first part of the sample and negatively in the latter. This result is clearly addressed by the absence of a long-term trend in the European stock market during the period under investigation. Specifically, the European market was characterized by a strong bearish trend from the early 2008 to the first quarter of 2009. After a quick rebound in 2009, stock prices moved in a narrow range until mid-2012. Finally, a bullish market trend was detectable in the last part of the sample.

4.2.4. Economic significance

In the previous sections, we evaluated statistical significance of the moment risk premia by means of different techniques. In this section, we investigate whether the obtained risk premia are significant also from an economic point of view. Chang et al. (2013) evaluate the economic significance of a risk factor by comparing the magnitude of its price of risk (λ) (estimated in Section 4.2.3) with the spread of betas (i.e. the portfolio exposure to the risk factor). For instance, in the model described by equations (8)-(9), the volatility risk-premium is computed as the price of volatility risk ($\lambda_{\Delta VOL}$) times the quantity of risk (proxied by $\beta_{\Delta VOL}$). The rationale is that an investor who aims to replicate a long position in volatility risk should take a long position in the portfolio with the highest $\beta_{\Delta VOL}$ and a short position in the portfolio with the lowest $\beta_{\Delta VOL}$. The return of the long-short portfolio is equal to the difference between the beta coefficients of the two portfolios (quantity of risk) times the price of risk.

Following this rationale, to assess the economic significance of the volatility risk premium, we take the following two steps. First, each month we compute the beta coefficients with respect to volatility risk by using the regression in equation (8). Second, we multiply the difference between the maximum $\beta_{\Delta VOL}$ and the minimum $\beta_{\Delta VOL}$ by the price of volatility risk reported in Table 6 (-0.0633). [4] We obtain an average return for the long-short portfolio equal to -0.51% on a monthly basis (-6.12% annual). We repeat this procedure for skewness risk and firm size risk and we obtain an average return for the long-short portfolios equal to 0.58% and 1.05% on a monthly basis, (6.96% and 12.6%, annual), respectively. Therefore, we consider the results to be significant also from an economic point of view.

[4] Monthly estimates for the beta of the portfolios are not reported for reasons of space but are available upon request.

5. Conclusions

In this study we investigated the pricing of volatility and higher moments and the associated risk premia in the European stock market, by using two different approaches. The first approach is based on the swap contracts proposed in Zhao et al. (2013), and is model-free. The second approach relies on an extension of the ICAPM model (Campbell, 1993, 1996; Merton, 1973), where the innovations in risk-neutral moments are considered as risk factors, in line with Chang et al. (2013). Our analysis of volatility and higher moment risk premia is motivated by the fact that there is no consensus on the existence and the sign of the risk premia in the US market and that there is almost no evidence in this regard in the literature on the European stock market. The European stock market presents many dissimilarities from the US one. In particular, the lower market depth and the higher sectoral diversification of the European market might affect investor behavior and their perception of moment risk. Moreover, most of the studies in the cross-section of stock returns are conducted in the periods prior to the financial crisis.

To fill this gap, we conducted our analysis based on the EURO STOXX 50-index options, which are European options on the EURO STOXX 50, a capital-weighted index composed of fifty of the largest and most liquid stocks in the Eurozone, during the 2008-2015 period. We obtained several results. First, the volatility risk premium was found to be negative, in line with Ang et al. (2006) and Adrian and Rosenberg (2008), suggesting that investors perceive an increase in market volatility as an unfavorable shock to the investment opportunity set and are willing to pay a premium in order to hedge against peaks in market volatility. As a result, stocks that act as a hedge against volatility risk (i.e. stocks that react positively to an increase in market volatility (positive $\beta_{\Delta VOL}$)), earned lower returns on average. Conversely, stocks that react negatively to an increase in market volatility (negative $\beta_{\Delta VOL}$) a significant positive return during the sample period.

Second, we found evidence of a positive skewness risk premium for the European stock market, in contrast with the results obtained in Chang et al. (2013), but in line with the findings of Kozhan et al. (2013), both based on the US market. In particular, investors are averse to decreases in market skewness and require a positive return for a long position on a skewness swap and higher returns on stocks with positive $\beta_{\Delta SKEW}$, i.e. high exposure to skewness risk, and expect to be compensated for their higher riskiness.

Third, the results for the sign of volatility and skewness risk premia were robust to different estimation methods employed in this study including moments' swap contracts, multivariate sorting, four-way sorting, and Fama-Macbeth (1973) regression, and also robust to model specifications which include other risk factors such as market excess return, size, book-to-market and momentum. It is notable, however, that the magnitude of the risk premia was different across the different estimation methods.

Fourth, we found a positive and large in magnitude risk premium for firm size in the European market (1.05% monthly, 12.6% annually) in the sense that stocks with low capitalization levels earn, on average, higher future returns than stocks with high capitalization. This result is in contrast with previous evidence in the US market (Chang et al., 2013), indicating that investors perceive European stocks with low capitalization levels as riskier and require higher future returns on these stocks.

Fifth, the volatility, skewness and firm-size risk premia were significant also from an economic point of view. Risk-tolerant investors can obtain significant returns by going short on volatility, long on skewness and increasing the share of small caps in their portfolios.

