EVIDENCE OF THE IMPACT OF COSKEWNESS ON THE LOW RISK ANOMALY IN EUROPEAN STOCKS

BARBARA RAŠIOVÁ[1]

Abstract: *This paper investigates the low risk anomaly, which suggests that less risky stocks outperform riskier ones. Focusing on the European stock market, the present study examines the influence of coskewness, a measure of asymmetry in stock returns with respect to the market return. Stocks are sorted into 2x5 quintile portfolios based on coskewness and beta volatility. Regression analysis using Fama-French three and five factor models reveals a significant low risk anomaly in the low coskewness category, where less risky portfolios consistently outperform riskier ones. However, as coskewness increases, the low risk anomaly weakens and loses significance. In the high coskewness category, less risky portfolios no longer consistently outperform riskier ones. In other words, accounting for coskewness significantly lowers the profitability of low risk and betting-against-beta strategies in Europe. These findings enhance the understanding of the relationship between risk and returns in the European market.*

Keywords: *low risk anomaly, coskewness, portfolio returns, stock market, portfolio analysis*

JEL Classification: G11, G12, G15

[1] Barbara Rašiová, MSc., University of Economics in Bratislava, Slovak Republic,
e-mail: barbara.rasiova@euba.sk https://orcid.org/0000-0002-3048-649X

EKONOMICKÉ ROZHĽADY – ECONOMIC REVIEW, 2023, 52(2), 81 – 103
https://doi.org/10.53465/ER.2644-7185.2023.2.81-103

1 Introduction

High risk, high return, that is how the equity market is supposed to operate according to the risk- return tradeoff principle. As specified by the traditional Capital Asset Pricing Model (CAPM), investors should be rewarded for facing risk by earning a higher expected return (Sharpe, 1964; Lintner, 1965). However, it is well known now that the CAPM is not considered the reliable model it has been deemed for decades. A number of studies suggest that return and risk within equity markets show no correlation, or if they do, they are negatively correlated. They reveal that CAPM betas only have little or no informative power for the cross-section of average returns, when implemented alone (Rosenberg, Reid and Lanstein, 1985; Bhandari, 1988). Furthermore, the relationship between average return and market beta is shown to be flat, or even negative in some cases (Black, Jensen and Scholes, 1972; Fama and MacBeth, 1973).

Ever since the honored article of Ang et al. (2006) confirmed a negative relation between the level of volatility and the cross-section of U.S. stock market returns, this contradiction was shown to be persistent and not varying largely with differences in markets and methodological choices, giving rise to the low risk anomaly. Since then, its existence has been profoundly discussed, and many reasons explaining or justifying it have been analyzed (Bali and Cakici, 2008; Fu, 2009; Baker and Haugen, 2012). Ultimately, newer research demonstrates that low risk anomalies can be justified by the equity returns skewness, which is repeatedly neglected by standard measures of risk. With increasing downside risk, the standard asset pricing models increasingly overestimate required equity returns relative to firms' true (skew-adjusted) market risk (Schneider, Wagner and Zechner, 2020). The U.S. specific findings show that anomalous empirical patterns do not constitute asset pricing puzzles if coskewness of equity returns with the market is considered. Instead, such strategies have been observed to collect supplementary premia that compensate for skew risk. This incites an immediate follow-up question to be addressed in this paper: Does coskewness reduce the low risk anomaly in other equity markets too?

With the aim of evaluating the impact of equity returns' coskewness with the stock market on the intensity of the low risk anomaly outside the U.S., the attention of this study is shifted to European markets represented by the constituents of S&P Europe 350 Index. In order to compare the existence and the magnitude of the low risk anomaly across different coskewness levels, double sorted 2x5 stock portfolios are assembled. At first, each stock is assigned to either high or low coskewness category based on its coskewness with market return, and summary statistics are calculated. Subsequently, stocks in both categories are split into equally weighted quintile portfolios depending on their beta volatility estimated in the CAPM. The difference portfolio[2], specified as the difference of the lowest and the highest quintile portfolio, is created too in order to facilitate the inspection and comparison of the low risk anomaly in both coskewness groups. Finally, the low risk anomaly is tested for each portfolio in each coskewness category separately using Fama-French three factor (FF-3) and Fama-French five factor (FF-5) model. The addition of two factors should increase the model's explanatory power in the cross section of returns and decrease the excess returns by extension (Fama and French, 2015).

Results demonstrate that accounting for coskewness in the model remarkably decreases the profitability of low risk and betting-against-beta strategies in European data. As the coskewness becomes substantially less negative, the excess returns in such strategies decline, which confirms results of Schneider, Wagner and Zechner (2020). Results obtained for the low coskewness category confirm the existence of the low risk anomaly in the cross section of European stocks. The long-short portfolio is found to yield a positive average monthly return, and its alpha is discovered to be highly statistically significant for both models. In the high coskewness category, all estimated alphas are lower than in the previous category. None of the excess returns for the Q1-Q5 portfolio have been proved statistically different from zero, implying that the less risky portfolios no longer outperform the riskier ones. These results confirm the shrinkage, or even disappearance of the low risk anomaly in the high coskewness category.

The structure of the remainder of this paper is as follows. The second section provides a literature review on the low risk anomaly. The next section is focused on the presentation of data used in the empirical analysis and the description of methodology. The following section interprets the obtained results on the comparison of presence and magnitude of the low risk anomaly for all quintile portfolios across both coskewness categories. The final section summarizes the main findings and offers a conclusion.

[2] Throughout the whole of this paper the terms Q1-Q5, difference portfolio, and long- short portfolio are used interchangeably.

