5. LOW RISK ANOMALY IN THE CEE STOCK MARKETS

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Abstract

Using sorting and cross section, the study investigates the low risk anomaly in the CEE markets. The research examines four risk measures (beta, standard deviation, VaR, idiosyncratic volatility) and is based on performance of over 1.000 stocks from 11 countries for the years 2002-2014. The stock returns are non-monotonically related to a systematic component of risk and negatively related to an idiosyncratic component of risk. The top beta stocks underperform the market, while the portfolios with a low VaR or idiosyncratic volatility have positive abnormal returns, but some of the outperformance is explained by the momentum phenomenon. The VaR and idiosyncratic risk effects are largely reversed for microcaps. The risk-based strategies in the CEE to some extend comove with their international counterparts. Finally, the low-risk stocks do not provide an effective hedge against market distress.

Keywords: low risk anomaly, volatility anomaly, beta anomaly, Central and Eastern Europe, asset pricing, CEE stock markets, standard deviation, value at risk, idiosyncratic volatility, CAPM, value effect, size effect, momentum effect, multifactor models, market distress, investment strategies

JEL Classification: G11, G12, G15

I. Introduction

Are the safe stocks better investments than the risky ones? This question is one of the most profound in the financial literature. The crucial implication of the capital asset pricing model (CAPM) of Sharpe (1965), Lintner (1965), and Black (1972) is that there is a positive linear relationship between a stock systematic market risk measured by their betas. Initial tests of US stock market generally confirmed this relationship (Black, Jensen&Scholes, 1972; Fama&MacBeth, 1973; Blume, 1970, Miller&Scholes, 1972; Blume&Friend, 1973). The CAPM is built on a modern portfolio theory which suggests that investors diversify risk by holding a portfolio of stocks. However, for various reasons, the investors' portfolios are often not well diversified (Goetzman&Kumar, 2008). Assuming underdiversification, some theories predict that also idiosyncratic risk should be positively correlated with the expected returns in the cross-section (Levy,

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1978; Merton, 1987; Malkiel&Xu, 2004). Papers by Tinic and West (1986), Malkiel and Xu (1997), and Fu (2009) support the theoretical models and provide empirical evidence that portfolios with higher idiosyncratic volatility have higher average returns. As the systematic and idiosyncratic risk sums up to total volatility, also this parameter should be positively related to returns. Indeed, a few studies seem to confirm this preposition and show that risk measures related to total variability are positively correlated with the expected returns. For example, Bali and Cakici (2004) find that there is a strong positive relationship between average returns and value at risk, which is robust for different investment horizons and loss probability levels. Chen *et al.* (2009) confirm this observation in an emerging stock market in Taiwan. Additionally Ang *et al.* (2006a) focus on downside risk and show that the cross section of stock returns reflects a significant downside risk premium.

Surprisingly, numerous papers appear to provide results which totally contradict the above-described theories. This phenomenon has been called “a low risk anomaly” (Ang 2014, p. 332), and is a combination of three effects, with the third as a consequence of the first two:

1. Volatility is negatively related to future returns.
2. Realized beta is negatively related to future returns.
3. Minimum variance portfolios outperform the market.

The evidence of the anomaly has been mounting due to many studies throughout over forty years since the initial discovery in early ’70s. In their paper of 1970, Friend and Blume examined stock returns for years 1960-1968 with CAPM beta and volatility and concluded that the “risk-adjusted performance is dependent on risk. The relationship is inverse and highly significant (Friend&Blume, 1970). Shortly after, this observation was confirmed by Haugen and Heins (1975). The authors studied the US stock market in the period 1926-1971 and concluded that “over the long run, stock portfolios with lesser variance in monthly returns have experienced greater average returns than ‘riskier’ counterparts” (Haugen&Heins, 1975). Moreover, it appears that also the market beta is far from a perfect predictor of stock returns. Probably the first challenge was in the paper by Jensen, Black and Scholes (1972). These authors argue that although the relation between beta and returns is positive, it is “too flat” as compared to the CAPM predictions, which results in abnormal returns on low-beta stocks. Finally, an influential paper by Fama and French (1992) struck at the heart of CAPM by finding that after accounting for size and value effects, “beta shows no power to explain average returns” (Fama&French, 1992). These studies sparked a proliferation of further research providing evidence for the low-risk anomaly for the US stock market (Haugen&Baker, 1991; Chan *et al.*, 1999; Jangannathan&Ma, 2003; Clarke *et al.*, 2006; Ang *et al.*, 2006b, Baker *et al.*, 2011) and for other global equity markets (Blitz *et al.*, 2007, Ang *et al.*, 2009; Baker&Haugen, 2012; Blitz *et al.*, 2013).

Some recent studies offer also new asset pricing factors based on the risk anomaly. Frazzini and Pedersen (2014) propose a betting-against-beta (BAB) factor which refers to returns on a leveraged portfolio of low-beta stocks hedged with high-beta stock. Ang (2014, p. 339) constructs a volatility factor, similar in design, but based on a standard deviation rather than the market beta. These factors have not only deliver long-term positive abnormal returns, but also even do a good job in explaining alphas of Warren's Buffet investment portfolio (Frazzini *et al.,* 2013).

The low risk anomaly seems to be so astonishingly simple and powerful, that Robin Greenwood, a professor at Harvard Business School, called it in 2010 "the Mother of all inefficiencies" (Ang, 2014, p. 332). Nevertheless, it is still to large extent a mystery why it actually exists. Financial literature offers a few explanations. Some papers point out data mining concerns and indicate the sensitivity in the results illiquidity effects and portfolio weighting methods (Bali&Cakici, 2008; Han&Lesmond, 2011). However, probably the best counterargument is the anomaly's pervasiveness. The low risk effect has been detected in international stocks, sovereign and corporate bonds, credit derivatives, currencies (Frazzini&Pedersen, 2011), or even commodity (Blitz&de Groot, 2013) and option markets (Cao&Han, 2013). Frazzini and Pedersen (2014) try to explain the beta anomaly with leverage constraints, arguing that investors who cannot borrow money create excessive demand for high-beta stocks. However, the leverage story explains only low returns of risky stocks, and leaves the abnormal positive returns of safe stocks unexplained (Ang, 2014, p. 342). Ang (2014, pp. 342-343) blames agency problems for the risk anomaly and suggests that institutional investors have to stick to a benchmark and, therefore, are unable to take bets on extreme-beta stocks, which are characterized by a large tracking error. Furthermore, a few studies suggest that the underpricing of safe stocks and overpricing of risky stocks may be simply a result of investors' preferred habitats (Boyer *et al.*, 2010; Bali *et al.*, 2011; Ilmanen, 2012). Finally, Hou and Loh (2012) comprehensively examine plenty of explanations and find that even groups of them taken together are not able to explain more than a half of the anomaly.