Our findings demonstrate that innovations in volatility and skewness are priced risk factors in the cross-section of stock returns and play a role in asset pricing. This result is important for investors and financial institutions who could take into account the variability in higher moments of the risk-neutral distribution in order to improve hedging and portfolio strategies. Measuring the portfolio exposure to market volatility and skewness is important in investment diversification decisions with respect to moment risk. This applies particularly for volatility, which is found to be positively priced during crisis periods, suggesting that portfolios with a negative exposure suffer from major losses during market turmoil periods. Regulators should take into account innovation not only in volatility, but also in skewness in order to promptly ease the market in case of large variation in higher order moments of the aggregate stock market.

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Table 1 – Risk factors adopted in the cross-sectional analysis

Descriptive statistics				Correlation table					
				(pre-orthogonalization)			(post-orthogonalization)		
	AR(1)	MA(1)	Mean	ΔVOL	$\Delta SKEW$	$\Delta KURT$	ΔVOL	$\Delta SKEW$	$\Delta KURT$
ΔVOL	0.974	-0.037	-3.792e-05	1.00	0.13***	-0.17***	1.00	0.13***	-0.08***
$\Delta SKEW$	0.945	0.381	-1.031e-03		1.00	-0.85***		1.00	0.00
$\Delta KURT$	0.937	-0.371	1.024e-03			1.00			1.00
R_m - R_f			6.589e-07				-0.69***	-0.20***	0.07***
SMB			2.328e-04				0.13***	0.05**	0.00
HML			-3.773e-05				-0.37***	-0.11***	0.05**
UMD			3.980e-05				0.25***	0.06**	0.02

Note: The left-hand panel shows the average value for the risk factors ΔVOL, $\Delta SKEW$, $\Delta KURT$, R_m - R_f, SMB, HML, UMD, which are the daily innovations in implied volatility, skewness and kurtosis and the daily returns on the factor portfolios for market, size, book-to-market, and momentum risks. $\Delta VOL_t = VOL_t - VOL_{t-1}$, and $\Delta SKEW$, $\Delta KURT$, are the residuals from fitting an ARMA(1,1) to the time series of corresponding moments using the entire sample. The right-hand panel shows the correlation among innovations in risk factors, where for implied kurtosis we report both the pre-orthogonalization (column 6) and the post-orthogonalization correlations (column 9). The cross-section of STOXX Europe 600 returns. Significance at the 1% level is denoted by ***, at the 5% level by **, and at the 10% level by *.

Table 2 – Average values for the estimated daily physical and risk-neutral moments and for the three swap contracts

	Volatility	Skewness	Kurtosis	Swap contract correlations			
Physical	0.1816	0.0019	3.0004				
Risk-neutral	0.2650	-0.4729	3.6016				
Risk premium	-0.0835***	0.4749***	-0.6011***				
	(-16.91)	(58.51)	(-28.10)				
					VRP	SRP	KRP
				VRP	1.000	0.029	-0.078***
				SRP		1.000	-0.902***
				KRP			1.000

Note: This table shows the average values for the physical and risk-neutral moments of the EURO STOXX 50 distribution, the moment risk premia based on moment swap contracts (t-stats for the significance of the risk premia are in brackets) and the correlations among volatility risk premium (VRP), skewness risk premium (SRP) and kurtosis risk premium (KRP). Significance at the 1% level is denoted by ***, at the 5% level by **, and at the 10% level by *.

Table 3 – Average return and four-factor alpha for portfolios sorted based on exposure to innovations in implied volatility, skewness, and kurtosis

Panel A	Quintile Q1	Q2	Q3	Q4	Q5	Gap: Q5-Q1
$\beta_{\Delta VOL}$	-0.66	-0.25	-0.045	0.14	0.54	
Avg. Ret.	0.86%	0.63%	0.37%	0.30%	0.15%	-0.70%***
						(-2.88)
Alpha	0.56%	0.40%	0.14%	0.06%	-0.15%	-0.71%***
						(-2.87)
Panel B	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Gap: Q5-Q1**
$\beta_{\Delta SKEW}$	-0.14	-0.04	0.00	0.05	0.13	
Avg. Ret.	0.35%	0.40%	0.38%	0.44%	0.73%	0.38%*
						(1.67)
Alpha	0.03%	0.17%	0.16%	0.20%	0.45%	0.42%*
						(1.83)
Panel C	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Gap: Q5-Q1**
$\beta_{\Delta KURT}$	-0.10	-0.03	-0.00	0.03	0.10	
Avg. Ret.	0.45%	0.53%	0.36%	0.47%	0.51%	0.06%
						(0.25)
Alpha	0.13%	0.28%	0.12%	0.24%	0.22%	0.09%
						(0.38)

Note: This table shows the results for portfolios sorted on exposure to volatility (Panel A), skewness (Panel B) and kurtosis (Panel C). Quintile 1 (5) collects stocks with the lowest (highest) values of β, Q5-Q1 portfolios are obtained combining a long position in Quintile 5 and a short position in Quintile 1. For each quintile portfolio plus the Q5-Q1 we report the average return and the four-factor alpha computed with respect to the Carhart (1997) four-factor model (t-stats are in brackets). The four-factor alpha is computed as the intercept obtained by estimating the following equation:

$$R_{j,t} = \alpha^j + \beta^j_{MKT} MKT_t + \beta^j_{SMB} SMB_t + \beta^j_{HML} HML_t + \beta^j_{UMD} UMD_t + \varepsilon_{j,t},$$

where $R_{j,t}$ is the portfolio return (post-ranking) in day *t*, for *j=Q1, Q2, Q3, Q4, Q5, Q5-Q1* and MKT_t, SMB_t, HML_t and UMD_t are the daily factors used in order to evaluate the robustness of the intercept. Significance at the 1% level is denoted by ***, at the 5% level by **, and at the 10% level by *.

