Performance Evaluation and Portfolio Optimization in Emerging European Stock Markets: Evidence from Hungary and Romania

Edina Éva Kulcsár[1] – Edit Veres[1] – József Fogarasi[1,2]

ABSTRACT: The objective of this study is to conduct a comparative risk and performance analysis of two leading stock indices from Central and Eastern Europe: Hungary's BUX and Romania's BET. Specifically, the research addresses whether applying different risk and performance measures affects the assessment of investment attractiveness and examines how altering stock weights within portfolios can optimize returns and risk. Given the increasing global financial uncertainties and the distinct characteristics of emerging markets, the research holds significant scientific and practical relevance for both investors and policymakers. The analysis employed daily closing prices of BUX and BET indices, along with their component stocks' weights, spanning from January 2021 to April 2025. Advanced statistical methods, including traditional performance ratios (Sharpe, Treynor, Jensen) and advanced risk measures (VaR, CVaR, semivariance), were implemented using R statistical software for robust portfolio optimization. Results indicate that Hungarian portfolios exhibit higher "reward to variability", a more favourable risk–return combination.

Portfolio optimization revealed that strategic weight adjustments significantly enhance portfolio performance, demonstrating the effectiveness of modern statistical methods in portfolio management for emerging markets.

1 Partium Christian University, Faculty of Economics and Social Science, Department of Economics, kulcsar.edina@partium.ro

2 Obuda University, Budapest, Hungary, Keleti Karoly Faculty of Business and Management, 1084 Budapest, Tavaszmező str. 17, fogarasi.jozsef@kgk.uni-obuda.hu

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Introduction

In the contemporary financial environment, characterized by volatility, uncertainty, and increasing interconnectedness, effective investment decision-making has become both more complex and more resource intensive. In line with modern portfolio theory, rational investors are assumed to be risk-averse, seeking to optimize the trade-off between expected return and risk exposure (Elton & Gruber, 1997). Risk, in this context, is an inherent component of financial markets, and when appropriately managed, it can present opportunities for value creation (Shachmurove, 2000). This principle is particularly relevant in emerging European economies, where financial markets are still developing and structural differences persist across stock exchanges (Murinde et al., 2001). Emerging stock markets in Central and Eastern Europe (CEE) have become increasingly important due to their rapid growth and unique post-transition dynamics (Baele et al., 2015). These CEE markets are typically smaller and less liquid than their Western counterparts, with different investor and ownership structures, regulatory environments, and sensitivities to macroeconomic shocks (Stereńczak, 2024). The CEE countries, such as Hungary and Romania, provide an illustrative context for investigating the dynamics of risk and performance in capital markets. These economies have undergone significant transformation in the past three decades, moving from centrally planned systems to market-oriented frameworks. Consequently, their financial markets have matured unevenly and now exhibit distinct features in terms of market liquidity, investor behavior, regulatory environments, and exposure to macroeconomic shocks. Despite being geographically close and economically interlinked, the Hungarian and Romanian stock markets differ significantly in terms of size, composition, and investor structure.

Although portfolio performance and risk management practices have been extensively investigated, existing risk measures often exhibit significant limitations, especially in capturing downside and tail risks that are particularly pronounced in emerging markets. Traditional risk metrics, such as variance and Value-at-Risk (VaR), have faced criticism for their assumptions of normally distributed returns and insufficient sensitivity to extreme market events (Aldieri et al., 2023; Iglesias, 2015). Such metrics may underestimate the true investment risk in markets characterized by heightened volatility, thin trading volumes, and structural breaks, which are typical in Hungary and Romania (Mladenović et al., 2012; Smolović et al., 2017). Despite the growing importance of these markets, comparative empirical studies focusing specifically on portfolio optimization strategies and the robustness of alternative risk measures in the Hungarian and Romanian contexts remain limited. Addressing this gap is essential for refining portfolio optimization methodologies and improving investor decision-making within transitional and emerging European financial landscapes. This study aims to conduct a comparative performance and risk analysis of the leading stock indices in Hungary and Romania – namely the BUX (Budapest Stock Exchange) and the BET (Bucharest Stock Exchange). The analysis is structured around two core objectives. First, it aims to assess whether the application of different risk and performance measures yields varying interpretations of portfolio attractiveness. Second, it examines whether altering the composition and weight of stocks in a portfolio can enhance performance while effectively managing risk.

The objective of this empirical investigation is twofold: first, to examine the influence of various risk and performance metrics on the ranking and comparative assessment of the BUX and BET indices; and second, to determine whether adjusting the weighting can enhance portfolio performance.

The relevance of this research lies in the growing interest among investors in diversification across regional markets, particularly in the face of global financial uncertainties. Moreover, the regulatory harmonization under IFRS (International Financial Reporting Standards), including the adoption of IFRS 17 in the insurance sector, has underscored the importance of transparent and comparable financial reporting across borders, further enhancing the need for robust cross-country financial analyses.