The aim of this paper is to investigate the low risk anomaly in the Central and Eastern European emerging markets. The study contributes in a few ways. First, this is the first study which comprehensively investigates the anomaly in the CEE markets. Second, the research examines whether the phenomenon is equally strong across different sizes of companies. Third, it was examined whether investors following the risk-driven strategies could benefit from a "flight to quality" in times of market distress. Fourth, the paper tests the market integration by examining the correlations between local and global risk-based factors. Finally, the novelty is in the methods. This is the first study of this kind for the CEE markets, which controls for size, value, and momentum effects, and for the anomalous performance of micro-caps.

The study is based on stock-level data from eleven CEE countries (Bulgaria, Croatia, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, Slovenia) for the years 2002-2014. Using sorting and cross-section, the paper tests the performance of risk-based portfolios with various asset pricing models.

The principal findings could be summarized as follows. First, I detect an uneven and non-monotonic relationship between excess returns and systematic component of risk, and simultaneously a negative relationship with the idiosyncratic component of risk. The stocks with low value at risk or idiosyncratic volatility deliver significant abnormal returns, but some of the outperformance is explained with the momentum effect. The phenomenon is reversed for microcaps, and in their case the risky stocks are associated with higher returns. The CEE risk-based strategies to some extent comove with their global and European counterparts. Finally, the low-risk stocks do not provide effective, significant, and robust hedge against market distress.

The rest of the paper is organized as follows. Section 2 describes the data and research methods used. The findings are presented in Section 3 and the last section brings the conclusions.

II. Research Methods and Data Sources

The paper examines two hypotheses. First, it was tested whether the risk is a valid determinant of cross-sectional variation in the CEE emerging markets stock returns. The focus was placed on four distinct risk indicators: market beta, standard deviation, value at risk, and idiosyncratic variance. Second, it was investigated whether investors exhibit "flight to quality" in the sense that the low-risk stocks perform better in times of market distress than the high-risk stocks. Thus, I built value-weighted portfolios from sorts of stocks' characteristics and evaluated their performance with multifactor asset pricing models. Additionally, I also built ad-hoc asset pricing factors related to quality characteristics and regressed their intercepts from asset-pricing models on market distress proxies.

The Playing Field

This study was based on stock-level data obtained from Bloomberg. Both listed and delisted companies were considered in order to avoid any form of survivorship bias. Also, monthly time-series were implemented as they provide the sufficient number of observations (147) to ensure the power of conducted tests and allow the avoidance of excessive exposure to micro-structure issues (De Moor&Sercu, 2013a). The investigated returns were adjusted corporate actions (splits, reverse splits, issuance rights, etc.) and cash distributions to investors (dividends). The sample period runs from April 2002 to June 2014. The late start date in April 2002 was chosen in order to avoid a small sample bias and cover a broad range of companies. The initial sample includes 1307 stocks from 11 Central and Eastern European countries. However, in line with other studies on asset pricing, the data was screened with two crucial filters. First, I winsorised the return data by discarding stocks which delivered 2.5% of the highest single-month returns and 2.5% of the most extreme negative returns (both groups overlap to some extent). This method, aimed at eliminating miscalculated returns from a database, is employed for example by Rouwenhorst (1999), or Chui *et al*. (2010). Second, in order to screen out any invalid data, I removed the stocks top percentile of stock with extreme risk characteristics. The elimination of observations with suspiciously extreme values is an approach taken for instance by Lewellen (2011) or Novy-Marx (2013). The initial sample consists of companies from Bulgaria (128), Croatia (153), Czech Republic (14), Estonia (16), Hungary (39), Latvia (24), Lithuania (28), Poland (648), Romania (188), Slovakia (25), and Slovenia (44)[2]. A company is included in the sample in month *t* as it is when it is possible to compute its size at the end of month *t-1*, return in month *t*, and an appropriate risk proxy at the end of month *t-1*. The exact sample size varies slightly for the different quality indicators and its time-series average equals 700 for beta, 703 for standard deviation, 703 for value at risk, and 700 for idiosyncratic volatility. The initial market data are collected in local currencies, however,

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[2] *The precise definition of CEE countries may vary, so I followed the OECD glossary: http://stats.oecd.org/glossary/detail.asp?ID=303 (accessed 8 October 2014).*

I agree with Liew and Vassalou (2000), and Bali *et al*. (2013) that comparisons using different currency units could be misleading. This is especially true in the CEE developing countries, where inflation and risk-free rates are sometimes very high and differ significantly across markets. Therefore, I follow the approach of Liu *et al.* (2011), Bekaert *et al.* (2007), or Brown *et al.* (2008), and denominate all data in euro to obtain polled international results. In order to be consistent with the euro approach, excess returns are computed over the one month Euribor rate in this study.

Risk-Sorted Portfolios and Asset Pricing Models

In this paper, the performance of portfolios of various risk levels was investigated. Thus, in each month *t*, I ranked all stocks against their risk indicator. Four distinct risk proxies were used: beta, standard deviation, value at risk, and idiosyncratic volatility. The beta is the regression coefficient of returns of an examined portfolio on the returns on MSCI Eastern Europe Ex. Russia Total Return EUR Index. The standard deviation is a simple standard deviation of returns. The value at risk is measured as the empirical 5th percentile of historical observations. Idiosyncratic volatility is the stock's variance unexplained by a regression of its returns on the returns of MSCI Eastern Europe Ex. Russia Total Return EUR Index. I used 12 to 24 months horizon (as available) to estimate the risk proxies and all computations were based on monthly time-series. Next, five subgroups were formed. For each indicator I defined the 20th, 40th, 60th and 80th percentiles as breakpoints and, thus, obtained five subgroups. Finally, I value-weighted the stocks in the respective groups to obtain the portfolios[3].

The risk portfolios' excess returns were finally tested against three distinct asset pricing models. The first one is the classical Capital Asset Pricing Model (Sharpe, 1964, Lintner, 1965; Mossin, 1966). The model assumes that asset returns depend only on the market portfolio and is described by a regression equation below.

$$R_{i,t} = \alpha_i + R_{f,t} + \beta_{rm,i} \cdot \left(R_{mt} - R_{f,t}\right) + \varepsilon_{i,t}, \quad (1)$$

where: $R_{i,t}$, $R_{m,t}$ and $R_{f,t}$ are returns on the analyzed asset *i*, market portfolio and risk-free returns at time *t*, and α_i and $\beta_{rm,I}$ are regression parameters. The α_i intercept measures the average abnormal return (the so-called Jensen-alpha).

