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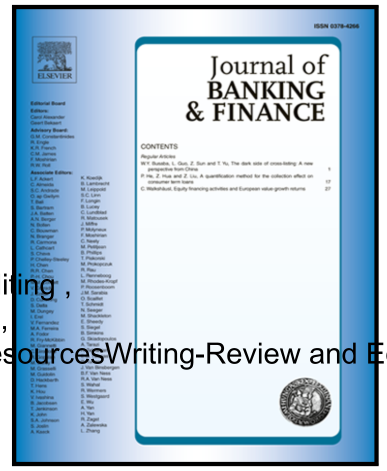

Moment risk premia and the cross-section of stock returns in the European stock market

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PII: S0378-4266(19)30305-X
DOI: https://doi.org/10.1016/j.jbankfin.2019.105732
Reference: JBF 105732

To appear in: *Journal of Banking and Finance*

Received date: 6 November 2017
Accepted date: 23 December 2019

Please cite this article as: Elyas Elyasiani ConceptualizationMethodologyWriting- Reviewing and Editing , Luca Gambarelli MethodologyData curationSoftwareWriting-original draft , Silvia Muzzioli ConceptualizationMetho Moment risk premia and the cross-section of stock returns in the European stock market, *Journal of Banking and Finance* (2019), doi: https://doi.org/10.1016/j.jbankfin.2019.105732

Highlights

- We investigate whether volatility, skewness, and kurtosis risks are priced.
- We use both a model-free approach and a model-based approach (portfolio sorting).
- The estimated premium for bearing market volatility risk is negative.
- The estimated premium for bearing market skewness risk is positive.
- There exists a small-size premium in the European stock market.

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

December 18, 2019

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Abstract

This article investigates whether volatility, skewness, and kurtosis risks are priced in the European stock market and assess the signs and the magnitudes of the corresponding risk premia. To this end, we adopt two approaches: a model-free approach based on swap contracts, and a model-based approach built on portfolio-sorting techniques. A number of 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), robust to the two approaches employed, and statistically and economically significant. Third, in contrast with studies on the US stock market, we identify the existence of a size premium in the European stock market: small capitalization stocks earn higher returns than high capitalization stocks.

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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 have been proposed for computing risk premia on moments of stock return distributions. In a model-free approach, these premia can be computed as the difference between the physical and the risk-neutral expectations of the corresponding moment, where physical expectation is a forecast computed from historical returns series of the underlying asset, and risk-neutral expectation is the estimate obtained indirectly from option prices listed on that underlying asset. Alternatively, risk premia can be computed directly as the difference between the realized physical moment and the risk-neutral one (Johnson, 2017).[1] In this case, the risk premium has a strong financial interpretation since it is estimated by means of 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 will be willing to pay a higher fixed rate relative to the floating rate to hedge against peaks of variance. The floating rate (i.e., subsequently realized variance) can be

[1] As noted by Johnson (2017), two main approaches have been used in the literature to estimate the variance risk premium:

i) the difference between option-implied and expected future realized variance, where the expectation of realized variance under the physical measure is based on a statistical model (see e.g. Bekaert and Hoerova, 2014, and others); and

ii) the difference between future realized variance and option-implied variance (see e.g. Carr and Wu, 2009).

measured only at the maturity of the contract. The difference between the floating and the fixed rates (negative in this case) can be used to estimate the variance risk premium.

In a model-based approach, these premia can be assessed by using portfolio sorting techniques, outlined in Sections 3 and 4.2, based on an extension of the intertemporal capital asset pricing model (ICAPM) (Merton, 1973; Campbell, 1993, 1996) and consumption-based CAPM (Campbell and Cochrane, 1999; Bansal and Yaron, 2004), which treat time-variation in the moments as risk factors.[2]

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. Specifically, because most studies focus on the US market, evidence on the European and other stock markets remains scant. The majority of studies that use the model-free approach based on moment swap contracts and time-series data find a negative risk premium for variance and kurtosis and a positive risk premium for skewness (e.g., Bakshi and Kapadia, 2003; Bakshi and Madan, 2006; Wu and Carr, 2007; Carr and Wu, 2009; Zhao et al., 2013; Elyasiani et al., 2016). However, the evidence is less clear in studies based on portfolio-sorting techniques and cross-sectional data. Ang et al. (2006) and Adrian and Rosenberg (2008) find a negative volatility risk premium, whereas Chang et al. (2013) find an insignificant volatility risk premium. Bali et al. (2019) find a positive relation between systematic and unsystematic variance and ex-ante expected returns, in line with a negative risk premium for variance. Chang et al. (2013), Bali and Murray (2013), and

[2] Other approaches have also been proposed in the literature to estimate the higher-order moment risk premia. For example, Bali and Murray (2013) exploit portfolio strategies consisting of positions in individual options and in the underlying assets. Although this approach is appealing to those assessing the existence and the signs of moment risk premia, it is not applicable to the European stock market because European options on individual stocks were introduced only recently and their historical series are not long enough to perform this analysis.

Conrad et al. (2013) identify a negative skewness risk premium, while Kang and Lee (2016), Kozhan et al. (2013), Elyasiani et al. (2016) and Sasaki (2016) report evidence of a positive risk premium. On the other hand, Bali et al. (2019) find that only the unsystematic (firm-specific) component of skewness and kurtosis risk matters for explaining the cross-section of stock returns and, therefore, market skewness and kurtosis risks are not priced factors in the cross-section of stock returns.

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 signs and the magnitudes of the corresponding risk premia over the period 2005–2017. Our contribution is threefold. First, we explore the pricing and assess moment risk premia using two different approaches (model-free and model-based) to check the robustness of our findings. Second, we provide evidence of the existence of moment risk premia both in the European aggregate market, which is studied only to a limited extent in the literature, and in the cross-section of European stock returns. Third, whereas most studies (especially papers focusing on the cross-section of stock returns) are limited to sample periods prior to the recent financial crisis, we include both the financial crisis and the European debt crisis in our dataset. This allows us to assess the behavior of moment risk premia in both calm and market turmoil periods.

We obtain five key 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., Ang et al., 2006; Adrian and Rosenberg, 2008; Cremers et al., 2015; Campbell et al., 2018; Bali et al., 2019). 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), Elyasiani et al. (2016), and Sasaki (2016), we find the skewness risk premium to be positive overall. Thus, skewness risk is also priced in the European stock market: investors are averse to negative changes in market skewness and willing to accept a lower future return for stocks serving 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 used (model-free and ICAPM-based), and these premia are both statistically and economically significant. Monthly premia are -0.49% and 0.22% for volatility and skewness, respectively, and cannot be explained by common risk factors such as market excess return, book-to-market, firm size and momentum. The implication of these findings is that it is sufficient to hedge exposure to volatility and skewness of the risk-neutral distribution while ignoring kurtosis risk.

Fourth, we find evidence of a positive risk premium for smaller firm size in the European market: stocks with low capitalization in general earned higher returns than stocks with high capitalization. This result is in contrast with evidence from the US market (Chang et al., 2013), suggesting that investors perceive European stocks with low capitalization levels as riskier and, as a result, require higher future returns on these stocks. Fifth, we use spanning regressions adapted from Barillas and Shanken (2017) and Fama and French (2017) to identify the relevant risk factors in explaining the time variation of expected stock returns. The size factor is found to contribute the most to the maximum squared Sharpe ratio of the model (0.100), followed by book-to-market (0.074), volatility (0.071) and skewness (0.050). The Gibbons et al. (1989) test (GRS), used to assess whether a factor enhances the model's ability to explain expected returns, shows that Carhart's (1997) four-factor model can be further improved by accounting for the volatility and skewness risks, whereas accounting for kurtosis risk does not significantly improve the model. Overall, we conclude that volatility and skewness risks play an important role in asset pricing.