EKONOMICKÉ ROZHĽADY – ECONOMIC REVIEW, 2023, 52(2), 81 – 103
https://doi.org/10.53465/ER.2644-7185.2023.2.81-103

2 Literature review

While the CAPM has provided a useful framework for understanding the relationship between risk and return in the equity market, its assumptions of homogeneous expectations, constant risk premia and the inability to explain the premium puzzle have been shown to be too restrictive (Fama and French, 2003; Dempsey, 2013; Chen et al., 2022). In response, several extensions to the model have been proposed, offering a selection of alternative approaches to explain observed market behavior, such as the Consumption Capital Asset Pricing Model (CCAPM), Hansen-Jagannathan Bounds, financial accelerator, and habit persistence model. The CCAPM has been shown to partially address objections against the CAPM, such as the predictability of stock returns based on consumption growth. It does so by offering an alternative approach to asset pricing in which investors are concerned about their overall consumption level over time, as opposed to simply their wealth at a single point in time (Breeden, Gibbons and Litzenberger, 1989). Another extension to the CAPM that relaxes the assumption of homogeneous expectations are Hansen-Jagannathan bounds, useful in the evaluation of the ability of asset pricing models to generate the variation in returns observed in the market. While this approach provides a useful framework for testing asset pricing models, it does not offer any new insights into the underlying factors driving asset prices (Hansen and Jagannathan, 1991).

Contrarily, the financial accelerator model proposes a reasoning as to why asset prices exhibit higher volatility in unfavourable market conditions. It suggests that the effects of economic shocks on asset prices can be amplified by changes in the financial system. For instance, an increase in the cost of borrowing due to a credit crunch can lead to a decrease in asset prices, which in turn can lead to a further tightening of credit and a further decline in asset prices. Acknowledging the asset prices fluctuations, the habit persistence model clarifies why investors may be willing to pay a premium for stable stocks that may provide more secure and predictable consumption streams over time and through all phases of the market cycle. It suggests that investors display a preference for maintaining their current levels of consumption, leading to a gradual adjustment of their consumption over time in response to changes in their wealth, which leads to a predictable component in stock returns. This can be thought of as a type of risk premium that compensates investors for bearing the risk of fluctuations in their consumption (Bernanke, Gertler and Gilchrist, 1999).

On a similar note, challenging the CAPM's assumption of a constant risk premium, the hypothesis of term and variable premia suggests that investors may demand higher expected returns for holding long-term bonds, and that this premium may vary over time due to changes in economic conditions and market expectations. Precisely, term premiums, refer to the additional return that investors demand for holding longer-term bonds instead of rolling over shorter-term bonds (Kim and Orphanides, 2007; Makovský, 2022). Variable premium, on the other hand, can be considered as a compensation for the risk of changes in interest rates and inflation. This hypothesis suggests that the premium investors require for holding risky assets may vary over time and depend on various economic conditions (Fama and French 1989).

Recent research documents a unique critique to the CAPM where the low volatility stocks are found to outperform their high risk counterparts. An extensive body of academic research has highlighted that the negative relationship between risk and expected return is observable within asset classes (for example equity class) if not across them. This phenomenon is called the low risk anomaly. According to the principal hypothesis, it occurs when a portfolio comprised of low risk stocks outperforms its high volatility equivalent over a period of full market cycle (Joshipura and Jushipura, 2015). Even though it is troublesome to explain its presence and persistence using traditional finance theory and models, there are some reasonable explanations, which provide meaningful clarifications on the profitability of low risk investment strategies. So far, two sets of explanations are circling in academia. The first one aims to offer evidence of low risk anomaly utilizing behavioral reasoning, while the collection of economic justifications attempts to explain it away by clearly removing its puzzling nature.

On the account of behavioral explanations, the majority of authors reached a conclusion that investors commonly exhibit a propensity to underestimate low risk stocks. A mental accounting interpretation sheds light on their preferences. Although investors can make rational risk-averse decisions for asset allocation choices, with regard to security selection within the asset class, they exhibit risk-seeking tendencies, and show strong preference for high volatility investments (Blitz and Vliet, 2007). On top of that, investors manifest a clear penchant for volatile, attention-grabbing stocks (Barber and Odean, 2008). Popular in-news stocks are favoured by institutional investors such as mutual funds as well (Falkenstein, 1996). Another explanation lies in overconfidence. A number of people are convinced that they are capable

EKONOMICKÉ ROZHĽADY – ECONOMIC REVIEW, 2023, 52(2), 81 – 103
https://doi.org/10.53465/ER.2644-7185.2023.2.81-103

of picking stocks successfully. In turn, retail investors may be biased toward higher risk (Falkenstein, 2009). The widespread heuristic that "risk creates returns premium" causes them to overweight risky stocks to generate return premium. This actually negates the effect through their collective action (Lewinski, 2015).

A notable stream of behavioral clarifications also stems from the investors' preference for lottery, which contradicts the general assumption of investors being risk averse under normal circumstances. The value function is concave over gains, but convex over losses, and individuals mainly allocate more weight on the tails of the distribution revealing a common preference for lottery-like gains (Kahneman and Tversky, 1979). It is demonstrated that individuals mainly allocate more weight on the tails of the distribution revealing a common preference for lottery-like gains. However, high volatility individual stocks with limited liability are also positively skewed. Buying a high volatility, low priced stock is similar to buying a lottery ticket: there is a high probability of losing money vs. a small chance of doubling or tripling money in short term (Mitton and Vorkink, 2007). Individual investors exhibit an apparent preference for stocks with lottery like payoff measured as idiosyncratic volatility or skewness (Kumar, 2009). Overweighting risky stocks with the aim of generating return premia indeed negates the effect via their collective action, giving rise to the low risk anomaly.

The stream of economic reasoning proposes several clarifications on the low risk anomaly as well. A substantial body of literature ties its existence to trading high risk stocks. To name a few, its presence can be attributed to the reality of institutional investors usually striving to surpass a chosen benchmark[3] (Baker, Bradley and Wurgler, 2011). Since pursuing riskier stocks is a simpler way of doing so, investments in low risk stocks are discouraged. This relates directly to the low risk anomaly and documents that low volatility is underpriced and high volatility is overpriced, even in the eyes of an institutional investor. Moreover, stocks with high idiosyncratic volatility face a higher probability of having greater divergence of opinion about their payoffs and therefore being more prone to speculative overpricing. Short selling constraints for individual as well as institutional investors prevent arbitrageurs from correcting the overblown prices of high beta stocks promptly by going long on ignored low

[3] The alternative way of doing so is by investing in low beta stocks using leverage to outperform a benchmark and benefiting from alpha as well. However, restrictions on borrowing including "long only" mandate leads to elimination of possibility of exploiting arbitrage opportunity between low beta-high alpha and high beta-low alpha stock.

risk stocks and shorting high risk stocks, which in turn gives rise to their underperformance. This arbitrage asymmetry leads to highly volatile stocks being mispriced and staying mispriced for longer than less volatile stocks, hence flattening the relation between return and risk (Hong and Sraer, 2016; Stambaugh, Yu and Yuan, 2015).