The second model is the Fama-French three factor model (Fama&French, 1993):

$$R_{i,t} = \alpha_i + R_{f,t} + \beta_{rm,i} \cdot \left(R_{m,t} - R_{f,t}\right) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \varepsilon_{i,t}, \quad (2)$$

where: $\beta_{rm,i}$, $\beta_{SMB,i}$, $\beta_{HML,i}$, andα_i ere the estimated parameters of the model. $\beta_{rm,i}$ is analogical to the CAPM beta, but it is not equal to it. The $\beta_{SMB,i}$, $\beta_{HML,i}$ are exposed to SMB_t (small minus big) and HML_t (high minus low) risk factors, which denote returns from zero-cost arbitrage portfolios. SMB_t is the difference in returns on diversified portfolios of small and large caps at time *t*, while $HML_t$is in general difference in returns on portfolios of diversified value (high B/V) and growth (low B/V) stocks. In other words,

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[3] In this paper, a quintile portfolio from a sort of stocks with the highest risk indicators is referred to as the most risky or simply a top portfolio, and a quintile portfolio from a sort of stocks with the lowest risk indicators is referred to as the safest portfolio or simply a bottom portfolio.

SMB and HML are returns on zero-cost market-neutral long/short portfolios formed based on size and value characteristics.

The third model is the four-factor model, which was originally introduced by Carhart (1997) and its corresponding regression equation is:

$$R_{i,t} = \alpha_i + R_{f,t} + \beta_{rm,i} \cdot \left(R_{m,t} - R_{f,t}\right) + \beta_{SMB,i} \cdot SMB_t + \beta_{HML,i} \cdot HML_t + \beta_{WML,i} \cdot WML_t + \varepsilon_{i,t}. \qquad (3)$$

The model additionally incorporates the momentum returns measured by returns on so-called winner and loser portfolios, which were used in the initial studies of this anomaly (Jegadeesh&Titman, 1993). The $WML_{,t}$ (winners minus losers) denotes the difference between returns on diversified winner and loser portfolios over the previous year.

The validity of the above-described multifactor asset-pricing models for the CEE markets was confirmed both for the entire region (Zaremba, 2015; Zaremba & Konieczka, 2015) and within single CEE countries (Tudor, 2009; Borys & Zemcik, 2011; Waszczuk, 2013; Anghel *et al.*, 2015).

I was also interested in examining whether there are any interactions between the quality and market capitalization of the investigated companies. To this end, I formed double-sorted portfolios from stocks sorted on the risk proxies and size. The computation procedure was consistent with similar studies of asset pricing (Fama&French, 2012). At the end of each month *t-1*, all stocks were sorted against size and quality. I defined the 20th, 40th, 60th and 80th percentiles as the size breakpoints. The five quality breakpoints were defined in the same way as for the single-sorted portfolios. The intersection of the independent 5x5 size sorts and quality produced 25 portfolios. Finally, I value-weighted the sorts to obtain portfolios, which were evaluated in a similar fashion to single sorted portfolios.

An established observation in the financial literature is that results of cross-sectional asset pricing tests could be seriously impacted and distorted by anomalous behavior of tiny stocks (Fama&French 2008, De Moor&Sercu 2013b, Waszczuk, 2013). This is especially true when it comes to the CEE market, which is heavily populated with micro-caps. Zaremba (2015) notices that in June 2014 the capitalization of over 50% of stock companies in CEE countries was 10 million euro or less and for almost 20% it was even smaller than 2 million euro. I tried to address this problem in two ways. First, besides the 5x5 double sorts on value, size and momentum, I additionally tested the 4x5 sort. The 5x5 results included all five size quintiles, while the 4x5 results excluded micro-cap portfolios (the quintiles of the smallest stocks). Second, following the suggestions of De Moor&Sercu (2013a), I used the cross-sectional model, which accounted for the risk of micro-cap companies. Specifically, I implemented the model proposed by Zaremba (2015), which replaces the small-minus-big (SMB) factor in the Fama-French three-factor (1993) and Carhart's four-factor (1997) models with the micro-minus-rest factor (MMR). The MMR factor returns are returns on a zero-cost portfolio, which is long in the quintile of the smallest stocks and short in the equal-average of the remaining quintile portfolios. In other words, the additional models had the following forms:

$$R_{i,t} = \alpha_i + R_{f,t} + \beta_{rm,i} \cdot \left(R_{m,t} - R_{f,t}\right) + \beta_{MMR,i} \cdot MMR_t + \beta_{HML,i} \cdot HML_t + \varepsilon_{i,t}. \qquad (4)$$

$$R_{i,t} = \alpha_i + R_{f,t} + \beta_{rm,i} \cdot (R_{m,t} - R_{f,t}) + \beta_{MMR,i} \cdot MMR_t + \beta_{HML,i} \cdot HML_t + \\ + \beta_{WML,i} \cdot WML_t + \varepsilon_{i,t}. \quad (5)$$

All regression models discussed in this paper are estimated using OLS and tested in a parametric way. In order to test whether the intercepts are statistically different from zero in a group of portfolios, I evaluated them with the popular GRS test statistic suggested by Gibbons *et al.* (1989). The test statistic is defined as:

$$GRS = \left(\frac{T}{N}\right) \cdot \left(\frac{T-N-L}{T-L-1}\right) \cdot \hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha} \cdot \left[1 + E_T(f)'\hat{\Omega}^{-1}E_T(f)\right]^{-1} \sim F_{N,T-N-K}, \quad (6)$$

where: *T* is the length of the time-series (sample size), *N* is the number of portfolios to be explained in the examined group and *L* denotes the number of explanatory factors. $E_T(f)$ is the vector of expected returns to asset pricing factors, $\hat{\Omega}$ is the covariance matrix of the asset pricing factors, $\hat{\alpha}$ is the vector of regression intercepts and $\hat{\Sigma}$ is a residual covariance matrix in the sample. The test's critical values are obtained from Fisher's distribution with *N* and *T-N-L* degrees of freedom.

Finally, I performed a battery of robustness checks. First, some studies suggest that various market anomalies may be influenced by the January effect, which is defined as the tendency of stocks to perform better in January than in the remaining months of the year. The issue is investigated, for example, by Horowitz *et al*. (2000) for size, Davis (1994) for value, Loughran (1997) for both or Yao (2012) for the momentum effect. In order to test this seasonality, I filtered out observations corresponding to Januaries and repeated the analysis without them. Second, analogously to numerous studies on asset pricing, I also computed the equally-weighted portfolios. I did not continue with analysis, as this weighting scheme may distort the results (Fama&French 1998, Lewellen 2011) and results of implicit returns on rebalancing (Willenbrock, 2011). Third, I also tested whether the results hold not only for EUR, but for USD and JPY as well. I detected no significant differences.