The paper proceeds as follows. Section 2 describes the data and the methods used to obtain the risk-neutral moments and the other risk factors. Section 3 presents the theoretical motivation and the two approaches used to explore the existence and the signs of moment risk premia. Section 4 examines the empirical application of the two methods to the European market, and Section 5 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 dataset used to compute the implied moments consists of the closing prices on EURO STOXX 50-index options (OESX), recorded from 21 January 2005 to 29 December 2017. OESX are European options on the EURO STOXX 50, a capital-weighted index consisting 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 Eq. (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 21 January 2005 to 29 December 2017, based on availability. 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 the Option Metrics IvyDB Europe, whereas the time series of the EURO STOXX 50 index and the STOXX Europe 600 individual stocks as well as the dividend yield and the Euribor rates are obtained from Bloomberg. 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 calculate the risk-neutral moments of the EURO STOXX 50 return distribution, following Muzzioli (2013), we apply several filters to the option dataset in order to eliminate arbitrage opportunities and other irregularities in the prices. First, we eliminate the options close to expiry (i.e., options with a time to maturity of less than eight days) because they may suffer from pricing anomalies that occur close to expiry. Second, following Ait-Sahalia and Lo (1998), only at-the-money 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 to make sure that butterfly spread strategies are non-negatively priced in order to avoid arbitrage opportunities.

We calculate the risk-neutral variance, skewness, and kurtosis for the EURO STOXX 50 index using the Bakshi et al. (2003) method.[3] The results are then interpolated 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 kurtosis (*KURT*) for the EURO STOXX 50 index return distribution—are presented in Fig. 1 (left-hand panel). This figure shows that the implied volatility is generally high from 2008 to 2012, a period characterized by a sharp decline in the EURO STOXX 50 level because of the Financial Crisis of 2008–2009 and the European Debt Crisis of 2011–2012. On the other hand, risk-neutral skewness and kurtosis present a larger number of peaks in the central part of our dataset (2010–2015) in connection with high volatility during the European Debt Crisis and low volatility in the last part of the period.

In line with Chang et al. (2013), we fit an autoregressive moving average (ARMA) model to the time series of volatility, skewness, and kurtosis in order to remove autocorrelation in the data. The autocorrelation functions indicate that ARMA (1, 1) models do remove the autocorrelation in the series for the innovations in skewness and kurtosis. For volatility, taking the first differences removes most of the autocorrelation in the data. As a result, we calculate daily innovations for volatility by using the first differences. In this way, we can also easily compare our results with those of previous studies, such as Ang et al. (2006).

We derive the market excess return (MKT) as the difference between the daily performance of STOXX Europe 600 index and daily risk-free rate (R_m-R_f). We also calculate other commonly used risk factors that account for the characteristics of the firm such as size and book-to-market,

[3] The number of option strikes traded for EURO STOXX 50 index options is around 200 for the near-term maturity and around 100 for the next-term maturity.

proposed by Fama and French (1993, 1996), and momentum, introduced by Carhart (1997). The size factor "small-minus-big" (SMB) captures the return compensation for additional risk attached to low capitalization stocks, which are exposed to greater economic and financial shocks. The book-to-market factor (or value factor), "high-minus-low" (HML), measures the difference in return between stocks with high book-to-market ratios (value stocks) and low book-to-market ratios (growth stocks). Finally, as proposed by Jegadeesh and Titman (1993), the momentum factor "up-minus-down" (UMD) accounts for the momentum of stock prices. To elaborate, stocks characterized by high past returns (winners) tend to have better future performance compared to stocks that have low past returns (losers). Hereafter, we refer to these factors as Carhart's (1997) four risk factors. These risk factors are calculated by applying the Fama and French (1993, 1996) method to our dataset. To obtain SMB and HML factors, we create six value-weighted portfolios using the intersections of two portfolios formed based on size and three portfolios formed based on book-to-market (low-medium-high). The size breakpoint for year *t* is the median market equity at the end of June of year *t*. The breakpoints for book-to-market are the 30th and 70th percentiles of the distribution of book-to-market (the book-to-market ratio for June of year *t* is the book equity for the last fiscal year end in *t-1* divided by the market equity for December of *t-1*).

The momentum factor (UMD) is defined in a similar way as HML, except that the factor is updated monthly rather than annually. We create six value-weighted *Size-Return 2−12* portfolios[4] at the end of month *t-1*. The six portfolios are obtained from the intersection of two portfolios formed based on size and three portfolios formed based on past stock returns. The

[4] *Size* is the market equity of a stock at the end of month t−1 and *Return 2−12* is its cumulative return for the 11 months from *t−12* to *t−2*.

monthly size breakpoint is the median market equity, whereas the breakpoints for past returns are the 30th and 70th percentiles of the monthly past (2-12) return. As a robustness check, we exploit the factors available on the online data library of Ken French,[5] and we find results that are consistent in terms of both sign and magnitude for the volatility, skewness, and kurtosis risk premia.

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 factors used to obtain the $\Delta SKEW$ and $\Delta KURT$ residuals, the correlation coefficients among innovations in market implied moments, and Carhart's (1997) four risk factors: market excess return (MKT), size (SMB), book-to-market (HML) and momentum (UMD). Several observations are in order. First, innovations in volatility and market skewness are strongly and negatively related to market excess return (correlation coefficient (ρ) = -0.70, and -0.21, respectively, and significant at 1%). Second, innovations in market kurtosis display a very weak positive relation with the MKT factor (ρ = 0.03, significant at 10%). These findings are similar in terms of both sign and magnitude to those obtained by Chang et al. (2013) for the US market, for the period 1996-2007. The correlation coefficient (ρ) between the moments and market returns are useful for the formulation of a-priori expectations about the signs of moment risk premia (Chang et al., 2013) and will be further discussed in the next section. Third, the relation between innovations in skewness ($\Delta SKEW$) and kurtosis ($\Delta KURT$) is strongly negative (ρ = -0.86, significant at 1%). This result is as expected: a low value in risk-neutral skewness points to a pronounced left tail, which is reflected in a high value of kurtosis. The high correlation between innovations in the third- and fourth-order moments may make it hard to

[5] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library

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:

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

Throughout the paper, we use the residuals of regression (2) as the innovations in kurtosis. This enables 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 to those of market volatility. Innovations in implied volatility, skewness, and kurtosis, shown in Fig. 1 (right-hand panel), indicate that, unlike volatility, innovations in higher order moments present greater changes in the central part of our dataset (2010–2015), in connection with both high volatility during the European Debt Crisis, and low volatility towards the end of the period.

3. Theoretical motivation

We exploit two approaches to investigate the moment risk premia in the European market. In the first approach, discussed in section 4.1, risk premia are calculated by resorting to swap contracts in the EURO STOXX 50 market. 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 result, it has a straightforward financial interpretation. To elaborate, the long side in a variance swap pays a fixed rate (i.e., 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 will be willing to pay a higher fixed rate in order to hedge against peaks of variance. The difference between the two rates can be used as a proxy for 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 approach, discussed in Section 4.2, we aim to obtain robust estimates of the moment risk premia using a portfolio-based method 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 enables 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 the size and value factors introduced by Fama and French (1993) and the momentum factor proposed by Jegadeesh and Titman (1993).

This second model-based approach relies on an extension of the Merton (1973) and Campbell (1993, 1996) intertemporal capital asset pricing model (ICAPM) and the consumption-based asset pricing literature (Campbell and Cochrane, 1999; Bansal and Yaron, 2004). In this connection, Bekaert and Engstrom (2017) propose an extension of the Campbell and Cochrane (1999) model with the introduction of a time-varying non-Gaussian distribution for consumption growth combined with stochastic risk aversion. In their model, consumption growth follows a "bad environment-good environment" (BEGE) process, being exposed in each period to two types of shocks (one with positive skewness and one with negative skewness), the relative importance of which varies over time. Given that returns "inherit" the non-Gaussianities from fundamentals, the richer proposed consumption dynamics allow the habits' model by Campbell and Cochrane (1999) to account for the variance risk premium. Campbell et al. (2018) extend the approximate closed-form ICAPM model of Campbell (1993) to allow for stochastic volatility. According to their model, investor opportunities can deteriorate either due to expected stock return declines or to the volatility of stock return increases. They find that volatility risk is important in explaining the cross-section of stock returns and that growth stocks display negative CAPM alphas because they hedge long-term investors against both declining future stock returns and increasing volatility. Drechsler and Yaron (2011) use an extension of the Bansal and Yaron (2004) long-run risks model as an alternative approach to generate variance risk premiums in equilibrium. These authors show that accounting for jumps in uncertainty (volatility) and in the persistent component of consumption and dividend growth in this extended model can generate many of the quantitative features of the variance premium. The model can explain the time variation and return predictability of the variance premium.