A more detailed analysis of the low risk anomaly reveals that it can be decomposed into micro and macro effects (Samuelson, 1998). In essence, the pattern of high return and low risk can originate from either the macro selection of lower risk countries and industries or the micro selection of low risk stocks within those countries and industries. Although both of them are shown to contribute to the low risk anomaly, micro selection provokes a substantial risk reduction accompanied with a modest difference in return. Contrarily, the macro selection motivates notable increases in return with slight differences in risk (Baker, Bradley and Taliaferro, 2014).

Finally, there is a collection of studies linking the low risk anomaly to the downside risk on the U.S. stock market, which inspires the present paper. Despite being a stylized statistical property of stock returns, conventional measures of risk, do not fully capture it, as they treat upside and downside deviations from the expected return symmetrically (Cont, 2001). In contrast, investors are often more concerned with the high sensitivities to downside market movements. Under these assumptions, low risk stocks are reported to feature lower downside risk explaining their higher returns. In other words, low risk stocks are not only less volatile, but also less likely to experience large negative returns, which makes them more attractive to risk-averse investors (Ang, Chen and Xing, 2006). Expanding upon existing research, Schneider, Wagner and Zechner (2020) show that this downside risk effect is distinct from other risk factors, such as value and momentum, and persists even after controlling for these factors. On top of that, authors confirm that controlling for the downside risk in asset pricing models renders betting against beta strategies insignificant, as the low risk anomaly vanishes.

3 Data and methodology

The empirical analysis is conducted on the monthly stock prices of the constituents of S&P Europe 350 Index retrieved from the Thomson Reuters Eikon terminal. S&P Europe 350 is a leading equity index comprised of 350

EKONOMICKÉ ROZHĽADY – ECONOMIC REVIEW, 2023, 52(2), 81 — 103
https://doi.org/10.53465/ER.2644-7185.2023.2.81-103

blue- chip companies and is one of seven headline indices[4] that are included in the S&P Global 1200. With intention of measuring the market performance of large capitalization companies trading on the 16 major developed European markets[5], it is float-adjusted and market capitalization weighted, while including both common and preferred shares. The obtained sample ranges from January 2010 to February 2020 in order for results not to be biased by the financial crisis of 2007-2009 and the later outburst of the Covid-19 crisis. Apart from the stock price data, the monthly Fama-French three and five factor European time series are fetched for the same period from the publicly available Kenneth French Data Library.

So as to prepare the data for the subsequent analysis, the application of extensive filtering methods is administered. All companies with missing data in the researched period are excluded from the study, which leads to the notable reduction of the sample size to 269 companies. For the purpose of analyzing, contrasting, and comparing the presence and the extent of the low risk anomaly across different coskewness and riskiness levels, double sorted 2x5 stock portfolios are constructed. In the first place, every stock is assigned to either high or low coskewness category based on the coskewness of its return with market return.

In the field of statistics, coskewness serves to measure to what extent two random variables change together. If applied in finance it can be utilized to assess security and portfolio risk. Investors favor positive coskewness, as it suggests a higher likelihood that two assets in the same portfolio are going to yield extreme, positive returns in excess of market returns simultaneously. In case return distributions of the two chosen assets feature negative coskewness, it implies that both assets have a higher probability of underperforming the market synchronously.

Stocks' coskewness with market return is determined by the first moment or the population mean (μ_m), market return (R_m) and historical stock returns (R_i). It is calculated using standard moment estimators as follows:

$$Coskew_{i,m} = \frac{\mathrm{COV}\left(R_i,(R_m-\mu_m)^2\right)}{E[(R_m-\mu_m)]^3} \tag{1}$$

[4] The remaining 6 indices are S&P 500, S&P Asia 50, S&P/ASX 50 Index, S&P/TOPIX 150, S&P Latin America 40 and S&P/TSX 60.
5 The constituents of S&P 350 Index must be domiciled in Italy, Sweden, Denmark, Finland, Belgium, the Netherlands, Spain, Ireland, Austria, Greece, United Kingdom, Portugal, Norway, or Luxembou-rg.

Secondly, the median coskewness is calculated and stocks are divided into two groups: those that exhibit high coskewness with market return, and those that feature low coskewness with market return, and subject to preliminary analysis. Subsequently, stocks in both coskewness categories are split into equally weighted quintile portfolios based on their beta volatility determined by the CAPM, which is a measure chosen to assess the riskiness of individual stocks. The difference portfolio Q1-Q5 is constructed as well.

The ongoing discussion about the relationship between beta and realized return in academia validates the usability of beta as a measure of the volatility of a security or portfolio in comparison to the market. In this paper, beta for the time series of each stock is estimated from regressions of stock returns on market excess returns (MKT) using the CAPM defined as:

$$E(R_i) - R_f = \alpha + \beta_i^{TS} MKT \tag{2}$$

Where α denotes the excess return. The estimated beta for the time series of a stock i (β_i^{TS}) is given by:

$$\beta_i^{TS} = \rho \frac{\delta_i}{\delta_m} \tag{3}$$

Where δ_i and δ_m are estimated standard deviations for the stock i and the market with their correlation being represented by ρ.