Table 4 – Portfolios sorted based on low (L), medium (M) and high (H) exposure (β) to market excess return and innovations in implied moments.

	R_m - R_f		ΔVOL		$\Delta SKEW$		$\Delta KURT$	
	Avg. Ret.	Alpha	Avg. Ret.	Alpha	Avg. Ret.	Alpha	Avg. Ret.	Alpha
L	0.51%	0.29%	0.71%	0.44%	0.37%	0.19%	0.43%	0.22%
M	0.52%	0.27%	0.45%	0.40%	0.50%	0.28%	0.50%	0.29%
H	0.37%	0.06%	0.24%	0.11%	0.53%	0.30%	0.47%	0.27%
H-L	-0.14%	-0.23%	-0.47%*	-0.47%**	0.16%*	0.18%*	0.05%	0.05%
	(-0.45)	(-1.22)	(-1.92)	(-2.34)	(1.65)	(1.80)	(0.53)	(0.55)

Note: This table shows the average return and the alpha computed with respect to the Carhart (1997) four-factor model in the factor portfolios obtained by using the four-way sorting method (t-stats are in brackets). Significance at the 1% level is denoted by ***, at the 5% level by **, and at the 10% level by *.

Table 5 – Average monthly risk premia for volatility, skewness, kurtosis and Carhart (1997) factors computed exploiting factor portfolio methodology.

Factors	Avg. Ret.	$FVOL$	$FSKEW$	$FKURT$	$R_m - R_f$	HML	SMB	UMD
$FVOL$	-0.47%* (-1.92)	1.00	-0.05**	0.09***	-0.03	-0.61***	0.04*	0.14***
$FSKEW$	0.16%* (1.65)		1.00	-0.03	-0.03	-0.01	-0.04*	0.03
$FKURT$	0.05% (0.53)			1.00	-0.12***	-0.11***	-0.00	0.09***
$R_m - R_f$	-0.01% (-0.02)				1.00	0.73***	0.09***	-0.16***
HML	-0.08% (-0.17)					1.00	0.09***	-0.30***
SMB	0.49%** (2.47)						1.00	0.11***
UMD	0.09% (0.26)							1.00

Note: In the left-hand panel of the table, we report the average risk premium for each factor (t-stats are in brackets); while in the right-hand panel, we report the correlation coefficients computed between the risk factors. $FVOL$, $FSKEW$ and $FKURT$ indicate zero-cost portfolios, which are exposed only to volatility, skewness and kurtosis risks, respectively, and are neutral to the other risk factors. $R_m - R_f$ is the excess market return, SMB measures the difference in returns between low capitalization stocks and high capitalization stocks, HML captures the difference in return between stocks with high book-to-market and low book-to-market and UMD accounts for the difference in return between stocks characterized by high past returns and stocks that have low past returns. Significance at the 1% level is denoted by ***, at the 5% level by **, and at the 10% level by *.

Table 6 – Estimation output of Fama-Macbeth (1973) regressions

Price of risk (λ)	FFC4 model (i)	Four-Moment CAPM (ii)	Augmented FFC4 model (iii)
λ_0	0.0055	0.0093	0.0088
	(1.0376)	(1.3012)	(1.5330)
λ_{MKT}	-0.0025	0.0183	-0.0052
	(-0.3074)	(0.9070)	(-0.5405)
$\lambda_{\Delta VOL}$		-0.0751*	-0.0633**
		(-1.7517)	(-2.3279)
$\lambda_{\Delta SKEW}$		0.1212	0.2360***
		(0.9852)	(2.6596)
$\lambda_{\Delta KURT}$		-0.3455	0.1257
		(-1.3633)	(0.9510)
λ_{HML}	0.0013		0.0018
	(0.2124)		(0.3029)
λ_{SMB}	0.0062***		0.0060**
	(2.6312)		(2.5492)
λ_{UMD}	0.0043		0.0011
	(1.0889)		(0.2357)
R^2 (Adj.)	57.73%	44.17%	80.36%

Note: This table shows the estimated price of risk by applying the two-pass Fama-Macbeth (1973) regression method to the 25 Fama and French (1993) portfolios sorted on capitalization and book-to-market. We test three different models:

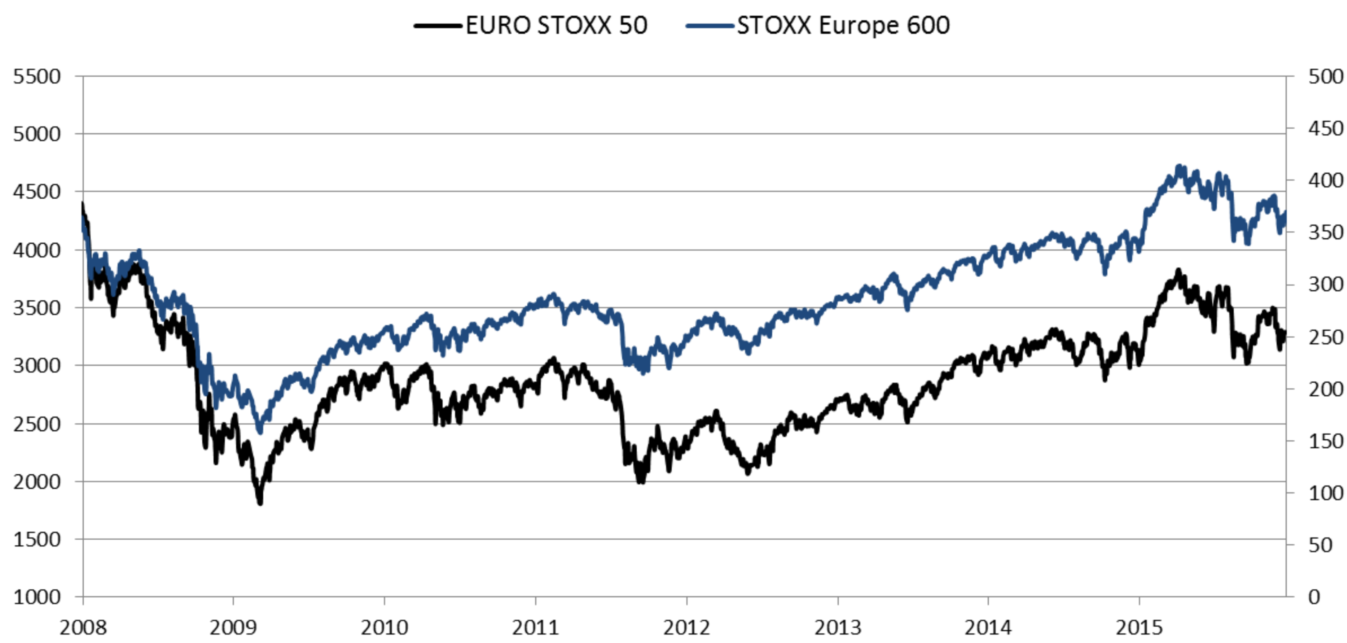
(i) $E[R_i]-R_f = \lambda_0 + \lambda_{MKT}\beta^i_{MKT} + \lambda_{SMB}\beta^i_{SMB} + \lambda_{HML}\beta^i_{HML} + \lambda_{UMD}\beta^i_{UMD}$

(ii) $E[R_i]-R_f = \lambda_0 + \lambda_{MKT}\beta^i_{MKT} + \lambda_{\Delta VOL}\beta^i_{\Delta VOL} + \lambda_{\Delta SKEW}\beta^i_{\Delta SKEW} + \lambda_{\Delta KURT}\beta^i_{\Delta KURT}$

(iii) $E[R_i]-R_f = \lambda_0 + \lambda_{MKT}\beta^i_{MKT} + \lambda_{\Delta VOL}\beta^i_{\Delta VOL} + \lambda_{\Delta SKEW}\beta^i_{\Delta SKEW} + \lambda_{\Delta KURT}\beta^i_{\Delta KURT} + \lambda_{HML}\beta^i_{HML} + \lambda_{SMB}\beta^i_{SMB} + \lambda_{UMD}\beta^i_{UMD}$,

(i) corresponds to the four-factor Carhart (FFC4) model in equations (10-11), (ii) corresponds to the Four-Moment CAPM model in equations (12-13) and (iii) corresponds to the four-factor Carhart (FFC4) model augmented with innovations in volatility, skewness and kurtosis, as described by equations (8-9); t-stats are in brackets. The lambda (λ) coefficients capture the price for each risk factor and play a key role in determining the sign (positive or negative) of the risk premia. Significance at the 1% level is denoted by ***, at the 5% level by **, and at the 10% level by *.

Figure 1 - European market performance during the sample period.



Note: EURO STOXX 50 index refers to the left-hand axis, while STOXX Europe 600 refers to the right-hand axis.

Figure 2 – Daily implied volatility (*VOL*), skewness (*SKEW*) and kurtosis (*KURT*) of EURO STOXX 50 index returns.