The theoretical contributions aimed at generating a skewness risk premium in equilibrium are as follows. Sasaki (2016) extends the long-run risks model proposed in Bansal and Yaron (2004) by introducing a stochastic jump intensity for jumps and variance in the consumption growth rate. The extended model provides an explicit representation of the skewness risk premium in equilibrium, and the empirical findings of the paper suggest that the skewness risk premium plays an independent and essential role in predicting the market index returns. Colacito et al. (2016) propose a model linking the dynamics of skewness to the degree of asymmetry of expected macroeconomic forecasts made by professional forecasters. Seo and Wachter (2019) suggest the presence of links between the probability of rare economic events, option prices, and equity risk premia and provide empirical evidence for the point that options reflect the risk of economic disasters. In particular, prices of put options are an increasing function of the probability of a disaster and reflect the risk of large consumption drops.

From an empirical point of view, the pricing of stochastic time-varying volatility is investigated by Ang et al. (2006), Cremers et al. (2015), Campbell et al. (2018) and Bali et al. (2019) who find the volatility risk premium to be negative and significant. The pricing of skewness risk premia in the cross-section of stock returns is investigated in Chang et al. (2013), who extend the analysis of Ang et al. (2006) 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 during the period 1996–2007. Chabi-Yo (2012), who proposes an intertemporal extension of the three-moment and the four-moment CAPM, also finds the price of market skewness risk to be negative.

These results cast light on an important question: the sign of the skewness risk premium. While Chabi-Yo (2012) and Chang et al. (2013) find a negative skewness risk premium, many others find a positive one (e.g., Kozhan et al., 2013; Elyasiani et al., 2016; Sasaki, 2016). In particular, the positive risk premium is consistent with investor preference for assets with high (positive) odd moments and low even moments, a well-documented phenomenon in the literature (Arditti, 1967; Kraus and Litzenberger, 1976; Scott and Horvath, 1980). This is consistent with a negative risk premium for volatility and kurtosis, and a positive one for skewness. Investors who prefer low even moments will be 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 (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 moment risk premia and their empirical implications, we use the regression model adopted by Chang et al. (2013) for the US market, where the market excess return and the innovations in volatility, skewness and kurtosis, represent the risk factors. This model can be described as:

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

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 second, the third, and the fourth 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. Stocks with positive $\beta_{\Delta VOL}$ react positively to an increase in market volatility. Conversely, stocks characterized by negative $\beta_{\Delta VOL}$, react negatively when the market volatility increases. Following Chang et al. (2013), the total risk premium, i.e., the excess return of stock i can be broken down into the sum of the market, volatility, skewness, and kurtosis risk premia, as:

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

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 prices of market, volatility, skewness and kurtosis risks, respectively, multiplied by the respective quantities of risk (β_{MKT}, $\beta_{\Delta VOL}$, $\beta_{\Delta SKEW}$, $\beta_{\Delta KURT}$). In the empirical application proposed in Section 4.2, the expected excess return $E[R_i] - R_f$ is proxied by the next-month return of each portfolio.

In order to formulate an *a priori* expectation about the sign of the lambda coefficients, we note that in the ICAPM model, 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. If an increase in market volatility is perceived as a deterioration in the investment opportunity set, stocks that react positively to an increase in volatility provide a hedge against such deterioration. In cases in which investors are risk-averse, these stocks are desirable for hedging purposes.

When market-implied volatility increases, investors hedge against volatility risk by holding stocks with positive exposure to innovations in market volatility ($\beta_{\Delta VOL}$). The result is that the high demand for stocks whose returns are highly correlated with innovations in market volatility leads to lower expected returns on these stocks. We, therefore, expect the price of volatility risk ($\lambda_{\Delta VOL}$) to be negative. According to the model in Eq. (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 formulate 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 a measure of downside jump risk. In this interpretation, a positive innovation in risk-neutral skewness points to a lower probability of realizations in the left tail of the distribution. An increase in market skewness is associated with a lower downturn risk for the stock market and is likely to be related to an improvement in the investment opportunity set. Conversely, negative innovations in market skewness correspond to a rise in downside jump risk and are, therefore, likely to be related to a deterioration in the investment opportunity set. When market-implied skewness decreases, investors hedge against skewness risk by holding stocks with negative exposure to innovations in market skewness ($\beta_{\Delta SKEW}$). As a result, the high demand for stocks whose returns are negatively correlated with innovations in market skewness leads to lower expected returns on these stocks. Following this rationale, we can expect the market price of skewness risk to be positive.

Finally, the rationale for kurtosis risk is similar to that for volatility risk. An increase in kurtosis means that the risk-neutral distribution becomes fatter-tailed, signifying an increased probability of extreme events. In cases in which investors are risk-averse, we can suppose that they consider an increase in market kurtosis to be an unfavorable shock to the investment opportunity set. As a result, similar to volatility, we expect a negative price for kurtosis risk.

4. Empirical analysis

In this section, we conduct an empirical analysis of the two approaches outlined in Section 3 for estimation of market volatility, skewness, and kurtosis risk premia in the European stock market.

4.1. The model-free method: moment swap contracts

Carr and Wu (2009) demonstrate that the payoff of a variance swap can be used to quantify the variance risk premium,[6] i.e., the amount that investors are willing to pay to hedge against peaks of variance (see Buraschi et al., 2014 and Cipollini et al., 2015 for the volatility risk

[6] Note that the variance risk premium is defined as the difference between the risk-neutral and the physical expectation of variance over the next month. In particular, Bekaert and Hoerova (2014) define the variance risk premium as: $VP_t = VIX_t^2 - E_t\left[RV_{t+1}^{(22)}\right]$ where *VIX* is the implied option volatility of the S&P500 index for contracts with a maturity of one month and $RV_{t+1}^{(22)}$ is the S&P 500 realized variance measured over the next month. The squared *VIX* is the conditional return variance using a risk neutral probability measure, whereas the conditional variance uses the actual "physical" probability measure. The unconditional mean of the variance risk premium is calculated as the average of $VIX_t^2 - RV_{t+1}^{(22)}$.

premium). 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 is:

$$N(\sigma_R^2 - VRS) \tag{5}$$

where N is a notional Euro amount, σ_R^2 is the realized variance (computed at maturity), and VRS is the fixed variance swap rate, equal to the implied variance at the beginning of the contract. Zhao et al. (2013) extend the variance swap to higher order moments and propose two new types of contracts: the skewness and the kurtosis swaps. In both swap contracts, the option-implied moment and the realized moment are, respectively, the fixed leg and the floating leg of the contract. Following the same rationale for variance risk premia, the payoffs of the skewness and kurtosis swap contracts can be used to quantify the skewness and kurtosis risk premiums, respectively.

In order to estimate variance, skewness, and kurtosis risk premia, each day we calculate 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 their 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, it may be seen that the risk-neutral distribution of market returns is more volatile, more negatively skewed, and more fat-tailed than the corresponding realized distribution, which is almost symmetrical.[7] 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 average value of the volatility and the kurtosis swap payoffs are negative and statistically significant (at 1%), pointing to a negative and significant volatility and kurtosis risk premiums. On the other hand, the average value of the skewness swap payoff is positive and statistically significant (at 1%), pointing to a positive and significant skewness risk premium. This suggests that investors are willing to pay a premium in order to hedge against either peaks of volatility and kurtosis or negative peaks (drops) in skewness. The correlation coefficients between moment swap payoffs presented in Table 2 show that the volatility and skewness swap payoffs are not correlated, whereas kurtosis and skewness swap payoffs are strongly and significantly correlated (ρ = -0.887, significant at 1%). Moreover, risk neutral skewness and kurtosis are 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, and this will be discussed in the next section. It is notable that correlations do not capture the non-linearities between moments.

4.2. Model-based portfolio sorting analysis of risk premia

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

[7] Physical skewness is close to zero, consistent with other studies investigating the skewness of aggregate index returns (see e.g. Haß et al., 2013; Liu and Faff, 2017).

data, instead of the EURO STOXX 50 used in Section 4.1. Our cross-sectional analysis is conducted using three different methods: multivariate sorting, four-way sorting, and spanning regressions, as described next.