Performance under Market Distress

In order to test the performance of safe and risky stocks during market distress and the predictive abilities of the quality spread, I formed ad-hoc asset pricing factors in the first place. Their computation procedure was consistent with similar studies of asset pricing (e.g. Fama&French, 1993; Asness&Frazzini, 2013). The explanatory factor returns were constructed from 2x3 sorts on size and risk. At the end of each month *t*, all the stocks were sorted on size and risk. Big stocks and small stocks were defined as those with the market value above and below median in a given month *t*, correspondingly. The risk breakpoints in the 2x3 sorts were the 30th and 70th percentiles of the given risk characteristics (beta, standard deviation, value at risk, idiosyncratic volatility) for all the stocks at time *t*. The intersection of the independent 2x3 sorts on size and risk produced six portfolios, SS, SN, SR, BS, BN, and BR, where S and B indicated small or big and S, N, and R indicated safe, neutral, and risky stocks (bottom 30%, middle 40%, and top 30% of a given quality indicator), respectively. Next, the monthly value-weighted returns for all the 6 portfolios were computed. Finally, the given risk factor was the difference between the equal-weighted average of returns on the risky portfolios (BQ, SQ) and the equal-weighted average of returns on the safe portfolios (BJ, SJ).

In order to test the performance of quality stocks during market distress, I followed the approach of Asness *et al*. (2014) and ran a regression of four-factor model intercepts. However, contrary to Asness *et al*. (2014), I used five distinct distress indicators instead of the market risk only. The regression equation had the following form:

$$\ln(1+\alpha_{i,t}) = \beta_{0,i} + \beta_{1,i}\ln\left(\frac{x_{j,t}}{x_{j,t-1}}\right) + \varepsilon_{i,t}, \quad (7)$$

where: $\alpha_{i,t}$ are *t*-month alphas from a four-factor asset pricing model described in the equation (3) of a zero-cost quality factor portfolio *i*, $\beta_{0,I}$ and $\beta_{1,I}$ are estimated model parameters, $\varepsilon_{i,t}$ is a zero mean disturbance term and $x_{j,t}$ is a value of a proxy of market distress (a crisis proxy) *j* in period *t*. To examine the resilience of the results, beside the Mkt-Rf returns, I used four different crisis proxies. To be consistent with the euro-convention, all the proxies were expressed in euros and referred to the Eurozone. As the representation of general financial market liquidity, I employed 3-month EUR TED spread, which is the difference between the 3-month Euribor rate and the yield on Eurozone benchmark 3-month treasury bills. The expected market volatility was represented by the Euro Stoxx 50 Volatility Index, a popular measure of the implied volatility of index options. BBB spreads of Eurozone 10-year corporate bonds over 10-year benchmark treasury bonds were proxies for the credit risk. Finally, the term-spread risk was the difference between yields of 10- and 2-year benchmark Eurozone treasury bonds[4].

III. Results and Discussion

This section presents and discusses the performance of risk-sorted portfolios and reports their behavior during market distress.

Table 1 presents the basic statistics of the value-weighted and equal-weighted portfolios of risk-sorted stocks. Focusing on the beta-sorted value-weighted portfolios first, no vivid return pattern is visible. Neither the low-beta stocks, nor the high beta stocks produce superior returns, and the market-broad pattern is rather uneven. The top-beta stocks outperform bottom-beta stocks by a small 0.22% monthly, however they are much more risky (standard deviation of 9.41% monthly as compared to 4.23% for the safest stocks), so the Sharpe ratio is actually a little higher for the safe stocks.

[4] For the credit, liquidity, term, and volatility risk, I use a following functional form of the equation (8): $\ln(1+\alpha_{i,t}) = \beta_{0,i} + \beta_{1,i}\ln(1 + x_{j,t} - x_{j,t-1}) + \varepsilon_{i,t}$. The difference stems from the nature of distress proxies.

Table 1

Excess Returns on Quintile Portfolios Sorted on Risk

	Value weighted portfolios							Equally weighted portfolios					
	Bottom	2	3	4	Top	T-B		Bottom	2	3	4	Top	T-B
Beta													
Mean	0.38	1.12	0.98	1.17	0.60	0.22		2.17	1.97	1.70	1.74	1.74	-0.43
Mean - ex. Jan.	0.23	1.03	0.96	1.34	0.70	0.47		2.04	1.69	1.43	1.51	1.49	-0.55
Standard dev.	4.32	4.76	5.78	7.39	9.41	8.05		4.81	5.53	6.50	7.20	8.78	7.04
Sharpe ratio	0.09	0.24	0.17	0.16	0.06	0.03		0.45	0.36	0.26	0.24	0.20	-0.06
Mean mkt. cap.	70	153	252	357	448								
Standard deviation													
Mean	0.81	0.72	1.26	1.03	1.11	0.30		0.88	1.28	1.46	2.32	3.70	2.83
Mean - ex. Jan.	0.90	0.85	1.30	0.86	0.72	-0.18		0.80	1.11	1.20	2.00	3.35	2.55
Standard dev.	4.77	6.76	8.57	8.80	9.84	7.83		3.80	5.72	6.37	7.57	8.51	6.62
Sharpe ratio	0.17	0.11	0.15	0.12	0.11	0.04		0.23	0.22	0.23	0.31	0.44	0.43
Mean mkt. cap.	434	452	227	130	32								
Value at risk													
Mean	1.14	0.66	0.56	0.95	0.81	-0.33		1.58	1.09	1.31	1.55	3.79	2.22
Mean - ex. Jan.	1.07	0.77	0.67	0.94	0.37	-0.70		1.54	0.95	1.10	1.18	3.39	1.85
Standard dev.	5.44	6.88	8.00	9.09	11.00	8.77		4.16	5.59	6.24	7.64	8.42	6.47
Sharpe ratio	0.21	0.10	0.07	0.10	0.07	-0.04		0.38	0.20	0.21	0.20	0.45	0.34
Mean mkt. cap.	444	341	308	153	33								
Idiosyncratic volatility													
Mean	0.84	1.21	0.80	1.08	0.19	-0.65		1.00	1.21	1.61	2.47	3.04	2.04
Mean - ex. Jan.	0.98	1.16	0.64	0.80	-0.32	-1.30		0.99	0.94	1.40	2.03	2.80	1.81
Standard dev.	6.46	7.19	7.46	7.47	8.83	7.47		4.29	6.01	6.38	7.20	7.79	5.40
Sharpe ratio	0.13	0.17	0.11	0.14	0.02	-0.09		0.23	0.20	0.25	0.34	0.39	0.38
Mean mkt. cap.	865	213	122	50	28								

Note: The table reports means, standard deviations, and Sharpe ratios of excess returns on quintile portfolios sorted on four distinct risk indicators: beta, standard deviation, value at risk, and idiosyncratic volatility. "Bottom" denotes companies with the lowest risk and "top" with the highest risk. "T-B" is a zero-cost portfolio, which is long the most risky stocks ("top") and short in the safest stocks ("bottom"). The means and standard deviations are expressed in percent, while market capitalizations are in million euros.