This study contributes to the literature in several ways. First, by applying both traditional (Sharpe, Treynor, Jensen) and advanced (VaR, CVaR, semivariance) performance and risk measures, it provides a nuanced assessment of two representative stock markets in the CEE region. Second, the study integrates modern portfolio optimization techniques using R-based statistical tools to construct efficient and tangency portfolios based on different covariance estimation methods. Lastly, the empirical analysis reveals how market-specific characteristics such as index composition, beta sensitivity, and risk decomposition affect overall investment attractiveness.

The next section of the study provides a review of relevant literature on financial risk, performance measurement, and portfolio optimization techniques. Then presents the research methodology, including data sources, sample characteristics, and analytical tools. Subsequently, it discusses the results of the empirical analysis and portfolio simulations. Finally, it summarizes the conclusions and implications for investors, policymakers, and further academic inquiry.

Literature review

Risk and performance measurement in financial markets has been a focal point in both theoretical and applied finance. Foundational to this domain is Knight's (1921) distinction between risk – which is quantifiable – and uncertainty, which is not directly measurable. This theoretical bifurcation laid the groundwork for subsequent frameworks seeking to assess the impact of risk on investment behavior and asset pricing.

Modern Portfolio Theory (MPT), pioneered by Markowitz (1952, 1959), posits that investors can construct optimal portfolios that minimize variance for a given level of return. This theory introduced diversification as a risk-mitigating strategy and set the foundation for risk-adjusted performance measures such as the Sharpe Ratio, Treynor Ratio, and Jensen's Alpha, each of which accounts for return about varying definitions of risk. These models continue to underpin empirical assessments of portfolio efficiency, particularly in comparative cross-market studies. However, as markets become increasingly globalized, the benefits of diversification can diminish. Salahuddin et al. (2020) show that emerging and frontier markets exhibited only a few post-crisis diversification opportunities for international investors compared to the pre-crisis period, underscoring that increased integration may limit the risk-reduction potential of international portfolios.

In extending MPT, the Capital Asset Pricing Model (CAPM) (Sharpe, 1964; Lintner, 1965; Treynor, 1961) integrated systematic risk into asset pricing models. The CAPM assumes that markets are efficient and investors are rational, risk-averse agents – assumptions that are often scrutinized in the context of emerging markets, such as those in Central and Eastern Europe (CEE). Research by Horobet & Dumitrescu (2009) and Stoica *et al.* (2014) demonstrate how macroeconomic volatility and institutional transitions in the CEE region affect market dynamics, making the CAPM assumptions only partially valid. Moreover, external shocks can introduce additional risk factors. For instance, Akbulaev et al. (2021) find that fluctuations in oil and natural gas prices have a significant impact on stock index returns in emerging markets, as exemplified by the Turkish stock exchange. Such global commodity influences highlight sources of systematic risk that traditional CAPM may not fully capture. Investor behavior in these markets also deviates from classical rationality. Lakatos & Botos (2024), drawing on prospect theory, observe that investment decisions often become risk-seeking under losses and risk-averse under gains, contrary to CAPM's risk-neutral assumptions. These behavioral biases can amplify market anomalies; in crisis periods, they manifest as herd behavior. Notably, during the COVID-19 turmoil, herding intensity in Eastern European stock markets surged, as recent evidence shows that the pandemic led to significantly heightened herd behavior and co-movement across all major CEE exchanges (Fang et al., 2021). This convergence of fundamental risks and behavioral factors emphasizes the need to augment traditional models with broader risk considerations in emerging markets.

Recent literature emphasizes the importance of employing downside risk measures, especially in volatile markets. Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) are now standard in performance evaluations, especially where return distributions deviate from normality. CVaR, or Expected Shortfall (ES), offers an advantage over VaR by accounting for tail risk, an important characteristic in non-normal return distributions, often observed in transitional and smaller markets like Hungary and Romania (Iglesias, 2015; Aldieri *et al.*, 2023). Moreover, semivariance has gained traction as a downside-only risk metric (Rigamonti, 2020), particularly relevant for portfolios aiming to protect against extreme losses. Its empirical value is apparent in performance ranking discrepancies in less-diversified portfolios, such as the Hungarian BUX basket, where three stocks dominate the index composition. These insights are crucial when comparing it with Romania's more balanced BET index, which shows better diversification – a key factor in mitigating unsystematic risk. Indeed, even minimal diversification can substantially reduce risk: Ahmar et al. (2025) demonstrate that combining two low-correlation stocks in an emerging market (Indonesia) yielded approximately a 37% reduction in portfolio VaR compared to holding either stock alone. This example highlights the practical benefits of diversification in enhancing risk-adjusted performance.