4.2.1. Multivariate sorting

The aim 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, 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 uses a two-step process. First, we use daily data on a one-month window to estimate the model described by Eq. (3), (Section 3), using the Ordinary Least Squares procedure (OLS). This step uses returns in excess of the risk-free rate and produces estimates of the beta coefficients for the risk factors considered for each individual stock. Second, we perform a cross-sectional analysis by creating five value-weighted portfolios based on quintiles of 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. At the end of the sorting procedure, we obtain the time series of daily post-ranking returns for each quintile portfolio. We calculate the return on each portfolio in the subsequent month as a proxy for its expected return.

To assess whether the effects of innovations in implied moments on stock returns continue to hold after controlling for Carhart's (1997) risk factors, we calculate the four-factor alpha for each of the five portfolios (Q1, Q2, Q3, Q4, Q5) plus the long-short portfolio (Q5-Q1) by estimating Eq. (6):

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

where $R_{j,t}$ is the portfolio return (post-ranking) in day *t*, for *j=1,…,6* and MKT_t, SMB_t, HML_t and UMD_t are the factors used to evaluate the robustness of the intercept. The intercept, referred to as the four-factor alpha by Carhart (1997), represents the amount of portfolio return not explained by Carhart (1997) risk factors. As a result, it is attributable to the risk factor under investigation (volatility, skewness or kurtosis). The long-short portfolio (Q5-Q1) is calculated 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, with the rebalancing performed monthly. Specifically, we estimate the betas on month *i*, we form quintile portfolios in month *i* and use them to calculate returns in month *i+1*; then we move to month *i+1* where we estimate betas and form portfolios and use them to compute returns in month *i+2*. No rebalancing occurs during the month in which we estimate the betas. We report the pre-ranking beta, the post-ranking average return and the four-factor alpha 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

If a positive innovation in market volatility is perceived by investors as a deterioration of the investment opportunity set, then stocks with positive exposure (positive $\beta^{i}_{\Delta VOL}$) to innovations in market volatility act as a hedge against volatility risk. This means they will become desirable for investors since they provide positive returns when market volatility increases (usually associated with 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 to compensate investors for the higher risk. We, therefore, 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. We thus expect a negative return and a negative alpha for the high-low portfolio (Q5-Q1) and a monotonic pattern in the average returns and the alphas for portfolios sorted based on their exposure to volatility risk.

The results are shown in Table 3, Panel A. We find 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 value weighted portfolios and the associated four-factor alphas present a monotonically decreasing pattern from the Q1 portfolio to the Q5 portfolio. This evidence points to a significant negative volatility risk premium, which is priced in the cross-section of stocks returns. This result is in line with Ang et al. (2006) but differs from Chang et al. (2013), where the volatility risk premium is insignificant, with both these studies being based on 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. This result is consistent with the negative sign for the volatility risk premium obtained in Section 4.1 using the volatility swap contract, suggesting that investors are averse to increasing market volatility and willing to pay a premium reflected in a lower return for stocks acting 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 by exposure to innovations in market skewness are reported in Table 3, Panel B. These findings suggest that the return and the Carhart four-factor alphas for the Q5-Q1 portfolios are not statistically different from zero, indicating that skewness risk is not priced in the cross-section of stock returns. In addition, we do not detect a monotonic pattern in the average returns and the associated four-factor alphas. This means that the preliminary analysis of the cross-section of stock returns does not produce evidence on the pricing of skewness risk. This stands in contrast to our previous findings based on the skewness swap contracts reported in Table 2. It should be noted that skewness innovations are correlated with both market excess return (negatively) and volatility innovations (positively). In order to deal with this issue, we exploit a four-way sorting procedure in Section 4.2.2.

4.2.1.3. Portfolios sorted by exposure to innovations in market kurtosis

The results for portfolios sorted in relation to exposure to innovations in market kurtosis are reported in Table 3, Panel C. The findings show the average return of the portfolios and the associated four-factor alphas observe a decreasing pattern (for Q1 to Q3 though not for the Q4 and Q5 portfolios). Moreover, the average return and the four-factor alpha for the long-short portfolio (Q5-Q1) are negative and marginally significant, suggesting a negative kurtosis risk premium. This is in line with the evidence obtained in our swap contracts analysis. We conclude that investors are averse to positive changes in market kurtosis and accept a lower future return for stocks that act as a hedge against kurtosis risk (stocks with positive $\beta^{i}_{\Delta KURT}$).

To sum up, the empirical evidence based on multivariate portfolio sorting confirms the results obtained in Section 4.1 for volatility and kurtosis, namely that the second- and the fourth-order moments matter in explaining individual stock returns. However, we do not find evidence on pricing of skewness risk. We discuss this result further in the next section.

4.2.2. Four-way sorting

One disadvantage of the multivariate sorting analysis (Section 4.2.1) is the difficulty in separating the effect of each risk factor due to the fact that the exposures to the different factors introduced in Eq. (3) are correlated. In particular, market excess returns, innovations in volatility and innovations in skewness show a high degree of pairwise correlation that must be isolated (ρ = -0.70 for market excess returns and innovations in volatility, +0.20 for innovations in skewness and innovations in volatility and -0.21 for innovations in skewness and market excess returns, all significant at 1%). In order to address this issue, we follow the four-way sorting method proposed in Chang et al. (2013), isolating the pricing effects of different risk factors. This procedure is preferable to that of 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 based on the differences in exposure to innovations in skewness (low, medium, or high). This method produces a total of 27 groups. Fourth, we sort again according to innovations in kurtosis (low, medium, high). We thus obtain 81 groups of stocks ranked by high, medium, or low exposure to market, volatility, skewness, and kurtosis risk.

Given that we exploit a four-way conditional sorting procedure, the order in which the factors are sorted has an effect on the outcome (i.e., the factor sorted first impacts the second sort). This means that the portfolios formed according to the second factor are ‘conditional’ on the first factor. Theoretically, portfolios sorted based on the first factor are not diversified with respect to the second factor. It follows that portfolios sorted based on the second factor are diversified with respect to the first one, and portfolios sorted on the last factor (kurtosis in our case) are diversified with respect to all other factors.

There are several reasons for our choice of the ranking order. First, excess market return is a widely recognized and long-standing factor in the literature that is commonly adopted without any diversification with respect to other risk factors. Thus, we choose to sort based on this factor first. Second, given the highly negative correlation between market and volatility risks as well as the importance of volatility in the literature, we choose to sort based on volatility risk as the second factor. This also allows us to diversify volatility risk with respect to market risk. Third, since higher order moments require the first and second moment in their formula (see Bakshi et al., 2003), we account for them in the sorting procedure only after volatility risk (it should be noted that kurtosis risk was orthogonalized with respect to skewness risk). Fourth, our choice allows us to compare our results with those obtained in previous papers. This sorting is consistent with Chang et al. (2013), who implement the same four-way sorting procedure, and with Ang et al. (2006), who adopt a two-way sorting procedure based on market (first) and volatility risk (second).

Moreover, compared to the unconditional sorting procedure,[8] conditional sorting has at least two advantages. First, it is closer to the way investors approach asset allocation in practice (Lambert and Hübner, 2013). Investors generally deal with one problem at a time and thus likely

[8] In the unconditional sorting procedure, assets are first sorted based on each factor from low to high exposure independently (at the same time). Then, sub-portfolios are formed by taking the stocks that are in the intersection of the two independently sorted portfolios in the first step.

consider different risk factors sequentially in order of importance rather than simultaneously. Second, conditional sorting is particularly suited to data sets characterized by a limited number of stocks, as in our case. Due to moderate levels of correlation between risk factors, performing independent sorts could lead to imbalanced or empty buckets (Lambert and Hübner, 2013). On the other hand, conditional sorting ensures a balanced number of stocks in each portfolio and, therefore, increases the number of stocks in buckets with maximum or minimum sensitivity to any risk factor (Cohen et al., 2013).[9] In our procedure, we calculate the return on value-weighted portfolios within each group over the next month. We then sort the 81 groups into terciles (each consisting of 27 groups) according to their low, medium, and high exposure to a single risk factor.