Furthermore, the companies with low beta are considerably smaller. The average market capitalization is only 70 million EUR, contrary to 448 million in the case of riskiest companies. Summing up, the initial scanning of the behavior of beta-sorted portfolios in the CEE markets does not confirm the implications of the CAPM (Sharpe, 1964; Lintner, 1965; Mossin, 1966). The equal weighting scheme shows quite different results. The low-beta stocks deliver high returns and the smaller is the beta, the higher are the Sharpe ratios. However, these results should be treated with caution, as some of the profits may stem from the return to rebalancing, which is usually higher for assets with high idiosyncratic risk and low correlations (Erb&Harvey, 2006).

The sorting of portfolios according to their standard deviation shows slightly higher returns for the riskiest firms. The value-weighted portfolio with the highest standard deviation delivers average monthly excess return of 1.11%, while the safest stocks have excess returns equal to 0.81%. This pattern is confirmed by the equal-weighting scheme, but with much higher cross-sectional variation. The riskiest stocks are also the smallest in this case. Interestingly, again in the case of value weighting the Sharpe ratios are actually higher for the safe companies. Finally, it is important to note that exclusion of Januaries from the sample alter the results, and after this operation the safe stocks have higher excess returns. To sum up, the initial outcomes of the statistical analysis are rather mixed and similar to results of Fama and MacBeth (1970), who found that the volatility is insignificant. The data in Table 1 do not favor either the implications of the modern portfolio theory, or the low risk anomaly presented for example by Ang (2014, p. 334).

What is interesting, the outcomes of the analysis of sorting according to VaR and idiosyncratic volatility show a reverse pattern as compared to beta or standard deviation. In both cases, generally the safe stocks have higher average excess returns (with and without Januaries) and are associated with higher Sharpe ratios, although the cross-sectional pattern is not very monotonic. Thus, the presented results generally contradict the evidence of Tinic and West (1986), Malkiel and Xu (1997), and Fu (2009), who support the thesis that higher idiosyncratic risk is rewarded with a risk premium, and are also not in line with computations of Bali and Cakici (2004), who argue that the higher value at risk is accompanied by higher returns. Again, the cross-section of market capitalization indicates that these are the smallest companies which are the riskiest. Thus, it is possible that application of the Fama-French three-factor model (1993) would further amplify the abnormal returns.

Generally, what is suggested in Table 1 is that the risk seems to be composed of two components, which are differently related to the expected returns. The systematic component (beta) is positively (but non-monotonically) related and the idiosyncratic component (idiosyncratic volatility) is negatively related. Dependent on which component prevails in a given risk measure, the final relation is positive or negative.

Table 2 reports the intercepts of models to explain monthly returns on value-weighted portfolios investigated in Table 1. The Table provides additional interesting insights. First, it is important to point out that, on the basis of the GRS tests, no cross-sectional patterns are detected at the 95% confidence level. In other words, the outcomes of this study may support some theory, but are not conclusive. The application of the CAPM model to the beta sorted portfolios confirms the observation of Black, Jensen, and Scholes (1972), and Haugen and Heins (1975) that the risk-adjusted performance is dependent on risk. The top-beta stock have significant negative excess returns of -0.57% monthly and the second portfolio of lowest betas have significant positive excess returns of 0.64.% monthly (the GRS test statistic is significant at 90% level). This observation is consistent with the studies of Baker *et al*. (2014) and Blitz *et al.* (2013). However, these authors do not make an attept to adjust the abnormal return for the additional asset pricing anomalies, like value, size and momentum effects. The intercepts are somewhat diminished after the application of the three-factor model, but the negative alphas of top beta stocks remain significant. Finally, the application of the four-factor model erases the abnormal returns. In other words, it appears that the momentum factor is able to explain the low-risk anomaly in the CEE market, at least when the risk is proxied by a market beta.

Table 2

Intercepts from Asset-pricing Models to Explain Monthly Excess Returns on Portfolios from Sorts on Risk

	Bottom	2	3	4	Top	T-B		GRS	p-value
Beta									
CAPM	0.01	0.64	0.31	0.24	-0.57	-0.58		2.12	6.70
	(0.03)	*(2.51)*	*(1.32)*	*(1.25)*	*(-2.16)*	*(-1.32)*			
Three-factor	-0.19	0.40	0.21	0.14	-0.55	-0.37		1.37	24.07
	(-0.66)	*(1.55)*	*(0.88)*	*(0.68)*	*(-1.95)*	*(-0.80)*			
Four-factor	-0.55	-0.08	-0.06	0.19	0.14	0.69		0.82	53.54
	(-1.84)	*(-0.30)*	*(-0.24)*	*(0.88)*	*(0.51)*	*(1.53)*			
Standard deviation									
CAPM	0.23	-0.15	0.18	-0.03	0.15	-0.08		0.84	52.10
	(1.41)	*(-1.05)*	*(0.79)*	*(-0.10)*	*(0.26)*	*(-0.13)*			
Three-factor	0.24	0.01	-0.01	-0.13	-0.41	-0.65		0.51	76.68
	(1.40)	*(0.10)*	*(-0.02)*	*(-0.39)*	*(-0.77)*	*(-1.09)*			
Four-factor	-0.01	-0.03	0.04	0.22	-0.17	-0.17		0.11	99.05
	(-0.04)	*(-0.18)*	*(0.15)*	*(0.60)*	*(-0.30)*	*(-0.26)*			
Value at risk									
CAPM	0.48	-0.21	-0.44	-0.16	-0.29	-0.77		1.70	13.91
	(2.58)	*(-1.26)*	*(-2.09)*	*(-0.54)*	*(-0.48)*	*(-1.14)*			
Three-factor	0.43	-0.17	-0.53	-0.39	-0.82	-1.25		1.72	13.32
	(2.12)	*(-0.96)*	*(-2.30)*	*(-1.22)*	*(-1.32)*	*(-1.75)*			
Four-factor	-0.13	-0.07	0.02	0.21	-0.07	0.06		0.23	94.80
	(-0.73)	*(-0.37)*	*(0.10)*	*(0.63)*	*(-0.11)*	*(0.08)*			
Idiosyncratic volatility									
CAPM	0.00	0.32	-0.07	0.27	-0.55	-0.54		1.49	19.78
	(-0.05)	*(1.45)*	*(-0.21)*	*(0.74)*	*(-0.95)*	*(-0.87)*			
Three-factor	0.12	0.04	-0.42	-0.23	-0.81	-0.93		0.84	52.35
	(1.21)	*(0.18)*	*(-1.30)*	*(-0.70)*	*(-1.45)*	*(-1.56)*			
Four-factor	0.18	0.07	-0.43	-0.28	-1.02	-1.20		2.05	7.50
	(1.73)	*(0.28)*	*(-1.23)*	*(-0.77)*	*(-1.68)*	*(-1.86)*			