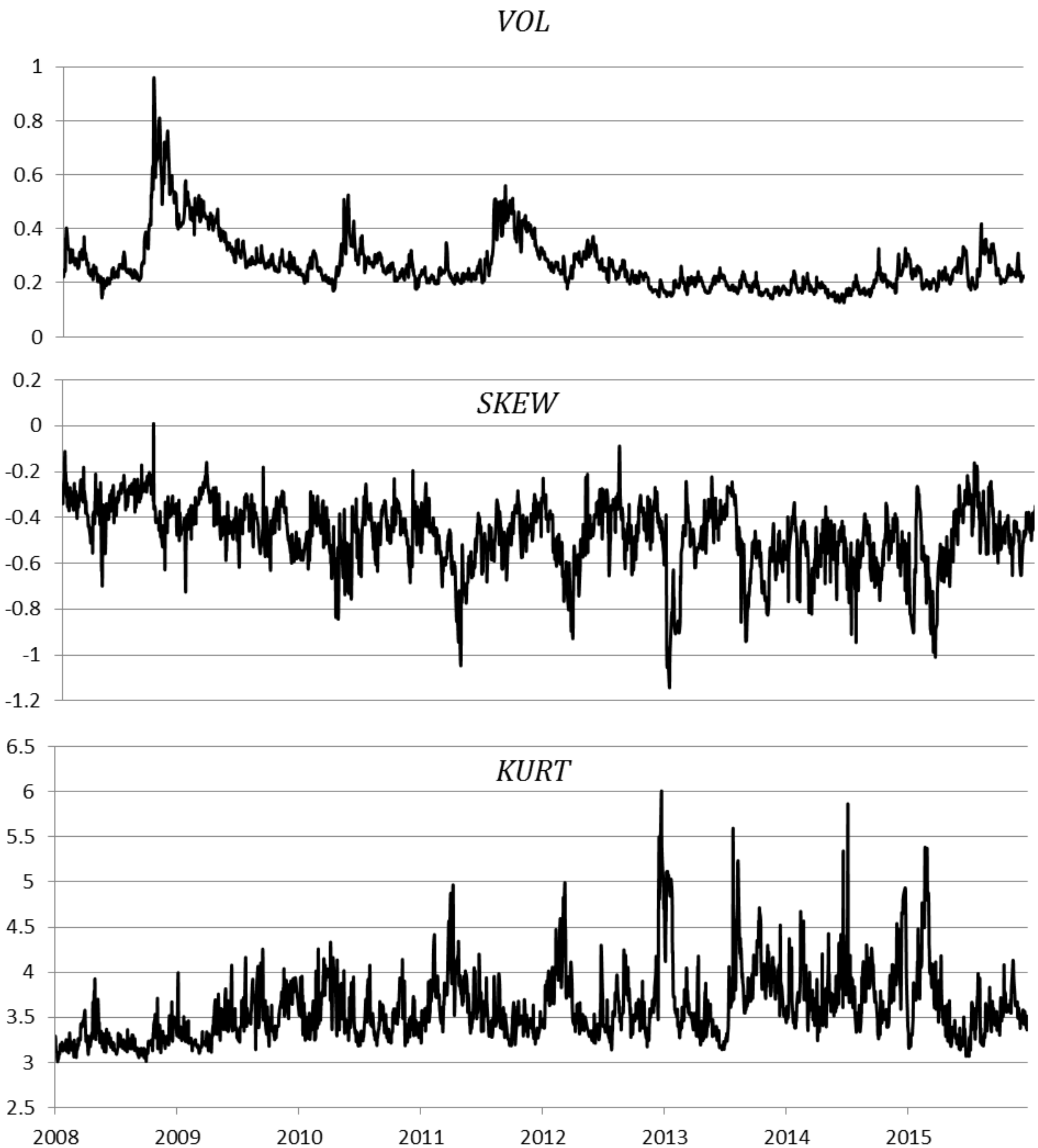


Figure 3 – Daily innovations in market implied moments

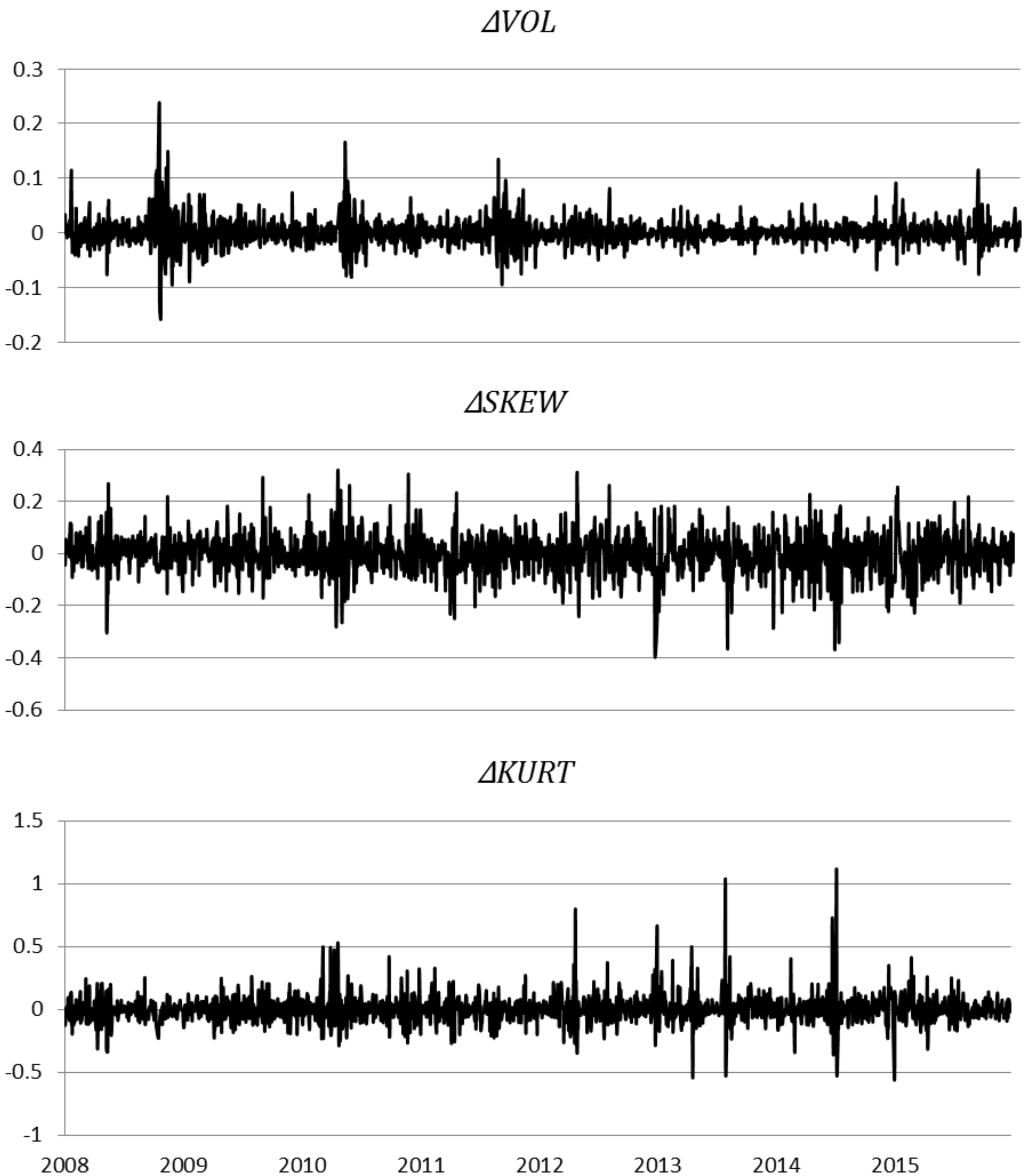


Figure 4 – Relation between portfolio average return