In the interest of reducing the influence of outliers, the time series estimate of β_i^{TS} undergoes a shrinkage procedure towards the cross- sectional mean β^{XS} using the shrinkage factor ω_i (Vasicek, 1973):

$$\beta_i = \omega_i \beta_i^{TS} + (1 - \omega_i)\beta^{XS} \tag{4}$$

In favor of enhanced simplicity, rather than employing time varying shrinkage factors as in the model of Vasicek (1973), an alternative approach of is pursued by setting $\omega_i = 0.6$ and $\beta^{XS} = 1$ for all periods and across all stocks (Frazzini and Pedersen, 2014). The selection of the shrinkage factor does not influence the manner in which individual securities are assigned into portfolios, since the common shrinkage does not alter the ranks of the security betas. This approach allows for a straightforward estimation of betas without the need for more complex models that may introduce additional uncertainty in the results. Based on the estimated and shrunk betas, stocks are divided into equally weighted quintile portfolios, and employed in FF-3 and FF-5 models.

EKONOMICKÉ ROZHĽADY – ECONOMIC REVIEW, 2023, 52(2), 81 — 103
https://doi.org/10.53465/ER.2644-7185.2023.2.81-103

Ultimately, the existence and magnitude of the low risk anomaly is tested for each portfolio in each coskewness category separately using FF-3 and FF-5 model. Then, the low risk anomaly, defined as an identified positive difference in estimated excess returns of the least and most risky portfolio, is measured.

3.1 Fama-French models

Fama-French asset pricing models have been widely studied and expanded upon in academic research over the years. As asset pricing models, they were initially proposed to clarify many inconsistencies in the CAPM. Firstly, observing that average returns of small stocks are too big relative to their beta estimates, and vice versa for larger stocks, the size effect is discovered[6] (Banz, 1981). Furthermore, it is observed that earnings- to -price ratio has explanatory power on the cross- section of average returns (Basu, 1983). Another discrepancy is the reported positive relationship between stocks' average returns and firm's book-to-market ratio (Rosenberg, Reid and Lanstein, 1985). Finally, a positive relationship between leverage and average returns is documented. In fact, leverage facilitates the explanation of the cross-section of average stock returns, when tested alongside size and market beta (Bhandari,1988).

Taking everything into consideration, it is asserted that all existing inconsistencies are only different variations of stock prices scaling (Fama and French, 1992). As a consequence, the evaluation of the combined roles of market beta, size, book-to-market equity, earnings-to-price and leverage is launched in the cross-section of stock returns. The conclusions stemming from the inclusion of additional elements fail to present support of the CAPM as no positive relationship of average stock returns and market betas is found.

Building on their 1992 findings, Fama and French (1993) introduce the FF-3 model for stock returns given by the following equation:

$$E(R_i) - R_f = \alpha + \beta_1 MKT + \beta_2 SMB + \beta_3 HML \tag{5}$$

Where β_1, β_2, β_3 denote factor coefficients with the three factors being: the market portfolio (MKT), the size (SMB) and the book-to-market- equity factor (HML), respectively. SMB stands for the difference in average returns between small and big stock portfolios, while HML symbolizes the difference

[6] The phenomenon in which stocks with lower market capitalizations on average, outperform those with higher market capitalizations over time.

between the average returns of high book-to-market and low book-to-market firms' portfolios.

Including two additional factors called operating profitability (RMW) and investment (CMA), a five-factor model is published (Fama and French, 2015). The RMW factor is designed to capture the effect of differences in profitability across companies. In particular, companies with higher operating profitability tend to have higher expected returns than companies with lower profitability. The CMA factor is designed to capture the effect of differences in investment rates across companies. Explicitly, companies that invest more tend to have lower expected returns than companies that invest less.

In the FF-5 model, expected return of a stock i is defined as:

$$E(R_i) - R_f = \alpha + \beta_1 MKT + \beta_2 SMB + \beta_3 HML + \beta_4 RMW + \beta_5 CMA \quad (6) \qquad (6)$$

Which is shown to describe the cross- section of returns even more accurately than the FF-3. To put in another way, by controlling for additional factors, the abnormal returns of the model should be diminished, as low volatility stocks are affiliated with firms characterized with comparably strong operating profitability and a conservative investment approach. The FF-5 model, nevertheless, does not succeed in completely capturing average returns, as the low risk anomaly is still recognized.

4 Results

For stocks in both coskewness categories, the same methodology is applied for the sample period from January, 2010 to February, 2020. Firstly, summary statistics such as mean, standard deviation and all quartiles are presented to allow for the initial comparison of portfolios. As a next step, equally weighted quintile portfolios are formed by sorting stocks based on their beta volatility determined by the CAPM. The portfolio with the highest (lowest) beta volatility is denoted Q5 (Q1) and buying Q1 and selling Q5 yields the long-short portfolio[7] denoted Q1-Q5. Excess return denoted alpha is estimated for each portfolio when accounting for the systematic risk given by FF-5 or FF-3.

[7] Also known as betting-against-beta, or betting-against-volatility (Frazzini and Pedersen, 2014; Schneider, Wagner and Zechner, 2020).

EKONOMICKÉ ROZHĽADY – ECONOMIC REVIEW, 2023, 52(2), 81 — 103
https://doi.org/10.53465/ER.2644-7185.2023.2.81-103

4.1 Low coskewness

A concise overview of the summary statistics for the low coskewness category is presented in Table 1. The column "N" denotes the number of stocks in the portfolio. The mean log return presented in "Mean" column is lower than the midpoint of a frequency distribution of observed values, i.e. median (column "Median") for the observed period, which is an indication of negative skewness with longer tail on the left side of the distribution. Since the negative skewness is associated with a proclivity for frequent small gains and scarce, sizeable losses, it is associated with higher expected returns on average and preferred by investors (Barberis and Huang, 2008).

Columns "Pctl(25)" and "Pctl(75)", featuring the first and third quartile of the log returns' distribution, reveal the interquartile range of 0.0811, which is almost ten times bigger than the average portfolio return in stocks with low coskewness with the market return. Its high value can be attributed to a large number of stocks from different countries, industries and with heterogeneous characteristics being included in the analysis, thus driving the dispersion of returns. Comparing their distance from the mean and median portfolio return, reported minimum ("Min") and maximum ("Max") portfolio returns serve as an additional confirmation of the negative portfolio skewness.