From a methodological standpoint, portfolio optimization tools such as efficientPortfolio and tangencyPortfolio available in R provide researchers with robust mechanisms to simulate optimal asset allocations based on varying risk metrics and estimation methods. The use of robust estimators (e.g., shrinkage, minimum volume ellipsoid, and orthogonalized Gnanadesikan-Kettenring) reflects advanced best practices in finance, especially when applied to datasets with potential outliers or small sample sizes, a common feature in regional market analyses (Pfaff, 2016; Würtz *et al.*, 2015).

Empirical studies in the CEE region, such as those by Mladenović *et al.* (2012) and Smolović et al. (2017), highlight the relevance of GARCH and Extreme Value Theory (EVT) models in improving the precision of VaR and CVaR estimations. Their findings underline the need for more flexible and dynamic modelling techniques to accurately reflect market-specific characteristics and volatility clustering – features that affect the portfolios analyzed in this study.

The inclusion of additional studies such as Su (2015), who examined market interdependencies and spillover risks, also complements the cross-country dimension of the present paper. Su's findings – that emerging markets tend to exhibit higher volatility and stronger currency market connections – are particularly relevant when comparing the sensitivity of Romanian and Hungarian indices to regional or global shocks.

In terms of practical investment strategy, the research supports the notion that adjusting portfolio weights – as simulated in this study through the tangency and efficient frontier approaches – can substantially improve performance, even in structurally constrained environments. This aligns with findings from Bastin (2017) and Scherer (2010), who noted that minimum-variance portfolios tend to outperform market-cap weighted strategies in terms of risk-adjusted returns.

These outcomes reinforce the notion that as financial markets globalize, achieving portfolio risk reduction through international diversification becomes increasingly challenging.

Research methodology

The present comparative risk and performance analysis focuses on the Romanian BET and Hungarian BUX stock indices. In the first quarter of 2022, the Hungarian BUX index was dominated (88.24%) by three companies (Table 1.): a commercial bank (OTP), an oil and gas company (MOL), and a pharmaceutical company (Richter Gedeon).

Table 1. Research data sample – Hungarian BUX index stock basket

No.	Stock Code	Company name	Weight in BUX
1	OTP BANK	OTP BANK	37.55%
2	RICHTER GEDEON	Richter Gedeon Nyrt.	25.91%
3	MOL	MOL Nyrt.	24.78%
4	MAGYAR TELEKOM	Magyar Telekom Nyrt.	5.29%
5	OPUS	OPUS Global Nyrt.	2.13%
6	GRAPHISOFT SE	GRAPHISOFT PARK SE	0.72%
7	4IG	4iG Nyrt.	0.71%
8	ANY	ANY Nyrt.	0.44%
9	MASTERPLAST	Masterplast Nyrt.	0.42%
10	CIGPANNONIA	CIGPANNONIA	0.41%
11	AUTOWALLIS	AutoWallis Nyrt.	0.31%
12	AKKO INVEST	AKKO Invest Nyrt.	0.29%
13	ALTEO	Alteo Nyrt.	0.28%
14	PANNERGY	PannEnergy Nyrt.	0.27%
15	WABERERS	WABERER`S INTERNATIONAL Nyrt.	0.27%
16	APPENINN	Appeninn Nyrt.	0.23%

Source: www.bet.hu

The analysis provides empirical evidence on risk and portfolio performance in the context of recent geopolitical changes and the ongoing energy crisis. In Hungary, inflation rose to 22% in November 2022, driven by increases in fuel prices (Toth *et al.*, 2023). Hence, the study is particularly relevant for understanding the interrelated negative effects of geopolitical shifts and the corresponding monetary policy responses (Kandrács, 2023). Similarly, in the context of the energy crisis and geopolitical changes, the Romanian economy also experienced elevated inflation, price volatility, and heightened risk, especially in the energy sector (Topor *et al.*, 2022).

Daily closing prices for both indices and the weights of their constituent stocks were examined over a five-year period, from 4 January 2021 to 30 April 2025, which were obtained from the official websites of the Budapest Stock Exchange (www.bet.hu) and the Bucharest Stock Exchange (www.bvb.ro). In the first quarter of 2022, a substantial portion of the Romanian BET index (83%) comprises six stocks (Table 2.), namely two commercial banks (TLV and BRD), a joint stock company indemnifying individuals whose assets were expropriated under the communist regime (FP), an oil and gas company (SNP), a natural gas producer and principal supplier (SNG), a nuclear energy company (SNN), and a healthcare services provider (M). It is evident that the Romanian BET index exhibits greater diversification than the Hungarian BUX index. To determine the principal risk and performance indicators, the study employs the 10-year government bond yields from Hungary (7.13%) and Romania (6.65%) as risk-free rates for the investigated period.