Finally, in order to have portfolios exposed to a single risk factor, 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 factor. We check empirically the diversification of the portfolios with respect to other factors by examining the range of the betas (e.g., we consider whether the 27 portfolios with the highest exposure to market risk collect stocks with low, medium and high exposure to volatility, skewness and kurtosis risk). Table 4 shows the beta exposure for portfolios sorted based on low (L) and high (H) exposure to market, volatility, skewness and kurtosis risks obtained in the four-way sorting exercise. It may be seen that each of these portfolios presents a considerable spread between the minimum and maximum beta of the component stocks, suggesting a good level of diversification with respect to the other risk factors. In relation to the spread of the betas in the multivariate sorting exercise (see Table 3) it

[9] In our procedure, the conditional four-way sorting procedure produces 81 portfolios with a similar number of stocks (the average number of stocks in each of the 81 groups ranges from five to six stocks).

may be seen that the corresponding spread in Table 4 is comparable, suggesting that strong cross-factor correlation does not substantially lower the spreads and weaken the tests.

The average returns of factor portfolios exposed to excess return, volatility, skewness, and kurtosis (*FMKT*, *FVOL*, *FSKEW* and *FKURT*) are calculated 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 on 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 investor earnings for time-varying market excess return, volatility, skewness, and kurtosis risks and are reported in Table 5, Panel A. For instance, the return on the *FVOL* portfolio reflects the return of a zero-cost portfolio, which is exposed to volatility risk and diversified with respect to other risk factors. Therefore, the average return of each factor can be viewed as the risk premium for exposure to that risk factor.[10]

[10] The method based on value-weighting within the 81 buckets and equal weighting among the 27 portfolios is consistent with previous studies in the US market (e.g., Chang et al., 2013). This method is also consistent with the one used in Fama and French (1993, 1996) to obtain SMB and HML factors. For the sake of completeness, we also derive the results based on value-weighting among the 27 portfolios. The results, not shown here for reasons of space, (available on request) confirm only the significance of the volatility risk premium in the European stock market. However, caution should be exercised when considering these results because a single portfolio could have a very large weight (of more than 30%) in the 27 portfolios with the highest or lowest exposure to the risk factor, thus playing a predominant role in generating the resulting factor return. Moreover, using value-weighing among the

Table 5, Panel A shows that the average monthly volatility risk premium is equal to -0.49% (-5.88% if annualized), which is statistically significant. Moreover, both the average returns of the value-weighted portfolios and the associated four-factor alphas present a monotonically decreasing pattern from the portfolio with the lowest exposure (L) to the one with the highest exposure (H). 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 earlier analysis based on the volatility swap and multivariate portfolio sorting that revealed a negative risk premium for volatility (Table 2 and Table 3, Panel A).

The findings in Table 5, Panel A show that the estimated risk premium for skewness is positive and significant (at the 5% level). In terms of magnitude, this risk premium stands at 0.22% on a monthly basis (2.64% if annualized). Moreover, the average return of the portfolios and the associated alphas present a monotonically increasing pattern from the portfolio with the lowest exposure (L) to the one with the highest exposure (H). This result confirms the evidence of a positive skewness risk premium. In addition, the estimated risk premium is robust to the inclusion of other risk factors, such as market excess return, size, book-to-market, and momentum (the alpha statistic is equal to 0.26% on a monthly basis, significant at 1%). The results based on this four-way sorting procedure suggest that the insignificant risk-premium for skewness obtained in the multivariate sorting analysis was due to the correlation between innovation in skewness and excess market return and innovations in volatility.

27 portfolios, may weaken the exposure with respect to the risk factor under consideration since high capitalization stocks tend not to have extreme exposures to a single risk factor. As a result, in order to obtain the representative traded factors for volatility, skewness and kurtosis we adopt the value-weighting within the 81 buckets and equal weighting among the 27 portfolios as in Eq. (7).

This result contrasts with Chang et al.'s (2013) observation of a robust negative skewness risk premium in the US. The reasons for the dissimilarity are twofold. First, there are different institutional features in the European markets in this study and the US market studied by Chang et al. (2013), e.g., dissimilarity in market depth (US markets are deeper) and in sectoral diversification (European markets are concentrated on financial stocks). Second, there is also dissimilarity in the sample period. Specifically, we investigate the European market from 2005 to 2017, which was heavily influenced by the financial crisis and the European debt crisis and characterized by a greater level of volatility, compared to the US market from 1996 to 2007. Concerning kurtosis risk premium, we find that once we account for the different sources of risk, the kurtosis risk premium and Carhart alpha are insignificant.

Regarding the economic significance of a risk factor, Chang et al. (2013) evaluate it by comparing the magnitude of its price of risk (λ) with the spread of betas (i.e. the portfolio exposure to the risk factor). The rationale is that investors aiming to replicate a long position e.g., in volatility risk, should take a long position in the portfolio with the highest β_{FVOL}, and a short position in the portfolio with the lowest β_{FVOL}. The return on 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. Adopting the same methodology as Chang et al. (2013), we obtain an average monthly return of -0.99% (-11.88% annual) for the long-short portfolio on volatility, and an average monthly return of 0.53% (6.36% annual) for the long-short portfolio on skewness. Therefore, we consider the estimated risk premia for volatility and skewness risks to be also economically significant.

The cumulative gross returns for the factor portfolios based on innovations in volatility, skewness and kurtosis are shown in Fig. 2, along with the cumulative returns for the Carhart

(1997) four-factor portfolios based on market excess return, size, book-to-market, and momentum. The cumulative excess return was negative after the collapse of Lehman Brothers and in the years following the European debt crisis (2010–2012), recovering only in late 2014. The volatility risk premium is negative almost everywhere; it attains a few positive values in the 2005–2008 period, but since the collapse of Lehman Brothers, it has been markedly negative. Interestingly, the return on the volatility factor portfolio (*FVOL*), which captures the volatility risk premium, presents positive peaks both during the 2008 market decline and during the European debt crisis (2011–2012), suggesting a positive risk premium on volatility in that specific short-term period. The positive risk premium means that portfolios that take a long position on volatility (e.g., a 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 during the critical phase of the financial crisis of 2007–2009 and in 2011–2012, stocks serving 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 taking a long position on a variance swap is an insurance-buying strategy in the sense that the return on 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 positive return. This result highlights the importance of portfolio diversification also regarding volatility risk in order to avoid substantial losses during market turmoil periods. Specifically, investors could opt for a long position in a variance swap contract or increase the portfolio portion of stock characterized by positive volatility beta. In addition, a short position on stocks characterized by negative volatility beta would have significantly improved the portfolio performance.

A pattern similar to that of the volatility risk premium, but in the opposite direction, is detectable for the skewness risk premium. It fluctuates around zero in the first three years of the sample and it is markedly positive only after the Lehman Brothers collapse. The kurtosis risk premium does not vary significantly during the sample period: it fluctuates around zero, with low positive or negative values throughout the sample period.

Table 5, Panel B shows the average monthly returns for the Carhart risk factors. The results show that the SMB factor, which captures the excess return of low capitalization firms relative to high capitalization firms, is the only statistically significant factor. In terms of magnitude, the average return on the SMB factor is equal to 0.40% on a monthly basis (4.76% annualized). The positive price of size risk suggests that stocks characterized by low capitalization levels earn higher returns than those characterized by high capitalization levels, pointing to the existence of a small-size premium. Fig. 2 shows that size is the only factor that provides a constant positive performance over the entire sample period, highlighting the significant over-performance of small capitalization stocks relative to high capitalization ones. This finding is in contrast with the results in Chang et al. (2013), who found that the size risk factor is not priced in the US stock market. This dissimilarity highlights the differences in the structure of the two stock markets in the sense that the European market, which is more concentrated than the US market, is mainly concerned with size.