and exposure to innovations in implied moments

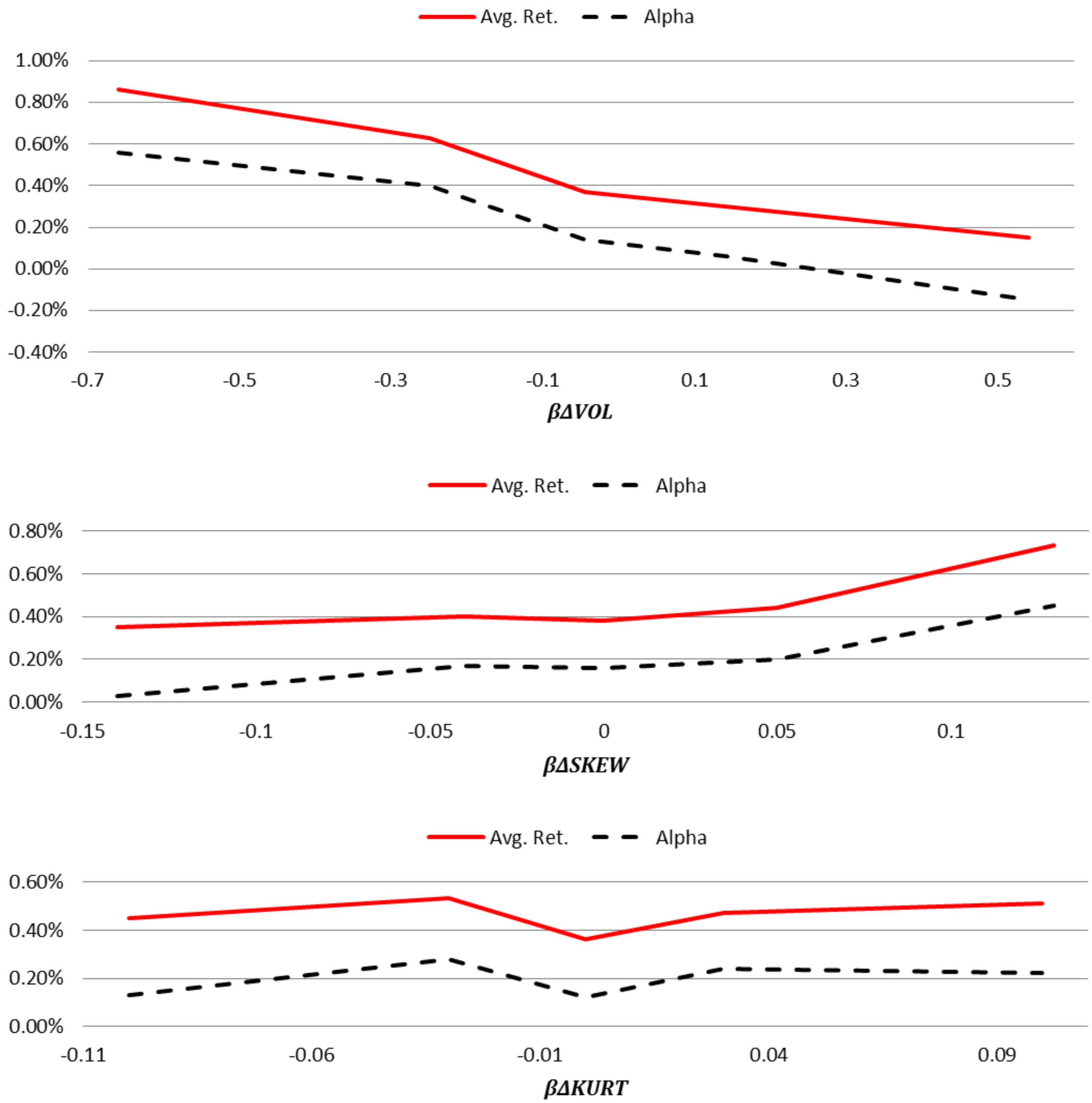


Figure 5 – Cumulative performance of portfolios sorted by exposure to innovations in implied moments