Note: The table reports intercepts from asset pricing of excess returns on quintile portfolios sorted by risk indicators: beta, standard deviation, value at risk, and idiosyncratic volatility. “Bottom” denotes companies with the lowest risk and “top” with the highest risk. “T-B” is a zero-cost portfolio, which is long the most risky stocks (“top”) and short in the safest stocks (“bottom”). The numbers in brackets are t-statistics. The table also shows GRS t-statistics with corresponding. The intercepts and p-values are expressed in percent. CAPM, 3F and 4F refer to the Capital Asset Pricing Model, three-factor model and four-factor models respectively.

The sorting on standard deviation reveals literally no cross-sectional pattern. This observation confirms the outcomes of Fama and Macbeth (1970). I detect no significant intercepts on any portfolio from any pricing model, and the GRS p-values vary from 52.10% to 99.05%.

The VaR sorting is very similar to sorting on standard deviation. Application of the CAPM and three-factor model produces insignificant negative abnormal intercepts on risky stocks and significant positive alphas on the safest companies. Again, these outcomes contradict the observations of Bali and Cakici (2004). Interestingly, when momentum is included as an additional asset pricing factor, the all significant abnormal returns vanish.

Finally, the outcomes of examination of the influence of idiosyncratic volatility seem to be the most interesting. Intercepts from all the three models show a monotonic relation, the abnormal returns falling with the increase in risk. This pattern remains valid even after inclusion of the momentum factor. Unfortunately, although the results support the low-risk anomaly, they are not conclusive, as none of the intercepts is statistically significant, and the highest GRS p-value, which comes from the four-factor model, is only 7.50%. In this way, these outcomes resemble the findings of Bali and Cakici (2008).

Table 3 provides additional insights by the use of double-sorting on size and risk. A few interesting conclusions could be drawn. First, what should not be found astonishing, in cases of all the risk proxies, the higher is the risk the higher is also the standard deviation of excess returns. Second, the behavior of the tiniest stocks is quite different to the large and mid-caps. With the exception of the sorting on betas, the higher is the risk parameter, the higher is also the return. The pattern is very strong and monotonic. On the contrary, the excess return patterns for larger stock are rather mixed. The stocks sorted on VaR and idiosyncratic confirm the low-risk anomaly, while the beta sorting delivers higher excess returns for the risky companies. The results for the standard deviation are rather mixed. In other words, the results of the analysis of large- and mid-caps reported in Table 3 support the component hypothesis, which implies that the idiosyncratic risk is negatively related to returns, while the relationship with the systematic risk is positive.

A formal application of the GRS-tests unfortunately does not confirm the statistical significance of the return patterns in the behavior of double-sorted portfolios (Table 4). Let us concentrate on the beta-sorted portfolios as an example. When the 5x5 sorting I used, the CAPM model is rejected with the test-statistic of 4.04 and average absolute intercept of 1.02%. The model explains on average 46.77% of the time-series variation of the portfolios' returns. When the three-factor model based on SMB is used, the GRS t-stat falls to 3.09 and average absolute intercept decreases to 0.77, but the model is still rejected.

The application of the four-factor model results in a further decrease of GRS (2.33) and average absolute alpha (0.71). The R-squared increases to 59.65. Nonetheless, the model is still rejected. The major change in outcomes takes place when the micro-minus-rest model is used. Both the three- and four-factor models are not rejected and the average absolute intercept falls significantly to 0.33-0.43. In other words, it appears that the anomalous behavior comes to a great extent from the group of micro-caps. After accounting for their influence, none of the models is rejected. The analysis of the 4x5 patterns confirms this observation. If the micro-caps are not included in the sample, none of the models is rejected. Summing up, it seems that sorting on beta to not produce abnormal returns across all-the size classes, which would enable to reject standard asset pricing models.

Table 3

Excess Returns on Portfolios from 5x5 Sorts on Size and Risk

	Mean						Standard deviation				
	Bottom	2	3	4	Top		Bottom	2	3	4	Top
						Beta					
Small	3.89	3.96	4.21	3.86	3.83		7.79	9.11	14.25	10.98	11.19
2	1.54	1.68	1.76	1.22	1.19		7.19	6.34	8.18	9.16	10.09
3	0.67	1.14	1.00	1.70	0.77		5.77	7.56	7.49	8.16	9.57
4	0.30	0.95	0.86	1.20	0.75		4.72	6.00	6.22	8.40	9.33
Big	0.16	1.07	0.89	1.12	0.63		4.72	4.86	5.96	7.52	9.62
						Standard deviation					
Small	1.52	2.44	2.84	4.03	5.13		8.28	7.49	8.92	9.39	9.35
2	0.45	1.96	1.38	2.15	1.21		4.33	6.93	7.04	8.63	10.31
3	1.07	0.91	1.04	1.06	1.71		8.66	6.56	7.08	7.71	9.86
4	0.38	0.82	1.21	1.24	0.84		4.21	6.30	7.42	8.58	11.61
Big	0.78	0.71	1.29	1.04	0.76		4.92	6.90	9.03	9.69	12.85
						VaR					
Small	1.95	1.89	3.12	3.38	5.28		7.53	8.38	10.09	9.69	8.77
2	1.54	1.47	1.53	1.20	1.60		5.61	7.78	7.00	8.48	10.22
3	1.69	1.00	0.75	0.86	1.37		7.82	6.00	7.12	8.28	10.89
4	1.10	0.76	0.69	0.75	1.19		4.46	6.74	6.90	8.69	13.81
Big	1.11	0.62	0.54	0.95	0.82		5.61	7.08	8.31	9.63	18.07
						Idiosyncratic volatility					
Small	0.65	2.05	2.62	5.02	4.50		5.97	9.59	7.26	9.66	8.51
2	1.28	1.35	2.01	1.42	1.16		7.75	6.73	7.34	7.70	9.93
3	1.56	0.56	0.73	1.91	0.77		11.74	6.59	6.85	7.48	8.96
4	0.66	1.09	1.10	0.90	-0.06		4.64	6.44	7.35	7.77	11.06
Big	0.82	1.21	0.76	0.90	0.14		6.57	7.48	8.17	8.78	13.32

Note: The table reports means and standard deviations of excess returns on 25 portfolios sorted on size (market capitalization) and risk indicators: beta, standard deviation, value at risk, and idiosyncratic volatility. “Bottom” denotes companies with the lowest risk and “top” with the highest risk. “T-B” is a zero-cost portfolio, which is long the most risky stocks (“top”) and short in the safest stocks (“bottom”). The numbers are expressed in percent.