Table 1: Summary statistics for the low coskewness portfolio returns.

N	Mean	St.Dev	Pctl(25)	Median	Pctl(75)	Min	Max	Coskew.
134	0.0083	0.0690	-0.0310	0.0098	0.0501	-0.4213	0.3529	-0.5804

Source: author's calculations

The low coskewness category is also characterized by significantly negative coskewness with market return. Its median is -0.5840, meaning that the market and low coskewness portfolios are likely to underperform at the same time.

The summary of results from the application of Fama-French models on the quintile portfolios is reported in Table 2. For the vast majority of quintile portfolios, a clear pattern of mean return decreasing, and standard deviation increasing is apparent, when moving towards riskier portfolios. The pattern is also confirmed in the long-short portfolio, which generates a positive average return of 0.16% per month. Such outperformance of less risky portfolios provides a next indication of the existence of the low risk anomaly.

Table 2: Analysis of the quintile portfolios formed of low coskewness stocks. Robust t-statistics are presented in square brackets.

Portfolio	Mean return	St. deviation	FF-5 Alpha	FF-3 Alpha
Q1	0.3185	1.3058	0.3199* [2.492]	0.2956* [2.423]
Q2	0.3110	1.3271	0.3049* [-2.332]	0.2739* [2.204]
Q3	0.2173	1.2575	0.2015 [1.644]	0.1859 [1.591]
Q4	0.1019	1.4954	0.0825 [0.578]	0.0544 [0.397]
Q5	0.1585	1.7660	0.1265 [0.757]	0.1003 [0.630]
Q1-Q5	0.1600	1.0241	0.1913* [2.158]	0.1932* [2.296]

Note: The symbol "*" implies significance at 1% level.
Source: author's calculations

Another piece of evidence in favor of its presence is obtained when controlling for systematic risk factors in FF-3 and FF-5 models. Alphas generated by both models are identified to be noticeably higher in less volatile portfolios. As a matter of fact, only two least risky long portfolios demonstrate statistically significant alphas at 1% level. Since estimated alphas for riskier portfolios are not statistically significant, the actual outperformance of less risky portfolios may be even higher.

Focusing on the difference portfolio, the Q1-Q5 portfolio yields a statistically significant positive alpha for both factor models, which further validates the presence of the low risk anomaly in low coskewness stocks. Results also demonstrate the decrease in excess returns for the long-short portfolios when controlling for two additional risk factors in FF-5 model compared to the FF-3 model. This confirms the findings of Fama and French (2015), who illustrate that the inclusion of supplementary factors leads to the reduction of the low risk anomaly.

EKONOMICKÉ ROZHĽADY – ECONOMIC REVIEW, 2023, 52(2), 81 – 103
https://doi.org/10.53465/ER.2644-7185.2023.2.81-103

4.2 High coskewness

The summary statistics for the high coskewness portfolio detailed in Table 3 enable us to draw comparisons with its low coskewness counterpart. In spite of the mean return being slightly higher, results report more pronounced volatility ("St.Dev") of the high coskewness portfolio. Moreover, the median is considerably larger than the mean, which expresses a shift in the shape of the returns' distribution in favour of positive skewness, implying that the outliers of the distribution curve are located rather towards the right tail, and closer to the mean on the shorter left tail. In contrast to negatively skewed stock returns in the previous category, this class has a propensity to frequent, rather small losses and a few hefty gains from the potential investment. Thus, it may be overpriced and consequently yield a lower average return, which insinuates that the low coskewness stocks are likely to constitute a more profitable investment choice (Barberis and Huang, 2008).

The analysis of distribution quartiles reveals a modest increase in the s range to 0.0892, supporting the increased dispersion of returns hinted by the heightened volatility. Furthermore, the maximum measured return for the studied period is more than two times bigger than in the low coskewness category. Rare, extremely positive returns serve as an additional demonstration of the positive skewness.

Table 3: Summary statistics for the high coskewness portfolio.

N	Mean	St.Dev	Pctl(25)	Median	Pctl(75)	Min	Max	Coskew.
135	0.0084	0.0788	-0.0378	0.0061	0.0514	-0.4271	0.8072	-0.2013

Source: author's calculations

The median coskewness of stocks in the high coskewness category is -0.2013, which is a 65% increase compared to the previous category. Main results are presented in Table 4. Overall, mean portfolio returns are substantially lower than in portfolios exhibiting low coskewness with market return. There is no observable trend, as mean returns are alternately increasing and decreasing, as well as standard deviations. The decrease in mean portfolio returns is notable in the Q1-Q5 portfolio too, where the positive average return falls to 0.04% per month, merely a quarter of what was measured in the low coskewness category.

Controlling for systematic risk factors in FF-5 and FF-3 model, all long portfolios demonstrate statistically significant excess returns on at least 5% level. Their closer inspection, however, suggests a substantial decrease in the magnitude of the low risk anomaly. Not only are all alphas lower than in the low coskewness category, but also the pattern of an outperformance of less risky portfolio is diminished, with exception of the least and most risky portfolio.

Table 4: Analysis of the quintile portfolios formed of high coskewness stocks. Robust t-statistics are presented in square brackets.

Portfolio	Mean return	St. deviation	FF-5 Alpha	FF-3 Alpha
Q1	0.2294	0.9536	0.2209* [2.350]	0.2066* [2.316]
Q2	0.2597	1.0375	0.2493* [2.442]	0.2333* [2.4111]
Q3	0.1794	0.9332	0.1826* [2.002]	0.1617 [1.811]
Q4	0.2374	0.9882	0.2272* [2.379]	0.2059* [2.256]
Q5	0.1914	0.9177	0.1750 [1.962]	0.1656 [1.939]
Q1-Q5	0.0380	0.4013	0.0438 [1.105]	0.0388 [1.016]

Note: The symbol "*" implies significance at 1% level and "." indicates significance at 5% level.
Source: author's calculations

The difference portfolio also demonstrates the shrinkage of the low risk anomaly. Although positive, alphas generated by both Fama-French models are considerably lower than for stocks exhibiting low coskewness with market return. Moreover, neither of the two alphas for the Q1-Q5 portfolio has been found statistically different from zero, meaning that the least risky portfolio no longer outperforms the riskiest one. These findings further support the decline, or even vanishing of the low risk anomaly in high coskewness category.