4.2.3 Spanning Tests

In order to further evaluate the significance of the risk factors in explaining the time variation of expected stock returns, we adopt the spanning test method used in Barillas and Shanken

(2017), Fama and French (2017), and Sakkas and Tessaromatis (2018). The rationale underlying this method is that a factor is useful if when regressed on the other factors, it produces a non-zero intercept, suggesting that it does contribute to describing average returns. To test whether one or more factors enhance the model's ability to explain expected returns, we adopt the GRS statistic of Gibbons et al. (1989). First, we perform a time-series regression in which the dependent variable is the monthly return of the candidate risk factor, and the independent variables are the monthly returns of the competing model risk factors. The spanning regression results are shown in Table 6, Panel A. The candidate factors are arranged in the first column, while the other factors are placed in the first row. Along with the intercept (reported in the second column) and the betas (reported in the column of the factor to which they refer), we show the maximum squared Sharpe ratio obtainable from the model factors ($Sh^2(f)$) and each factor's marginal contribution to a model's maximum squared Sharpe ratio, called $a^2/s(e)^2$. Panel B of Table 6 tabulates the GRS statistic, which tests whether multiple factors jointly provide an additional explanation to a baseline model. In particular, we test between four different models:

1) The three-factor model (market excess return, size, and book-to-market) proposed in Fama and French (1993, 1996) against the single-factor model (market excess return), or CAPM.
2) The three-factor model (market excess return, size, and book-to-market) augmented with the momentum factor (Carhart's, 1997 four factors model) against the single factor model (market excess return) or CAPM.
3) Carhart's (1997) four-factor model (market excess return, size, book-to-market, and momentum) augmented with volatility and skewness against Carhart's (1997) four-factor model.

4) Carhart's (1997) four-factor model (market excess return, size, book-to-market, and momentum) augmented with volatility, skewness, and kurtosis against Carhart's (1997) four-factor model augmented with volatility and skewness.

In order to adjust for the non-traded nature of innovations in volatility, skewness and kurtosis in spanning regressions, we use the traded mimicking portfolios *FVOL*, *FSKEW* and *FKURT*, obtained as in Eq. (7) in Section 4.2.2, as a proxy for volatility, skewness, and kurtosis risks, respectively. In fact, the *FVOL*, *FSKEW* and *FKURT* portfolios obtained through the four-way sorting procedure are zero-cost portfolios constructed to be highly exposed to the factor of interest and well-diversified to others. These factors, therefore, represent tradable assets, as well as the Carhart factors.[11]

The statistics shown in the last column of Table 6, Panel A, indicate that the size factor (SMB) contributes the most to the maximum squared Sharpe ratio of the model (0.100), followed by book-to-market (0.074), volatility (0.071), and skewness (0.050). The intercept for kurtosis is not statistically different from zero, suggesting that the factor under investigation does not improve the explanatory power of the model.

Table 6, Panel B presents the GRS statistic (Gibbons et al., 1989) testing whether multiple factors jointly provide additional explanation to a baseline model. The results suggest that the basic CAPM model could be improved by adding SMB, HML, BTM, volatility and skewness risks. However, accounting for kurtosis risk does not bring a significant improvement. This evidence is consistent with the result in Table 6, Panel A.

[11] An alternative method to construct traded mimicking portfolios is proposed in Barillas and Shanken (2017). In those portfolios, weights are equal to the slope coefficients in the regression of the factor on the available returns and a constant, normalized to sum to one. However, in this case, the portfolios are not guaranteed to be well-diversified with respect to other factors.

5. Conclusions

In this study, we use two approaches to investigate the pricing of volatility and higher moments, and the associated risk premia in the European stock market. The first approach is based on the swap contracts proposed in Zhao et al. (2013) and is model-free. The second approach is model-based and relies on an extension of the Merton (1973) and Campbell (1993, 1996) intertemporal capital asset pricing model (ICAPM) and the consumption-based asset pricing literature (Campbell and Cochrane 1999; Bansal and Yaron 2004). Our analysis of volatility and higher moment risk premia is motivated by the fact that there is a lack of consensus on the existence and the signs 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 market presents many dissimilarities in relation to the US market. In particular, the lower market depth and the more limited sectoral diversification of the European market might affect investor behavior and the perception of moment risks. Moreover, most of the studies in the cross-section of stock returns are conducted for the sample periods prior to the financial crisis.

To fill this gap, we conduct our analysis based on the EURO STOXX 50-index options, which are European options on the EURO STOXX 50, during the period 2005–2017. We obtain several results. First, the volatility risk premium is found to be negative (in line with Ang et al., 2006; Cremers et al., 2015; Campbell et al., 2018; Bali et al., 2019), 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.

Second, we find evidence of a positive skewness risk premium for the European stock market, in contrast with the results obtained for the US by Chang et al. (2013), but in line with the findings of Kozhan et al. (2013) and Sasaki (2016). In particular, investors are averse to decreases in market skewness and, thus, they require higher returns on stocks with positive exposure to skewness risk (positive $\beta_{\Delta SKEW}$) in order to be compensated for the higher risk.

Third, the results for the sign of the volatility and skewness risk premiums were robust to different estimation methods including moments' swap contracts, four-way sorting, and spanning regressions of Barillas and Shanken (2017) and Fama and French (2017), and also robust to model specifications that include other risk factors such as market excess return, size, book-to-market, and momentum. Notably, the magnitude of the risk premia varies across different estimation methods, and the cross-sectional results for the volatility risk premium are stronger than the ones obtained for the skewness risk premium.

Fourth, we find a positive and large risk premium for firm size in the European market (0.40% monthly, 4.76% annually) given that stocks with low capitalization earn higher future returns on average than those with high capitalization. This contrasts with evidence in the US (Chang et al., 2013). Our finding indicates that investors perceive European stocks with low capitalization as riskier, and require higher future returns on these stocks.

Fifth, the volatility and the skewness risk premia are significant also from an economic point of view. 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.

ROLES

Elyas Elyasiani: Conceptualization, Methodology, Writing- Reviewing and Editing.

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Silvia Muzzioli: Conceptualization, Methodology, Formal analysis, Software, Resources, Writing-Review and Editing, Supervision, Project administration, Funding acquisition.

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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	0.981	-0.086	-0.0000008	1.00	0.20***	-0.22***	1.00	0.20***	-0.09***
$\Delta SKEW$	0.949	-0.349	-0.0000348		1.00	-0.86***		1.00	0.00
$\Delta KURT$	0.941	-0.407	-0.0000093			1.00			1.00
MKT			0.008%				-0.70***	-0.21***	0.03*
SMB			0.019%				0.10***	0.00	0.02
HML			-0.010%				-0.37***	-0.10***	0.02
UMD			-0.010%				0.19***	-0.04**	0.04**

Notes. The left-hand panel shows the average value for the risk factors ΔVOL, $\Delta SKEW$, $\Delta KURT$, MKT, 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 (2005-2017). 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). ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

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

	Volatility	Skewness	Kurtosis	Swap contract correlations			
Physical	0.1953	0.0035	2.9995				
Risk-neutral	0.2312	-0.4901	3.6788				
Swap payoff	-0.0359***	0.4935***	-0.6794***				
	(-8.860)	(53.946)	(-25.659)				
					VSP	SSP	KSP
				VSP	1.000	0.034*	-0.085***
				SSP		1.000	-0.887***
				KSP			1.000

Notes. This table shows the average values for the physical and risk-neutral moments of the EURO STOXX 50 distribution, the average payoff based on moment swap contracts (t-stats for the significance of the payoffs are in brackets) and the correlations among volatility swap payoff (VSP), skewness swap payoff (SSP) and kurtosis swap payoff (KSP). ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

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

	Quintiles					
Panel A						Gap:
	Q1	Q2	Q3	Q4	Q5	Q5-Q1
$\beta_{\Delta VOL}$	-0.636	-0.231	-0.038	0.156	0.542	
Avg. Ret.	1.07%	0.97%	0.63%	0.51%	0.46%	-0.61%*
						(-1.95)
Alpha	1.13%	1.02%	0.63%	0.51%	0.46%	-0.67%**
						(-2.19)

	Quintiles					
Panel B						Gap:
	Q1	Q2	Q3	Q4	Q5	Q5-Q1
$\beta_{\Delta SKEW}$	-0.182	-0.067	-0.011	0.044	0.155	
Avg. Ret.	0.83%	0.83%	0.68%	0.85%	0.70%	-0.13%
						(-0.441)
Alpha	0.87%	0.87%	0.68%	0.86%	0.72%	-0.15%
						(-0.500)

	Quintiles					
Panel C						Gap:
	Q1	Q2	Q3	Q4	Q5	Q5-Q1
$\beta_{\Delta KURT}$	-0.098	-0.031	0.003	0.036	0.103	
Avg. Ret.	1.15%	0.85%	0.65%	0.63%	0.62%	-0.52%*
						(-1.86)
Alpha	1.15%	0.86%	0.65%	0.66%	0.65%	-0.50%*
						(-1.74)

Notes. This table shows the results for portfolios sorted by 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 Q5 and a short position in Q1. For each quintile portfolio plus the Q5-Q1 portfolio, we report the pre-ranking beta, the post-ranking return (monthly return in percent) and the four-factor alpha computed with respect to the Carhart (1997) four-factor model. 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 monthly 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. In line with Chang et al. (2013) and Christoffersen and Pan (2018), we report the monthly alpha computed as the daily alpha multiplied by 21. We also report the Newey and West (1987) t-statistics with 12 lags for the difference in average returns and alphas between the high and low exposure groups. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4
Exposure to risk factors of the portfolios obtained in the four-way sorting procedure.