Table 2. Research data sample – Romanian BET index stock basket

No.	Stock Code	Company name	Weight in BET
1	TLV	Banca Transilvania S.A.	19.90%
2	FP	Fondul Proprietatea	19.47%
3	SNP	Omv Petrom S.A.	18.11%
4	SNG	S.N.G.N. Romgaz S.A.	9.16%
5	BRD	BRD - Groupe Societe Generale S.A.	6.57%
6	SNN	S.N. Nuclearelectrica S.A.	6.00%
7	M	Medlife S.A.	3.38%
8	TGN	S.N.T.G.N. Transgaz S.A	2.84%
9	DIGI	Digi Communications N.V.	2.71%
10	EL	Societatea Energetica Electrica S.A.	2.23%
11	ONE	One United Properties	2.06%
12	TEL	C.N.T.E.E. Transelectrica	1.41%
13	TRP	Teraplast S.A.	1.36%
14	TTS	TTS (Transport Trade Services)	1.11%
15	BVB	Bursa De Valori Bucuresti S.A.	0.71%
16	ALR	Alro S.A	0.67%
17	AQ	Aquila Part Prod COM	0.65%
18	WINE	Purcari Wineries Public Company Limited	0.62%
19	SFG	Sphera Franchise Group	0.55%
20	COTE	Conpet S.A.	0.49%

Source: www.bvb.ro

The statistical analysis was conducted using the open-source R software, which offers extensive facilities for data analysis, modelling, and visualisation. In particular, this study made use of the '*PerformanceAnalytics*' and '*fportfolio*' packages.

Investment management is cyclical, with performance evaluation playing a pivotal role in shaping new investment objectives, policies, and strategies (Drake and Fabozzi, 2010). A fundamental question in the optimization of risky asset portfolios is the relationship between risk and return. The selection of portfolio constituents and the determination of their respective weights based on risk and return measures are crucial for constructing an efficient portfolio. A key expectation in decision-making is to achieve superior performance with minimal risk. In line with the Capital Asset Pricing Model (CAPM), portfolio performance measures also build on this principle.

This study employs the 'efficientPortfolio' and 'tangencyPortfolio' functions from the fPortfolio package in R to perform portfolio optimization. The 'efficientPortfolio' function generates portfolios that lie on the mean-variance efficient frontier, as introduced by Harry Markowitz in Modern Portfolio Theory (MPT). These portfolios maximize expected return for a given level of risk. In contrast, the 'tangencyPortfolio' function identifies the portfolio on the efficient frontier with the highest Sharpe ratio, thereby representing the optimal risk-adjusted return. The tangency point is determined by calculating the return-to-risk ratio, based on the target return and associated risk metrics obtained via the 'efficientPortfolio' function (Wuertz, et al., 2023). The main steps of this comparative analysis on portfolio optimization are listed in Table 3.

Table 3. Main steps of the research

No.	Step	Description
1.	Data collection and return data calculation	Historical daily data collection Calculation of simple returns and benchmark
2.	Main descriptive analysis	Summarize the main statistics: mean, standard deviation, skewness, kurtosis Visualization of the returns (histogram)
3.	Performance analysis of indices	Calculation of risk-adjusted performance ratios as Sharpe, Treynor ratio and Jensen's alfa and risk ratios as VaR, ES
4.	Analysis of cumulative daily return and drawdown	Cumulative daily return and drawdown calculation and visualization
5.	Portfolio optimization	Efficient Portfolio (minimum variance for a given return) Tangency Portfolio (maximum Sharpe ratio)
6.	Comparative analysis and interpretation	The resulted portfolios are analysed in terms of: stock weights allocation, risk-return

Source: Own editing

Numerous risk and performance ratios appear in the literature. The average return is a common performance indicator, but some studies also use the Relative Strength Index (RSI) to evaluate stock market performance. For instance, Burdekin and Harrison (2021) examined the impact of the coronavirus on 80 stock markets using panel regression and employed RSI as a measure of relative performance.

Several widely recognised performance measures include the Sharpe ratio, the Treynor ratio, and Jensen's alpha. In this study, these metrics were used to evaluate portfolio performance. The Sharpe ratio (Sharpe, 1994) is particularly useful in creating an optimal portfolio by maximising returns and minimising risk.