The aforementioned findings in are in accordance with the U.S. stock market research of Schneider, Wagner and Zechner (2020). Controlling for the coskewness in the model eliminates the benefit of betting-against-beta strategies. As soon as the coskewness is considered, such strategies do not render statistically significant excess returns and low risk anomalies disappear.

5 Discussion

The low risk anomaly has sparked a lot of interest in recent years due to its puzzling nature conflicting with the traditional finance theory. There are several plausible hypotheses ranging from behavioral reasonings to economic justifications, which provide meaningful explanations as to why a portfolio consisting of low volatility stocks outperforms its high risk counterpart.

On the account of behavioral theories, it is suggested that investors tend to underestimate low-risk stocks and prefer high-volatility investments (Blitz and Vliet, 2007). Investors also have a strong preference for volatile, attention-grabbing stocks and are biased toward higher risk due to overconfidence (Barber and Odean, 2008; Falkenstein, 1996). The common preference for lottery-like gains and a focus on the tails of the distribution is another explanation for the low risk anomaly. High-volatility individual stocks with limited liability are also positively skewed, similar to buying a lottery ticket (Kahneman and Tversky, 1979). This preference for stocks with lottery-like payoffs leads to the overweighting of risky stocks, which ultimately negates the effect through their collective action, giving rise to the low-risk anomaly (Lewinski, 2015).

In view of the economic reasoning, the low risk anomaly can be explored from different angles. Institutional investors are known to pursue riskier stocks to surpass a chosen benchmark, which discourages investments in low risk stocks and causes their underpricing (Baker, Bradley and Wurgler, 2011). Short selling constraints for both individual and institutional investors prevent arbitrageurs from correcting overblown prices of high beta stocks, leading to highly volatile stocks being mispriced for longer than less volatile ones (Hong and Sraer, 2016; Stambaugh, Yu and Yuan, 2015). The low risk anomaly can even be decomposed into micro and macro effects by switching focus between low risk stocks and low risk industries/countries, with both contributing to it in a different way. The micro selection provokes a substantial risk reduction with a modest difference in return, while macro selection motivates notable increases in return with slight differences in risk (Baker, Bradley and Taliaferro, 2014).

Another branch of research demonstrates that the low risk anomaly is linked to the downside risk on the U.S. stock market, as conventional measures of risk are unable to capture it fully. At the same time, investors are more concerned with high sensitivities to downside market movements, and low risk stocks are reported to feature lower downside risk, making them more attractive to risk-averse investors (Ang et al., 2006). This effect is distinct from other risk factors and persists even after controlling for them. The downside risk effect is confirmed to render betting against beta strategies insignificant, therefore controlling for it in asset pricing models makes the low risk anomaly disappear (Schneider, Wagner and Zechner, 2020).

Encouraged by the US findings tying the existence of the low risk anomaly to the downside risk, this study investigates the role of coskewness in European stock returns. All stocks are sorted on coskewness and beta volatility into 2x5 quintile portfolios. The low coskewness category is characterized with significantly negative skewness and negative median coskewness of -0.58. Obtained results confirm the existence of the low risk anomaly in the cross section of European stocks. Interestingly enough, the study found that alphas estimated by FF-3 and FF-5 models were only significant in the two least risky portfolios. Moreover, the less volatile portfolios exhibited much higher alphas compared to riskier portfolios, indicating that the real outperformance of less risky portfolios may be even higher than reported. This highlights the importance of considering coskewness when constructing portfolios and assessing the risk-return trade-off. On top of that, long- short portfolios yield a positive average monthly return of 0.16% for the duration of the examined period. Its alpha is found to be highly statistically significant for both models, which further validates the presence of the low risk anomaly in low coskewness stocks.

In the high coskewness category, the findings point towards the positive skewness being present in the data. As there is a higher probability that two assets in a portfolio will have positive returns in excess of market returns, it is usually favored by investors. The median coskewness of stock return with market return is 65% higher than in the previous category, implying a material difference between the two groups. Although all long portfolios demonstrate statistically significant excess returns in FF-3 and FF-5 models, their analysis signals a sizeable decrease in the low risk anomaly, since the difference in alphas for the least and most risky portfolios declines. Although all estimated alphas for the quintile portfolios are lower than in the low coskewness category, the decrease is more serious in less risky portfolios, driving the convergence of alphas. The mean return of the difference portfolio in the high coskewness category is more than four times smaller than in the low coskewness category, which also demonstrates the reduction in the size of the low risk anomaly. Despite their positive values, alphas generated by

EKONOMICKÉ ROZHĽADY – ECONOMIC REVIEW, 2023, 52(2), 81 – 103
https://doi.org/10.53465/ER.2644-7185.2023.2.81-103

both Fama-French models are substantially lower for the long-short portfolio too. In addition, neither of the excess returns for the Q1-Q5 portfolio has been proved statistically different from zero, implying that the less risky portfolios no longer outperform the riskier ones. These results further confirm the shrinkage, or even disappearance, of the low risk anomaly as the stocks' coskewness with the market increases.

Results suggest that the low risk anomaly exists in the cross section of European stocks, confirming the findings of a plethora of previous studies scrutinizing the US stock market (Haugen and Baker, 1991; Blitz and Vliet, 2007; Baker, Bradley and Wurgler, 2011; Hong and Sraer, 2016; Frazzini and Pedersen, 2014; Stambaugh, Yu and Yuan, 2015). In other words, the micro selection of low volatility stocks defined in Baker, Bradley and Taliaferro (2014) is documented to give rise to the low risk anomaly. This implies that investors in Europe can benefit from investing in less risky stocks, which reach higher risk-adjusted returns relative to their riskier counterparts. Although less volatile stocks are shown to outperform more volatile ones, this outperformance is only significant for stocks with low coskewness with the market. As the coskewness with the market increases, the outperformance of less risky stocks diminishes rapidly and the low risk anomaly disappears, which validates the contributions of Schneider, Wagner and Zechner (2020) and Ang, Chen and Xing (2006).