	Avg.	Median	Min.	Max.		Avg.	Median	Min.	Max.
Portfolio with low exposure with respect to R_m-R_f					Portfolio with high exposure with respect to R_m-R_f				
β_{MKT}	0.055	0.176	-2.365	0.504	β_{MKT}	1.737	1.590	1.204	4.337
β_{VOL}	-0.317	-0.275	-1.982	0.658	β_{VOL}	0.235	0.213	-0.972	1.889
β_{SKEW}	-0.029	-0.025	-0.475	0.366	β_{SKEW}	0.004	0.003	-0.459	0.478
β_{KURT}	0.003	0.002	-0.242	0.254	β_{KURT}	0.002	0.003	-0.300	0.267
Portfolio with low exposure with respect to ΔVOL					Portfolio with high exposure with respect to ΔVOL				
β_{MKT}	0.737	0.779	-2.181	2.838	β_{MKT}	1.029	0.921	-0.845	4.151
β_{VOL}	-0.447	-0.372	-2.088	0.035	β_{VOL}	0.352	0.282	-0.106	1.942
β_{SKEW}	0.017	0.017	-0.416	0.461	β_{SKEW}	-0.043	-0.040	-0.511	0.349
β_{KURT}	-0.019	-0.017	-0.296	0.234	β_{KURT}	0.024	0.022	-0.220	0.293
Portfolio with low exposure with respect to $\Delta SKEW$					Portfolio with high exposure with respect to $\Delta SKEW$				
β_{MKT}	0.794	0.780	-1.445	2.957	β_{MKT}	1.044	0.993	-0.852	3.436
β_{VOL}	-0.015	-0.018	-1.329	1.282	β_{VOL}	-0.079	-0.070	-1.402	1.190
β_{SKEW}	-0.147	-0.123	-0.480	-0.044	β_{SKEW}	0.122	0.100	0.020	0.441
β_{KURT}	0.051	0.045	-0.104	0.255	β_{KURT}	-0.046	-0.039	-0.261	0.101
Portfolio with low exposure with respect to $\Delta KURT$					Portfolio with high exposure with respect to $\Delta KURT$				
β_{MKT}	1.024	1.013	-0.799	2.883	β_{MKT}	0.921	0.896	-0.829	2.872
β_{VOL}	-0.095	-0.085	-1.293	0.946	β_{VOL}	0.000	-0.003	-1.009	1.085
β_{SKEW}	0.062	0.056	-0.173	0.323	β_{SKEW}	-0.093	-0.083	-0.371	0.127
β_{KURT}	-0.077	-0.063	-0.247	0.006	β_{KURT}	0.083	0.072	0.005	0.229

Notes. This table shows the statistics about the average beta exposure for portfolios sorted on low (L) and high (H) exposure to market, volatility, skewness and kurtosis risks obtained in the four-way sorting procedure.

Table 5
Four-way sorting results.

Panel A: Portfolios sorted based on low (L), medium (M) and high (H) exposure (β) to:				
Market	L	M	H	FMKT
Avg. Ret.	0.68%	0.66%	0.80%	0.12%
				(0.422)
Alpha	0.58%	0.57%	0.71%	0.13%
				(0.590)
Volatility	L	M	H	FVOL
Avg. Ret.	1.00%	0.62%	0.52%	-0.49%**
				(-2.16)
Alpha	0.92%	0.55%	0.39%	-0.53%***
				(-2.84)
Skewness	L	M	H	FSKEW
Avg. Ret.	0.62%	0.68%	0.84%	0.22%**
				(2.24)
Alpha	0.52%	0.60%	0.75%	0.23%**
				(2.39)
Kurtosis	L	M	H	FKURT
Avg. Ret.	0.75%	0.70%	0.69%	-0.06%
				(-0.62)
Alpha	0.65%	0.61%	0.59%	-0.06%
				(-0.57)
Panel B: Average returns of the Carhart (1997) four-factor portfolios				
Market (MKT)				0.16%
				(0.37)
Size (SMB)				0.40%***
				(3.05)
Book-to-Market (HML)				-0.20%
				(-0.72)
Momentum (UMD)				-0.22%
				(-0.83)

*Notes.*This table shows the results for portfolios sorted based on exposure to market, volatility, skewness and kurtosis risks in the four-way sorting exercise. Portfolios are sorted based on low (L), medium (M) and high (H) exposure (β) to innovations in market (R_m-R_f), volatility, skewness and kurtosis. FMKT, FVOL, FSKEW and FKURT are obtained combining a long position in the high (H) tercile and a short position in the low (L) tercile (H-L). For each tercile portfolio plus the H-L portfolio, we report the post-ranking return (monthly return in percent) and the four-factor alphas computed with respect to the Carhart (1997) four-factor model. 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=L, M, H, H-L* and MKT_t, SMB_t, HML_t and UMD_t are the daily factors used in order to evaluate the robustness of the intercept. In line with Chang et al. (2013) and Christoffersen and Pan (2018), we report the monthly alpha computed as the daily alpha multiplied by 21. In Panel B we report the average returns of the Carhart four factors. We also report the Newey and West (1987) t-statistics with 12 lags for the difference in average returns and alphas between the high and low exposure groups and for the Carhart four factors. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6
Factor time series tests

Panel A: Spanning Regressions

	a	MKT	SMB	HML	UMD	FVOL	FSKEW	FKURT	R^2 (%)	$Sh^2(f)$	$a^2/s(e)^2$
MKT	-0.05% (-0.129)	--	0.268	0.670	-0.074	-0.242	0.347	-0.489	33.67%	0.096	0.000
SMB	0.48% (3.613)	0.032	--	0.161	0.114	0.014	-0.145	-0.021	15.90%	0.096	0.100
HML	-0.69% (-3.080)	0.221	0.442	--	-0.287	-0.462	0.057	0.294	53.42%	0.096	0.074
UMD	-0.54% (-1.999)	-0.034	0.440	-0.403	--	-0.090	0.185	0.107	18.37%	0.096	0.032
FVOL	-0.60% (-3.005)	-0.062	0.029	-0.360	-0.050	--	0.055	-0.185	31.70%	0.096	0.071
FSKEW	0.28% (2.503)	0.027	-0.094	0.013	0.031	0.017	--	0.168	4.84%	0.096	0.050
FKURT	-0.09% (-0.884)	-0.034	-0.012	0.062	0.016	-0.050	0.151	--	7.18%	0.096	0.006

Panel B: Multi-factor tests

RHS returns (Base model)	LHS returns (Augmented factors)	GRS	p-value
CAPM MKT	Size, Book-to-market (SMB, HML)	5.858	0.003
CAPM MKT	Size, Book-to-market, Momentum (SMB, HML, UMD)	4.326	0.005
FF4 (MKT, SMB, HML, UMD)	Volatility, Skewness (FVOL, FSKEW)	6.702	0.001
FF4, Volatility, Skewness (MKT, SMB, HML, UMD, FVOL, FSKEW)	Kurtosis (FKURT)	0.498	0.480

Notes. This table shows the spanning regression results (Panel A) and the GRS statistic of Gibbons et al. (1989) (Panel B). In Panel A we test whether the factor under investigation (reported in the first column) is significant in explaining the time variation of expected stock return, i.e. whether it shows a non-zero intercept when regressed on the other factors reported in each row (t-stats are in brackets). We report the intercept (column 2), the slope coefficients of the other factors (columns 3–9), the R^2 (column 10), the maximum squared Sharpe ratio ($Sh^2(f)$ in column 11) and the increase in the max squared Sharpe ratio for a model's factors when the factor under investigation is added to the model ($a^2/s(e)^2$, column 12). In Panel B we present the GRS statistic (Gibbons et al., 1989) which tests whether multiple factors jointly provide additional explanation to a baseline model.