William Sharpe's (1961) ratio, also referred to as the "reward-to-variability ratio," compares the excess return over a risk-free asset with the total risk of the portfolio

(Amenc & Le Sourd, 2003). Wilson and Shlyakhter (in Molak, 1997) define variability as the temporal and spatial heterogeneity of values. In the context of financial investments, we find the approaches of Molak (1997) and Cullen-Frey particularly relevant. In stock prices and returns, risk manifests through variability and volatility. Tarnóczi and Fenyves (2010) highlighted the role of risk components in the economic decision foundation. Interpreted as the return per unit of variability, a higher Sharpe ratio indicates a more favourable risk–return combination. It is calculated as:

$$S_P = \frac{E(R_p) - R_F}{\sigma(R_P)} \tag{1}$$

where, $E(R_p)$ – the expected return of the portfolio; R_F – the return on the risk-free asset; $\sigma(R_p)$ – standard deviation of the portfolio returns. Because it relies solely on observed data, the Sharpe ratio is straightforward to calculate, expressing the portfolio risk premium relative to its total risk (i.e., standard deviation). Higher Sharpe ratios correspond to better portfolio performance, making this metric a key tool for ranking portfolios by their risk-adjusted returns (Claransia & Sugiharto, 2021; Sangeetha *et al.*, 2021; Soegoto *et al.*, 2024). For example, Soegoto et al. (2024) applied the Sharpe ratio to investigate the performance of stock indices in both Indonesia and the United States, reporting that the US indices (NASDAQ, S&P 500, DJI) exhibited higher average returns and lower risk than Indonesian indices. Despite the Sharpe ratio's importance in investment decisions, it is nonetheless prudent to consider additional factors when analysing stock performance. Demetrescu *et al.* (2022) found that investors can forecast price movements of financial instruments (e.g., stocks, indices) over both short and long horizons, which is particularly significant for investment strategy. Similarly, Dai *et al.* (2020) observed that forecasting stock prices is relatively easier for companies with smaller capitalisation. Artini and Sadhi (2020) investigated the performance of SME and manufacturing company stock portfolios in the capital markets of Indonesia, China, and India using both the Sharpe ratio and one-way ANOVA. Their findings indicate that the Chinese and Indian portfolios outperformed the Indonesian portfolios.

The Treynor ratio (Treynor, 1965), or the "reward-to-volatility ratio," is closely associated with the CAPM. Like the Sharpe ratio, it compares the excess return over a risk-free asset to a risk measure, but in this case the risk measure is the portfolio's systematic risk (beta) rather than its total risk. In a well-diversified portfolio, Sharpe and Treynor ratios often lead to similar results. The Treynor ratio is calculated as follows:

$$T_P = \frac{E(R_p) - R_F}{\beta_P}$$

where β_P denotes the systematic risk of the portfolio, $E(R_p)$ denotes the expected return of the portfolio and R_F denotes the return on the risk-free asset. Sharpe and Treynor ratios used in combination can enhance portfolio performance measurement (Atmaca, 2022).

Jensen's alpha (Jensen, 1968) is also grounded in the CAPM, assuming that portfolios are not perfectly diversified and may exceed the capital market line (CML). Jensen's alpha captures the portion of the portfolio return that surpasses the return predicted by the CAPM. A positive alpha indicates that the portfolio outperforms the model's expected return. Jensen's alpha is expressed as:

$$\alpha_P = \mathrm{E}(\mathrm{R_P}) - \mathrm{R_F} - \beta_\mathrm{P}(\mathrm{E}(\mathrm{R_M}) - \mathrm{R_F})$$

where $E(R_M)$ is the expected market return and β_P is the portfolio's systematic risk. One limitation of Jensen's alpha is that it only permits comparisons among portfolios with comparable levels of systematic risk (Vidal-García & Vidal, 2023).

Based on Markowitz's seminal work, Portfolio Selection, various portfolio construction strategies have emerged, including efficient portfolios, minimum-risk portfolios, high-performance portfolios, and market capitalisation-weighted portfolios. Bastin (2017) compared the market-cap-weighted investment strategy with a minimum-risk approach for the German stock market from 2002 to 2015, concluding that the minimum variance portfolio exhibited lower risk with equal or higher returns than the market-cap-weighted CDAX index. Scherer (2010) also examined minimum variance portfolios, finding that they typically incorporate low-beta, low-volatility stocks.

When a portfolio is well diversified, the Sharpe, Treynor, and Jensen ratios produce similar performance rankings. For less diversified portfolios, the Sharpe ratio is most appropriate (Verma & Hirpara, 2016). Chen and Lee (1985) investigated the statistical distributions of these three performance ratios and their respective risk measures, demonstrating that sample size, investment horizon, and market conditions significantly influence performance metrics. Zakarias and Tumewu (2015), who used the Sharpe ratio, Treynor ratio, and Jensen's alpha to assess the performance of Jakarta Stock Exchange LQ45 stocks, found no significant differences among their results.

Variance (or its square root, standard deviation), semivariance, Value-at-Risk (VaR), Expected Shortfall (ES), and Conditional Value-at-Risk (CVaR) are all prominent portfolio risk measures. Semivariance, as a measure of downside risk, captures deviations below the mean. Value-at-Risk (VaR) is a widely used metric in financial risk evaluation (Costello *et al.*, 2008). Introduced by J.P. Morgan, VaR represents the maximum probable loss over a given timeframe for a specified confidence interval (Morgan, 1996; Angelidis *et al.*, 2004).