However, it's important to note that the low risk anomaly detected in this article is a statistical observation captured in stable market conditions and does not serve as a guarantee for future performance. One potential avenue for future research could be to investigate how the low risk anomaly reported in European stock data responds to market downturns or crises. Understanding how this anomaly performs under different market conditions could provide valuable insights for investors and help inform their investment decisions. Additionally, exploring the role of other moments, such as kurtosis, may further enhance our understanding of this phenomenon and potentially uncover additional factors that drive the outperformance of less risky stocks. Such investigations could prove useful for investors seeking to optimize their portfolios in various market conditions and risk tolerances. Nonetheless, it is crucial to keep in mind that while the low risk anomaly is an interesting factor to consider, it is not the only one. Other factors such as market conditions, industry trends and investment horizon should also be taken into account when making investment decisions.

6 Conclusion

The present paper aims to investigate the role of coskewness in the low risk anomaly on the wide range of European stocks, which are constituents of the S&P 350 Index, to obtain representative results for the whole region. With the goal of avoiding the distortions in the data caused by large, irregular price jumps and volatility fluctuations typical for market crises or downturns, the sample period from January 2010 to February 2020 is considered. With that objective in mind, double sorted 2x5 stock portfolios are assembled. At first, stocks are assigned to either high or low coskewness category based on their coskewness with market return. Afterwards, both categories are divided into equally weighted quintile portfolios conditional on their beta volatility estimated by the CAPM, and the difference portfolio of the lowest and the highest quintile portfolio. Finally, the low risk anomaly is assessed for each of the five portfolios in both coskewness categories using FF-3 and FF-5 model.

Altogether, the findings are in line with existing U.S. specific research and provide further extensions. Results confirm the robust presence of the low risk anomaly on the European stock market. Additionally, they demonstrate that accounting for coskewness in the model remarkably decreases the profitability of low risk and betting-against-beta strategies. As the coskewness becomes substantially less negative, the excess returns in such strategies decline. Reported conclusions are meaningful for both individual and institutional investors rebalancing their portfolios with the intention to maximize potential returns. To deepen the understanding of the relationship between the coskewness and the low risk anomaly, the present analysis can be advanced to the study of its magnitude across different phases of the market or economy cycle.

REFERENCES

[1] Ang, A., Chen, J., & Xing, Y. (2006). Downside Risk. The Review of Financial Studies, 19(4), 1191 – 1239. https://doi.org/10.1093/rfs/hhj035

[2] Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross- section of volatility and expected returns. The Journal of Finance, 61(1), 259 – 299. https://doi.org/10.1111/j.1540-6261.2006.00836.x

[3] Baker, M., Bradley, B., & Wurgler, J. (2011). Benchmarks as limits to arbitrage:

Understanding the low-volatility anomaly. Financial Analysts Journal, 67(1), 40 – 54. https://doi.org/10.2469/faj.v67.n1.4

[4] Baker, N. L., & Haugen, R. A. (2012). Low risk stocks outperform within all observable markets of the world. https://doi.org/10.2139/ssrn.2055431

[5] Baker, M., Bradley, B., & Taliaferro, R. (2014). The low-risk anomaly: A decomposition into micro and macro effects. Financial Analysts Journal, 70(2), 43 ─ 58. https://doi.org/10.2139/ssrn.2210003

[6] Bali, T. G., & Cakici, N. (2008). Idiosyncratic volatility and the cross section of expected returns. Journal of Financial and Quantitative Analysis, 43(1), 29 ─ 58. https://doi.org/10.1017/S002210900000274X

[7] Banz, R. W. (1981). The relationship between return and market value of common stocks. Journal of Financial Economics, 9(1), 3 – 18. https://doi.org/10.1016/0304-405x(81)90018-0

[8] Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. The Review of Financial Studies, 21(2), 785 ─ 818. https://doi.org/10.1093/rfs/hhm079

[9] Barberis, N., & Huang, M. (2008). Stocks as lotteries: The implications of probability weighting for security prices. The American Economic Review, 2066 ─ 2100. https://doi.org/10.1257/aer.98.5.2066

[10] Basu, S. (1983). The relationship between earnings yield, market value and return for NYSE common stocks: Further evidence. Journal of Financial Economics, 12(1), 129 – 156. https://doi.org/10.1016/0304-405X(83)90031-4

[11] Bernanke, B. S., Gertler, M., & Gilchrist, S. (1999). The financial accelerator in a quantitative business cycle framework, in: J. B. Taylor & M. Woodford (ed.), Handbook of Macroeconomics, 1(21), 1341 ─ 1393. https://doi.org/10.1016/S1574-0048(99)10034-X

[12] Bhandari, L. C. (1988). Debt/equity ratio and expected common stock returns: Empirical evidence. The Journal of Finance, 43(2), 507 – 528. https://doi.org/10.1111/j.1540-6261.1988.tb03952.x

[13] Black, F., Jensen, M. C., & Scholes, M. S. (1972). The Capital Asset Pricing Model: Some Empirical Tests. In M. C. Jensen (ed.), Studies in the Theory of Capital Markets, 79 ─ 121. New York: Praeger Publishers Inc.