The results are almost identical in the case of standard deviation. However, in the case of the value at risk, and – particularly – in the case of idiosyncratic risk, the GRS test statistics are not that high. The p-value from the MMR-based three-factor model in 5x5 sorting on the size and the idiosyncratic risk is only 15.32%, which translates into the fact that the model is actually on the brink of rejection.

Table 4

Summary to Explain Monthly Excess Returns on Portfolios from Sorts on Size and Risk

	5x5						4x5				
	GRS	p-val.	|α|	R^2	s(α)		GRS	p-val.	|α|	R^2	s(α)
Beta											
CAPM	4.04	0.00	1.02	46.77	1.28		1.23	23.92	0.45	52.87	0.47
3F (SMB)	3.09	0.00	0.77	58.15	0.42		0.89	60.19	0.36	63.32	0.38
4F (SMB)	2.33	0.13	0.71	59.65	1.06		0.68	83.63	0.32	64.97	0.31
3F (MMR)	0.86	66.45	0.43	51.55	0.48		0.79	71.54	0.36	54.35	0.40
4F (MMR)	0.68	86.51	0.33	53.12	0.40		0.67	84.50	0.32	56.09	0.36
Standard deviation											
CAPM	3.75	0.00	0.84	49.31	1.14		1.10	35.62	0.40	55.43	0.44
3F (SMB)	2.82	0.01	0.64	60.41	0.39		0.73	78.89	0.34	65.51	0.43
4F (SMB)	2.45	0.07	0.60	61.23	0.98		0.97	50.50	0.31	66.34	0.36
3F (MMR)	0.63	90.99	0.35	54.26	0.39		0.65	86.43	0.38	57.07	0.66
4F (MMR)	0.70	84.52	0.39	55.10	0.49		0.73	78.88	0.41	57.93	0.49
VaR											
CAPM	4.31	0.00	0.88	47.59	1.15		1.26	21.66	0.46	53.52	0.53
3F (SMB)	3.57	0.00	0.74	58.70	0.42		1.05	40.86	0.50	63.48	0.33
4F (SMB)	2.89	0.01	0.59	60.90	0.96		0.54	94.39	0.31	65.80	0.33
3F (MMR)	1.27	19.67	0.53	51.93	0.38		1.19	27.56	0.54	54.91	0.62
4F (MMR)	1.12	33.20	0.44	54.19	0.59		0.92	56.79	0.38	57.31	0.49
Idiosyncratic volatility											
CAPM	5.06	0.00	0.86	47.64	1.21		1.38	14.34	0.47	52.84	0.58
3F (SMB)	3.93	0.00	0.65	59.51	0.39		0.95	53.03	0.42	63.66	0.70
4F (SMB)	3.37	0.00	0.66	59.97	1.06		1.28	20.49	0.46	64.18	0.48
3F (MMR)	1.34	15.32	0.55	52.49	0.37		1.20	26.32	0.56	54.78	0.96
4F (MMR)	1.29	18.09	0.56	52.98	0.74		1.22	24.61	0.55	55.32	0.73

Note: The table reports regression results for the CAPM, three-factor and four-factor models. The models aim to explain the excess returns of 25 and 20 portfolios formed on risk indicators (beta, standard deviation, value at risk, idiosyncratic volatility) and size (market capitalization). GRS is the Gibbons, Ross and Shanken (1989) statistic, |α| is the average absolute intercept, R2 is the average R2 and s(α) is the standard deviation of the intercepts. The p-values, intercepts, R-squared and standard deviations of the intercepts are expressed in percent. The 5x5 results include all five size quintiles; the 4x5 results exclude microcap portfolios. “SMB” and “MMR” refer to models based on small-minus-big and micro-minus-rest factors, respectively.

When analyzing the information in Table 4, it is very important to remember that the distinct size quintiles are not of equal economic significance. Actually, the performance of the quintile of the smallest stocks could be only marginally important for some group of individual investors. Due to the illiquidity considerations, these companies might be completely beyond the scope of financial institutions. As the result, from the practical point of view, the figures reported in Table 2 are rather more important for stock market participants. The outcomes set out in Table 4 should be generally regarded as supplemental.

Table 5 reports the basic statistics of ad-hoc asset pricing factors. The statistics generally confirm the observations form Tables 1 and 2. The long/short portfolios based on betas and standard deviations yield positive returns, which means that risky stocks perform better than the safe companies. The returns on VaR and idiosyncratic risk are negative, but close to zero. As a result, all the Sharpe ratios are not much different from zero. The exclusion of Januaries generally does not change the picture.

Table 5

Ad-hoc Asset Pricing Factors Related to Risk

	Beta	Standard deviation	VaR	Idiosyncratic volatility
Mean	0.23	0.55	-0.03	-0.07
t-statistic	*(0.45)*	*(1.20)*	*(-0.06)*	*(-0.17)*
Mean - ex. January	0.26	0.29	-0.30	-0.36
Standard deviation	6.14	5.57	6.20	5.15
Sharpe ratio	0.04	0.10	0.00	-0.01

Note: The table reports means, standard deviations, skewness, kurtosis and Sharpe ratios of excess returns on ad-hoc asset pricing factors related to risk indicators: beta, standard deviation, value at risk, and idiosyncratic volatility. The means and standard deviations are expressed in percent. The numbers in brackets are t-statistics.

Table 6 provides information on the correlation of risk-based factors with local and global counterparts, as well as with the local traditional asset pricing factors. First, all the local risk-based factors are strongly and positively correlated with each other. The correlations coefficients vary from 0.52 to 0.82. The only exception is the correlation coefficient between beta- and idiosyncratic volatility-based factors-returns, which is equal to 0.13 and not significantly different from zero.