Despite VaR's relative ease of calculation, it has important drawbacks, including a lack of convexity and sub-additivity, which complicates its use in optimisation (Cheng *et al.*, 2004; Zhang & Zhang, 2022). Furthermore, VaR does not offer information about potential losses exceeding the threshold. Gaio *et al.* (2018) also underscore the role of normality assumptions in VaR estimation. To address these limitations, three main approaches have been proposed for VaR calculation: extreme value theory (EVT) (Danielsson & Vries, 1997), heteroscedastic time series models (Engle, 1982), and copula-based methods (Nelsen, 1999; Lucas, 2003; Cheng *et al.*, 2007). Huang *et al.* (2009) combined GARCH-based heteroscedastic models with copulas (conditional copula-GARCH) to estimate VaR for NASDAQ and TAIEX portfolios, while Gaio *et al.* (2018) demonstrated the superiority of ARCH models and the copula method during periods of high volatility.

Aldieri *et al.* (2023) explored the relationship between performance, risk, and ESG scores for S&P 500 companies using key risk-adjusted indicators such as the Sharpe ratio, Sortino ratio, VaR, and Expected Shortfall (ES). Their findings suggest that ESG factors, although integrated into corporate strategies, do not exhibit a clear direct impact on financial performance. Iglesias (2015) assessed the performance and risk of major European financial markets using VaR, alongside average returns, to guide investment decisions. Owing to the small sample size, the unconditional VaR approach was applied (Iglesias & Linton, 2009; Iglesias, 2012). This method offers insight into long-term risk, whereas the conditional VaR method assesses both current and future risk. The study concluded that Sweden and the UK are best suited for risk-averse investors, with the UK notably less affected by European financial cycles, while other European markets (France, Greece, the Netherlands, Italy, Spain, and Sweden) show greater integration with continental trends. Austria emerged as the highest-return market (though also with the highest VaR). Mladenovic *et al.* (2012) used GARCH and EVT models to evaluate VaR in Central and Eastern European stock indices. Their results indicate that EVT is generally more effective than GARCH for VaR calculations, yet they recommend employing both methods for optimal outcomes. Tarnóczi and Kulcsár (2013) assessed the risk and performance of the Hungarian BUX and Romanian BET indices using the Sharpe ratio, VaR, ES, and semivariance, concluding that the Romanian portfolio exhibited both higher risk and higher performance than the Hungarian portfolio.

Similarly, Smolović *et al.* (2017) used the GARCH framework to estimate VaR for the Montenegrin MONEX index. Backtesting at 99% confidence indicated that seven out of eight models passed the Kupiec test (Kupiec, 1995), while at 95% confidence, three out of eight models passed the Christoffersen test. They therefore recommend supplementing GARCH models with EVT methods. Su (2015) studied the relationship between price trends in developed and emerging markets, factoring in currency market spillover effects, and found that stock market risk can be anticipated from exchange rate movements. His analysis also confirmed that emerging markets typically exhibit both higher returns and higher risk.

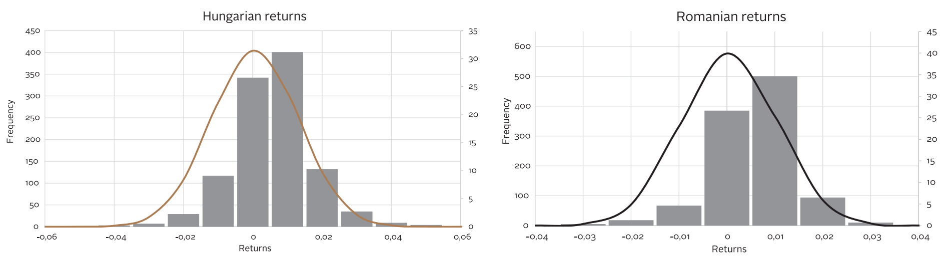
A viable alternative to VaR is Conditional Value-at-Risk (CVaR), also called Expected Shortfall (ES), which is a coherent risk measure and thus possesses properties such as convexity and sub-additivity (Sarykalin *et al.*, 2008; Mansini *et al.*, 2007; Artzner *et al.*, 1999; Acerbi & Tasche, 2002). Both VaR and ES are crucial building blocks in risk management (Christoffersen & Gonçalves, 2005). Nonetheless, Rigamonti (2020) notes that semivariance and CVaR, while effective for capturing downside risk, may be susceptible to estimation errors (Rigamonti & Lučivjanská, 2022). Expected Shortfall (ES) reflects the average of the worst 5% of losses. It is more appropriate for distributions with fat tails, as it captures the risk in the tail more accurately (Yamai & Yoshiba, 2005).