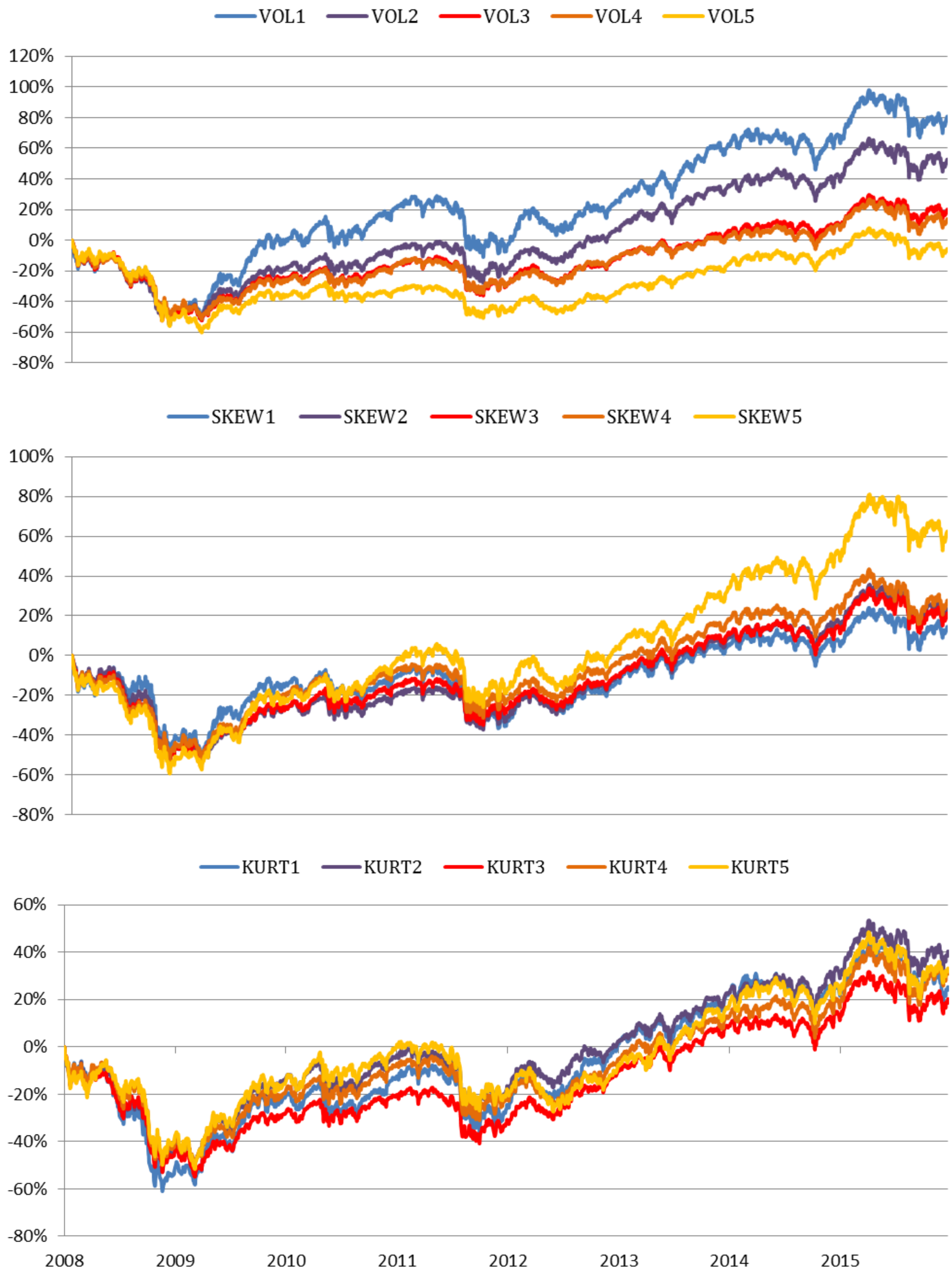
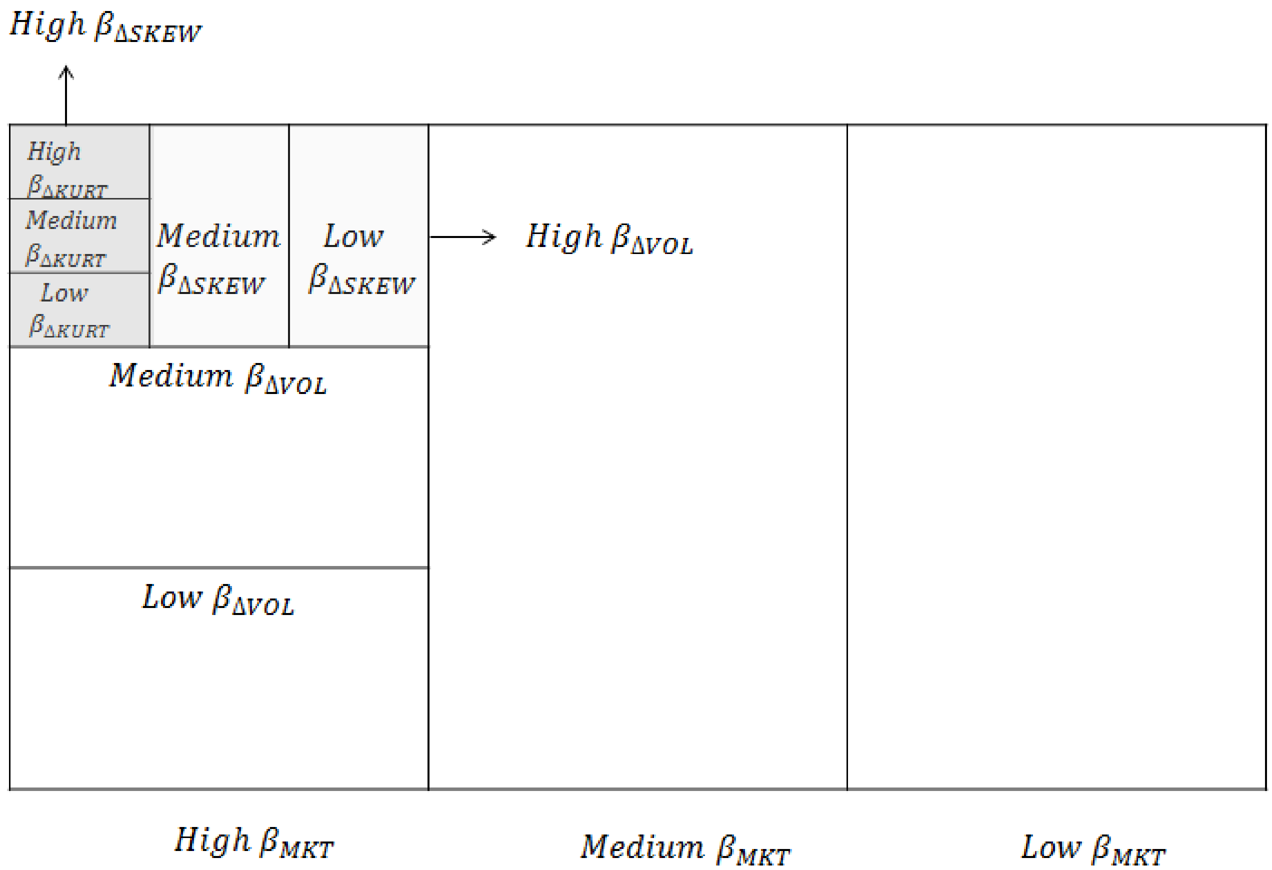