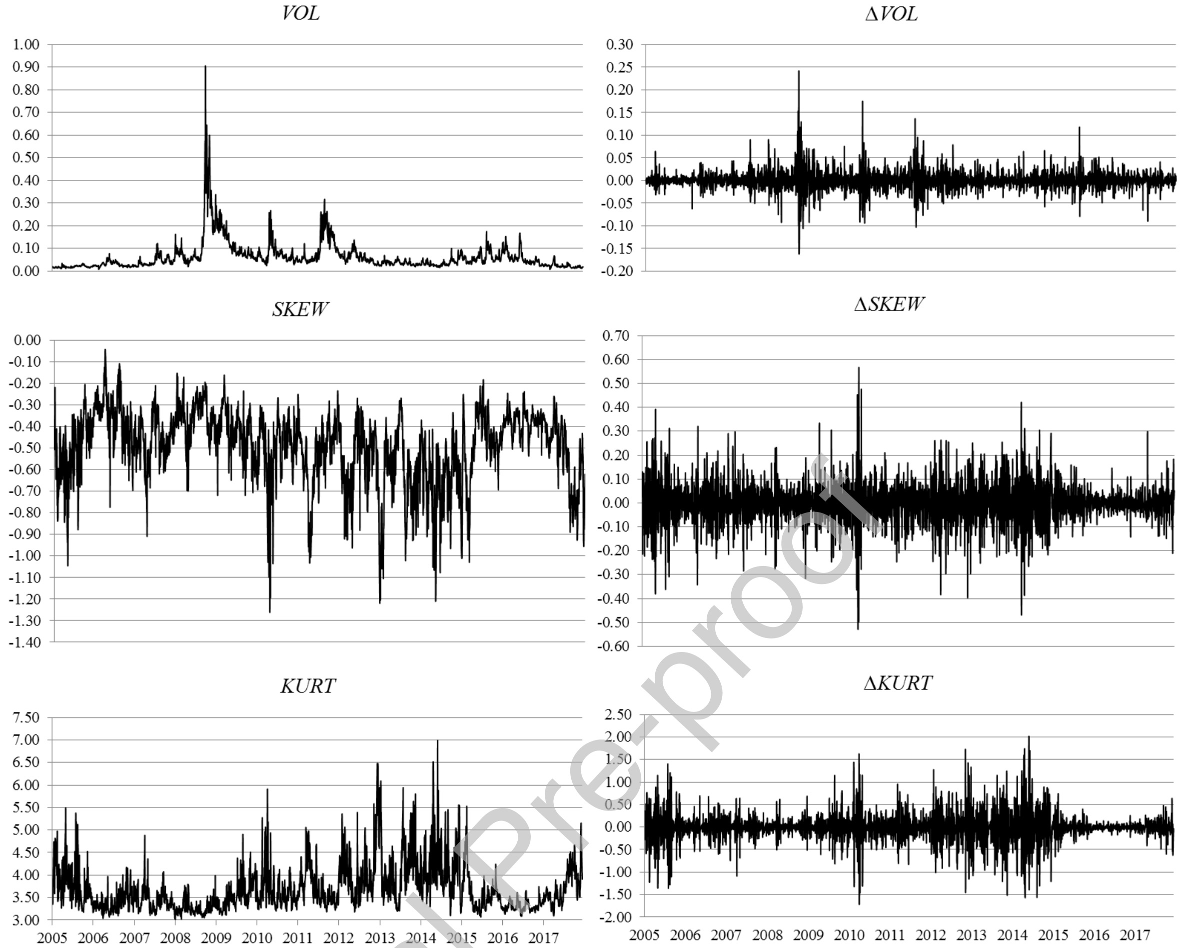

Fig. 1. Daily closing values and innovations in option implied moments.
The left-hand panel shows the daily closing value of volatility (VOL), skewness (SKEW) and kurtosis (KURT) of EURO STOXX 50 index returns. For each series depicted in the left-hand panel, we report the corresponding daily innovations in the right-hand panel.

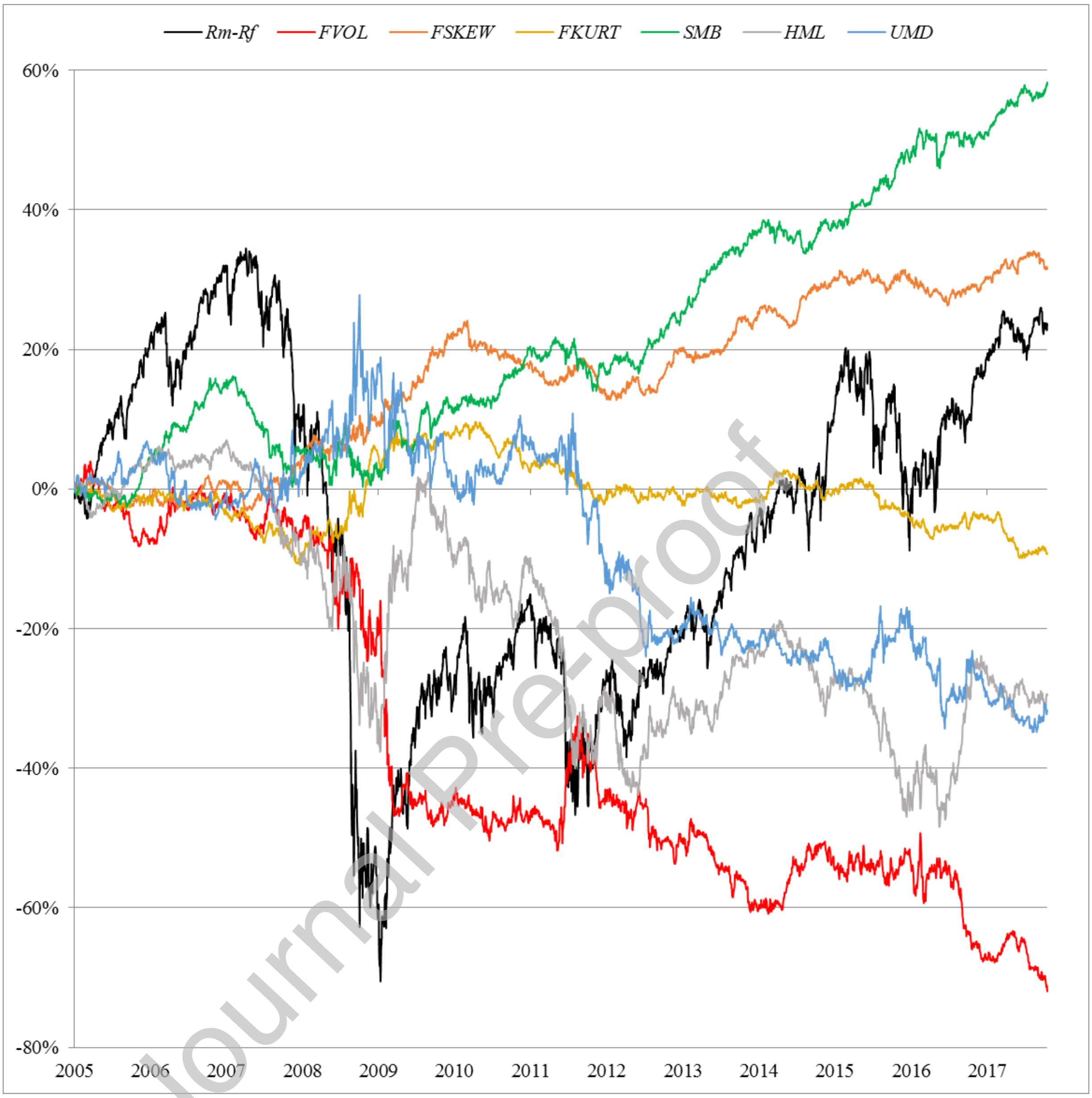

Fig. 2. Cumulative performance on factor portfolios for exposure to moment risk and Carhart (1997) factors.
The figure reports cumulative gross returns. Only the market risk factor is in excess of the risk-free rate. All the factors are rebalanced on a monthly basis.