The originality of this article lies in its use of risk-adjusted indicators, such as the Sharpe and Treynor ratios, rather than relying solely on average stock returns. These measurements are more beneficial in stock index portfolio risk and performance analysis. This could be the main advantage of the used risk-to return ratios in this study. The relevance of this study is underlined also by its focus on Central and Eastern European stock markets – particularly of Hungary and Romania – which remains underexplored on this topic of portfolio optimization. By addressing this regional and market specific gap, this research enhances the empirical understanding of portfolio performance and optimization in emerging European countries. The empirical analysis can be considered a practical tool and framework for investors interested in emerging European stock markets, demonstrating how to apply modern portfolio theory with real stock market data, manage risk by following drawdowns, and improve decision-making by implementing risk and performance metrics.

Empirical results

In the initial phase of our comparative performance and risk analysis of the leading Hungarian and Romanian indices, we begin by examining the distribution of portfolio returns, as illustrated in Figure 1. We also present the key descriptive statistics in Table 4. for the leading indices of these two neighbouring countries, namely the Hungarian BUX and the Romanian BET.

Figure 1. The distribution of Hungarian and Romanian returns



Source: Authors' calculation

From Table 4., it is evident that the Hungarian portfolio returns more closely approximate a normal distribution than the Romanian returns. Specifically, 50% of the Hungarian portfolio returns lie between -0.0056 and 0.0073, whereas 50% of the Romanian portfolio returns fall between -0.0034 and 0.0052. Regarding standard deviation (StdDev), the Hungarian portfolio exhibits higher variability (0.0127) compared to the Romanian portfolio (0.0100), indicating greater risk. The larger interquartile range observed for the Hungarian returns further reinforces this higher variability.

In contrast, the overall range (the difference between the minimum and maximum) is wider for the Romanian portfolio, indicating more extreme observations at both the lower and upper ends. Owing to the presence of both positive and negative return values, the mean return is very close to 0 in both cases. The mean return of the two indices differs only marginally (0.0001).

Table 4. Main statistics of Hungarian and Romanian return

	Hungarian portfolio returns	Romanian portfolio returns
Minimum	-0.1172	-0.1557
Quartile 1	-0.0056	-0.0034
Median	-0.0012	0.0010
Mean	0.0006	0.0005
Quartile 3	0.0073	0.0052
Maximum	0.0633	0.0638
StdDev	0.0127	0.0100

Source: Authors' calculation

The skewness in both portfolios reflects slightly left-skewed distributions. Turning to kurtosis, neither distribution aligns with the normal distribution benchmark of 3. The Romanian portfolio has a leptokurtic distribution and extreme tails, whereas the Hungarian portfolio's kurtosis signals a leptokurtic distribution with fat tails. Consequently, neither of the two return series (Hungarian and Romanian) is normally distributed based on the shape of the histograms.

Table 5. Performance and risk ratios of Hungarian and Romanian returns

Indicator	Hungarian portfolio returns	Romanian portfolio returns
StdDev Sharpe	-0.4206	-0.5041
VaR Sharpe	-0.2548	-0.3160
ES Sharpe	-0.0981	-0.2504
Jensen Alpha	-0.0546	0.0547
Treynor Ratio	-0.7490	-1.7229
Semivariance	0.0137	0.0116
ES	-0.0543	-0.0201
VaR	-0.0209	-0.0159
Skewness/Kurtosis Ratio	-0.0748	-0.0612
Total risk	0.2014	0.1586
Systematic risk	0.1978	0.0589
CAPM beta bull+	1.0469	0.5225
CAPM beta bear-	1.0053	0.4842

Source: Authors' calculations

The first three indicators pertain to Sharpe ratios, which measure return per unit of risk by using different denominators: standard deviation (StdDev), Value at Risk (VaR), and Expected Shortfall (ES). In this analysis, the 10-year government bond yields for Hungary (7.13%) and Romania (6.65%) served as risk-free rates (Table 5.). According to the first two performance measures (Sharpe ratios using StdDev and VaR), the Hungarian portfolio exhibits higher "reward to variability" values, implying a more favourable risk–return combination. In both cases, however, these Sharpe ratios are negative owing to negative returns (the numerator), suggesting that each portfolio's performance is below its respective risk-free rate. Consequently, the BET index return does not exceed the Romanian risk-free rate, indicating weak overall performance. When the Sharpe ratio is computed using StdDev, ES, and VaR, the Romanian portfolio underperforms the Hungarian portfolio.

A negative Jensen's alpha value for the Hungarian portfolio indicates that its returns are below those predicted by the CAPM model. Numerically, the Romanian portfolio's alpha is higher and positive, indicating that it outperforms the CAPM benchmark. The Treynor ratio, which measures return per unit of systematic risk, is lower in the Romanian case, implying a less favourable risk–return profile when only systematic risk is considered.