Table 6

Correlations between Asset Pricing Factors

	Beta	SD	VaR	IVol	Mkt-RF	SMB	HML	WML	BAB_{gl}	BAB_{eu}
Beta	1.00	0.52	0.66	0.13	0.74	-0.27	-0.07	-0.46	-0.35	-0.33
	(-)	*(7.38)*	*(10.59)*	*(1.59)*	*(13.41)*	*(-3.39)*	*(-0.84)*	*(-6.29)*	*(-4.56)*	*(-4.27)*
SD	0.52	1.00	0.82	0.76	0.50	0.22	-0.13	-0.23	-0.12	-0.09
	(7.38)	*(-)*	*(17.42)*	*(14.08)*	*(6.97)*	*(2.73)*	*(-1.55)*	*(-2.88)*	*(-1.51)*	*(-1.06)*
VaR	0.66	0.82	1.00	0.59	0.55	0.06	0.00	-0.48	-0.25	-0.21
	(10.59)	*(17.42)*	*(-)*	*(8.87)*	*(7.83)*	*(0.76)*	*(-0.02)*	*(-6.55)*	*(-3.16)*	*(-2.61)*
IVol	0.13	0.76	0.59	1.00	0.18	0.39	-0.22	0.07	0.09	0.12
	(1.59)	*(14.08)*	*(8.87)*	*(-)*	*(2.26)*	*(5.07)*	*(-2.76)*	*(0.90)*	*(1.03)*	*(1.41)*

Note: The table reports correlation coefficients. The numbers in brackets are t-statistics. “SD” is a standard deviation, “VaR” is a value at risk, “IVol” is idiosyncratic volatility, “Mkt-RF” is a market risk factor, “SMB” is small minus big, “HML” is high minus low, and “WML” is winners minus losers. “BAB” is betting-against-beta factor, and “gl” and “eu” subscripts refer to global and European factors respectively. The data on BAB returns comes from Andrea’s Frazzini website (http://www.econ.yale.edu/~af227/data_library.htm).

The correlation with BAB factors, both and in the European and global approach, are negative and statistically significant for beta and VaR, although the values of coefficients are rather low. This observation suggests that there is some market integration and that there are comovements between global and local asset pricing factors[5]. On the other hand, the correlation with standard deviation-based and idiosyncratic volatility-based is negligible and the corresponding coefficients are close to zero.

Table 7

Coefficients of Regressions with Market Distress Proxies

	Beta	Standard deviation	VaR	Idiosyncratic volatility
Mkt-Rf	-0.02	-0.01	-0.01	-0.01
	(-0.31)	*(-0.14)*	*(-0.19)*	*(-0.11)*
Volatility	-0.08	-0.04	-0.09	0.08
	(-1.36)	*(-0.51)*	*(-1.14)*	*(1.04)*
Term spread	1.48	-2.32	0.16	-0.32
	(0.69)	*(-0.89)*	*(0.05)*	*(-0.12)*
Credit spread	1.69	0.67	-0.92	0.89
	(1.29)	*(-0.42)*	*(-0.52)*	*(0.52)*
TED spread	-1.68	-1.97	-2.75	-1.51
	(-0.91)	*(-0.87)*	*(-1.12)*	*(-0.63)*

Note: The table reports coefficients of regression between monthly intercepts from four factor model applied to returns on ad-hoc asset pricing factors related to risk (beta, standard deviation, value at risk, idiosyncratic volatility) with market distress proxies: a CEE stock market excess returns (“Mkt-Rf”), Euro Stoxx 50 Volatility Index (“volatility”), a spread between Eurozone 10- and 2-year yields (“term spread”), a BBB Eurozone spread (“credit spread”), 3-month EUR TED spread (“TED spread”). The numbers in brackets are t-statistics.

The correlation coefficients with traditional risk factors vary across the factors. The correlation with Mkr-Rf is in all cases positive, which is in line with the observations of Ang (2014, p. 240), who finds the correlation between BAB and market risk negative. The coefficients with SMB are negative for beta and positive for all other factors. Again, this finding does not contradict the results of Ang (2014, p. 240), who finds negative correlation of SMB with volatility-based factor and positive with BAB. Finally, the results of HML are mixed and the outcomes of WML are mostly negative. Ang (2014, p. 240) presents positive regression coefficients of volatility and beta-based portfolios with both HML and WML.

Finally, the “flight-to-quality” properties of risk-based strategies are depicted in Table 7. The outcomes of the computations suggest that returns on asset pricing factors based on risk do not reveal such properties. The regression coefficients are mixed and in all cases insignificant. In other words, the safe stocks do not provide an effective hedge against a market distress. Besides, it is worth noting that the original BAB factor of Frazzini and Pedersen (2014) actually revealed positive correlation with the changes in

[5] *It is important to stress out, there are major differences between the BAB factor and the ad-hoc pricing factors in this study. First, BAB goes long safe stocks and short risky ones, while ad-hoc factors in this paper do exactly opposite. As the result, the positive BAB returns would be equivalent to negative returns on ad-hoc factors. Second, the BAB factor assumes built-in leverage to equalize betas of long and short portfolios, while the ad-hoc factors assume no leverage in their design.*

TED spread, so the return to safe stocks deteriorated when the liquidity conditions worsened.

IV. Concluding Remarks

The low-risk anomaly has been recently one of the most intensively explored phenomena in finance. This study is the first which comprehensively examines this anomaly in the CEE markets. The results indicate that the returns reveal uneven relation with the systematic component of risk (although the top beta stocks have negative CAPM alphas) and are negatively related with the idiosycratic component of risk. The stocks with low idiosyncratic risk deliver significant abnormal returns, but some of them are explained with the momentum effect. The phenomenon is reversed for microcaps and, in their case, the risky stocks are associated with higher returns. The CEE risk-based strategies to some extent comove with their global and European counterparts. Finally, the low-risk stocks do not provide effective, significant, and robust hedge against market distress.

The findings imply some conclusions for investors, asset managers and fund pickers. First, it may be sensible for portfolio managers to implement some strategies based on volatility in the CEE markets. Second, when evaluating the performance of portfolios of CEE stocks, either for investment decisions or for academic research, one should consider the influence of idiosyncratic risk.

The research findings have a few vital limitations. First, the paper does not take into account any investment and capital flow restrictions within the investigated countries. However, these are rather marginal, as all countries in my sample are EU members. Second, the period I study (2002-2014) may be regarded as relatively short and additionally unique, as it covers the times of the Global Financial Crisis. Nonetheless, longer time-series for the CEE markets are hardly available. Third, the study does not account for limited liquidity and transaction costs which tend to be higher in emerging markets, especially across small and tiny companies.

Further research on the issues discussed in this paper could be pursued in several directions. First, this research builds the paradigm for future studies on pricing models and could be applicable to the CEE countries, which would take into account risk-based factors. Second, some interactions and synergy effects between the low-risk anomaly and the traditional factors should be examined. Third, the impact of transaction costs and liquidity constraints on the performance of risk-based strategies could be investigated. As the risky stocks are usually illiquid and have high bid-ask spreads, the returns on cost-adjusted strategies could be superior to traditional strategies. Finally, the sources of anomalous outcomes regarding the inverted low-volatility premium among the micro-caps should be researched.

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