[14] Blitz, D., & van Vliet, P. (2007). The Volatility Effect: Lower Risk Without Lower Return. Journal of Portfolio Management, 102 ─ 113. https://doi.org/10.3905/jpm.2007.698039

[15] Breeden, D. T., Gibbons, M. R., & Litzenberger, R. H. (1989). Empirical Test of the Consumption-Oriented CAPM. The Journal of Finance, 44(2), 231 – 262. https://doi.org/10.2307/2328589

[16] Chen, Y., She, C., Wu, Q., & Wang, H. (2022). The ineffectiveness of capital asset pricing model and its possible solutions. In 2022 7th International Conference on Financial Innovation and Economic Development (ICFIED 2022) (pp. 105 ─ 111). Atlantis Press. https://doi.org/10.2991/aebmr.k.220307.017

[17] Cont, R. (2001). Empirical properties of asset returns: stylized facts and statistical issues. Quantitative Finance, 1(2), 223 ─ 236.
https://doi.org/10.1088/1469-7688/1/2/304

[18] Dempsey, M. (2013). The capital asset pricing model (CAPM): The history of a failed revolutionary idea in finance? Abacus, 49, 7 ─ 23.
https://doi.org/10.1111/j.1467-6281.2012.00379.x

[19] Falkenstein, E. (2009). Risk and Return in General: Theory and Evidence. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.1420356

[20] Falkenstein, E. G. (1996). Preferences for stock characteristics as revealed by mutual fund portfolio holdings. The Journal of Finance, 51(1), 111 ─ 135.
https://doi.org/10.1111/j.1540-6261.1996.tb05204.x

[21] Fama, E.F. and French, K.R. (1993) Common Risk Factors in the Returns on Stocks and Bonds. Journal of Financial Economics, 33, 3 ─ 56.
https://doi.org/10.1016/0304-405X(93)90023-5

[22] Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. Journal of Political Economy, 81(3), 607 – 636.
https://doi.org/10.1086/260061

[23] Fama, E. F., & French, K. R. (1989). Business conditions and expected returns on stocks and bonds. Journal of Financial Economics, 25(1), 23 ─ 49.
https://doi.org/10.1016/0304-405X(89)90095-0

[24] Fama, E.F., & French, K. R. (1992). The cross- section of expected stock returns. The Journal of Finance, 47(2), 427 – 465.
https://doi.org/10.1111/j.1540-6261.1992.tb04398.x

[25] Fama, E. F., & French, K. R. (2004). The capital asset pricing model: Theory and evidence. Journal of Economic Perspectives, 18(3), 25 ─ 46.
https://doi.org/10.1257/0895330042162430

[26] Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. Journal of Financial Economics, 116(1), 1 – 22.
https://doi.org/10.1016/j.jfineco.2014.10.010

[27] Frazzini, A., & Pedersen, L. H. (2014). Betting against beta. Journal of Financial Economics, 111(1), 1 – 25.
https://doi.org/10.1016/j.jfineco.2013.10.005

[28] Fu, F. (2009). Idiosyncratic risk and the cross-section of expected stock returns. Journal of Financial Economics, 91, 24 ─ 37.
https://doi.org/10.1016/j.jfineco.2008.02.003

[29] Hansen, L. P., & Jagannathan, R. (1991). Implications of Security Market Data for Models of Dynamic Economies. Journal of Political Economy, 99(2), 225 – 262. https://doi.org/10.1086/261749

[30] Haugen, R. and Baker, N. (1991) The Efficient Market Inefficiency of Capitalization-Weighted Stock Portfolios. Journal of Portfolio Management, 17, 35 ─ 40. https://doi.org/10.3905/jpm.1991.409335

[31] Hong, H., & Sraer, D. A. (2016). Speculative betas. The Journal of Finance, 71(5), 2095 ─ 2144. https://doi.org/10.1111/jofi.12431

[32] Joshipura, M., & Joshipura, N. (2015). Risk anomaly: A review of literature. Asian Journal of Finance & Accounting, 7(2), 138. https://doi.org/10.5296/ajfa.v7i2.8262

[33] Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision making under risk. Econometrica, 47, 263 ─ 291. https://doi.org/10.2307/1914185

[34] Kim, D. H., & Orphanides, A. (2007). The Bond Market Term Premium: What is it, and How Can We Measure it? BIS Quarterly Review.

[35] Kumar, A. (2009). Who Gambles in the Stock Market? The Journal of Finance, 64, 1889 ─ 1933. https://doi.org/10.1111/j.1540-6261.2009.01483.x

[36] Lewinski, P. (2015). Commentary: Extensional Versus Intuitive Reasoning: The Conjunction Fallacy in Probability Judgment. Frontiers in Psychology, 6. https://doi.org/10.3389/fpsyg.2015.01832

[37] Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. The Review of Economics and Statistics, 47, 13 ─ 37. https://doi.org/10.2307/1924119

[38] Makovský, P. (2022). Are Term Premiums Predictable in Central European Countries? The Forward Rates Agreements (FRA) Application. Eastern European Economics. 1 ─ 32. https://doi.org/10.1080/00128775.2022.2102507

[39] Mitton, T., & Vorkink, K. (2007). Equilibrium underdiversification and the preference for skewness. The Review of Financial Studies, 20(4), 1255 ─ 1288. https://doi.org/10.1093/revfin/hhm011

[40] Rosenberg, B., Reid, K., & Lanstein, R. (1985). Persuasive evidence of market inefficiency. The Journal of Portfolio Management, 11(3), 9 – 16. https://doi.org/10.3905/jpm.1985.409007

[41] S&P. Dow Jones Indices. Available at: https://www.spglobal.com/spdji/en/indices/equity/sp-europe-350/#data

[42] Samuelson, P. A. (1998). Summing up on business cycles: opening address. In Conference Series-Federal Reserve Bank of Boston (Vol. 42, pp. 33 ─ 36). Federal Reserve Bank of Boston.

[43] Schneider, P., Wagner, C., & Zechner, J. (2020). Low-risk anomalies? The Journal of

Finance, 75(5), 2673 – 2718. https://doi.org/10.1111/jofi.12910

[44] Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. The Journal of Finance, 19(3), 425. https://doi.org/10.2307/2977928

[45] Stambaugh, R. F., Yu, J., & Yuan, Y. (2015). Arbitrage Asymmetry and the Idiosyncratic Volatility Puzzle. Journal of Finance, 70, 1903 ─ 1948.
https://doi.org/10.1111/jofi.12286

[46] Vasicek, O. A. (1973). A note on using cross- sectional information in Bayesian estimation of security betas. The Journal of Finance, 28(5), 1233 – 1239.
https://doi.org/10.1111/j.1540-6261.1973.tb01452.x