Figure 6 – Diagram of the four-way sorting procedure



Note: This figure shows a schematic representation of the sub-samples based on different exposure to market, volatility, skewness and kurtosis risk. In this way we obtained 81 sub-samples (only few sub-samples are depicted in the diagram) of stocks ranked by their high, medium or low exposure to market, volatility, skewness and kurtosis risk.

Figure 7 – Cumulative performance on factor portfolios for exposure to moment risk

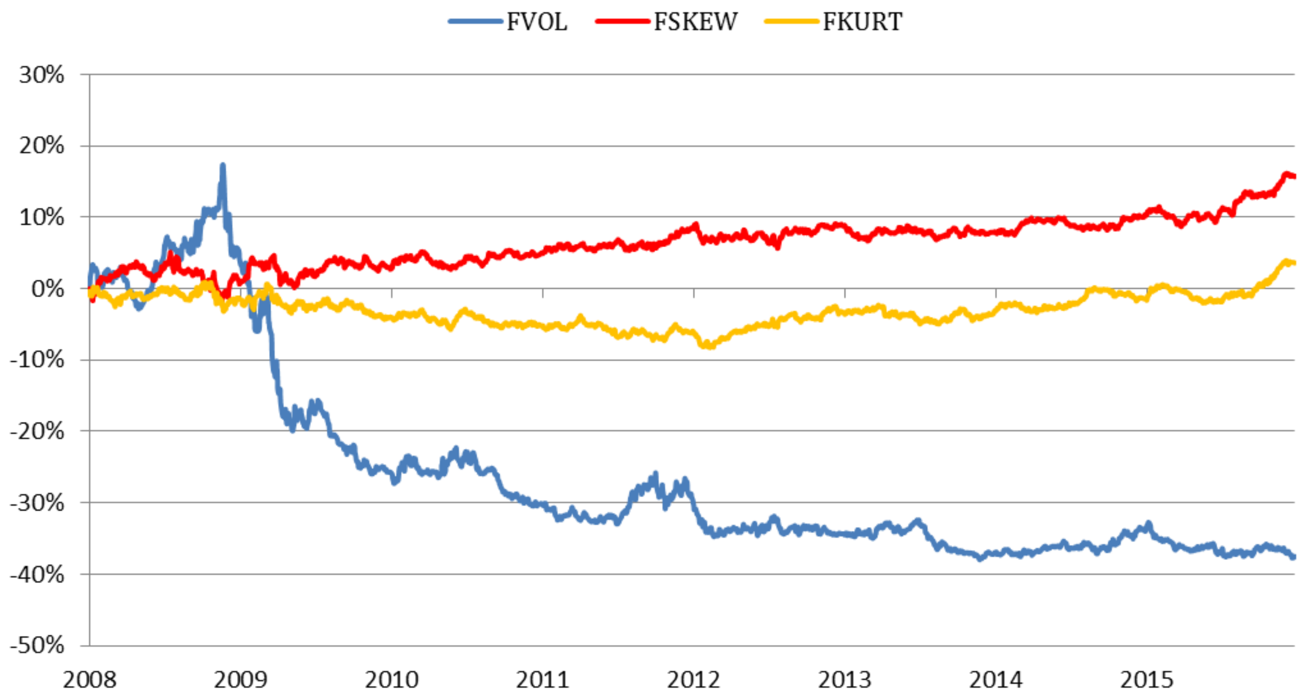


Figure 8 – Cumulative performance on Carhart (1997) factor portfolios