Semivariance is higher for the Hungarian portfolio, signifying a greater downside risk relative to the Romanian portfolio. Examination of VaR reveals a 5% probability of losses at or exceeding 2.09% for the Hungarian portfolio and 1.59% for the Romanian portfolio. The ES values (representing average losses in the worst 5% of cases) indicate a higher expected shortfall for the Romanian portfolio (-0.0201) compared with the Hungarian portfolio (-0.0543).

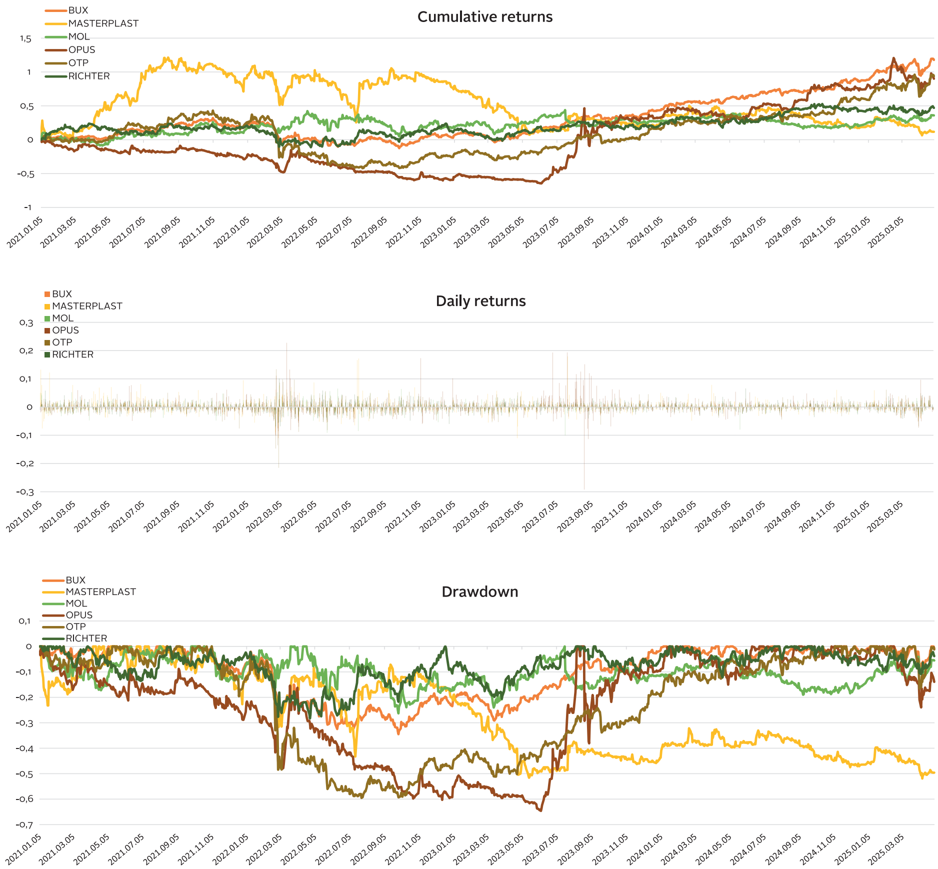
The Skewness–Kurtosis ratio is greater for the Romanian returns (-0.0612) than for the Hungarian returns (-0.0748). Conversely, both total risk and systematic risk are higher for the Hungarian portfolio, indicating that systematic factors contribute substantially to overall risk in Hungarian market. CAPM beta values (bull+ and bear-) capture the sensitivity of returns to positive and negative market movements. The Hungarian portfolio exhibits higher overall risk and demonstrates higher beta (exceeding 1), revealing greater sensitivity to market fluctuations.

These findings reveal that the Hungarian portfolio is riskier in terms of semivariance, systematic risk and total risk. Conversely, the ES and VaR show lower risk level for the Hungarian stocks. The Hungarian portfolio performs slightly better than the Romanian portfolio, but it is also more volatile and market-sensitive, as evidenced by a beta greater than 1.

In the next step of the analysis, we determine and visualise the cumulative returns and drawdowns of the leading stocks in the Hungarian BUX and Romanian BET baskets. Figures 2. and 3. illustrate the cumulative returns, reflecting the aggregate gains or losses over specific intervals for both indices and their constituent stocks.

Upon examining these figures, the BUX and BET indices display generally similar trends. The examined period can be segmented into three parts: the period before March 2022, the period between March 2022 and November 2023, and the period after November 2023. In the BUX basket Figure 2. major constituent stocks converge toward the index return in the last third of the studied period. However, in the first third of the examined period, MASTERPLAST stock substantially outperformed BUX returns before later falling below them. The increase in MASTERPLAST'S stock price in 2021 and 2022 can be attributed to favourable industry dynamics, strong financial performance, strategic diversification into new business segments, and regional expansion.

Figure 2. The cumulative daily drawdown of main Hungarian stocks and BUX

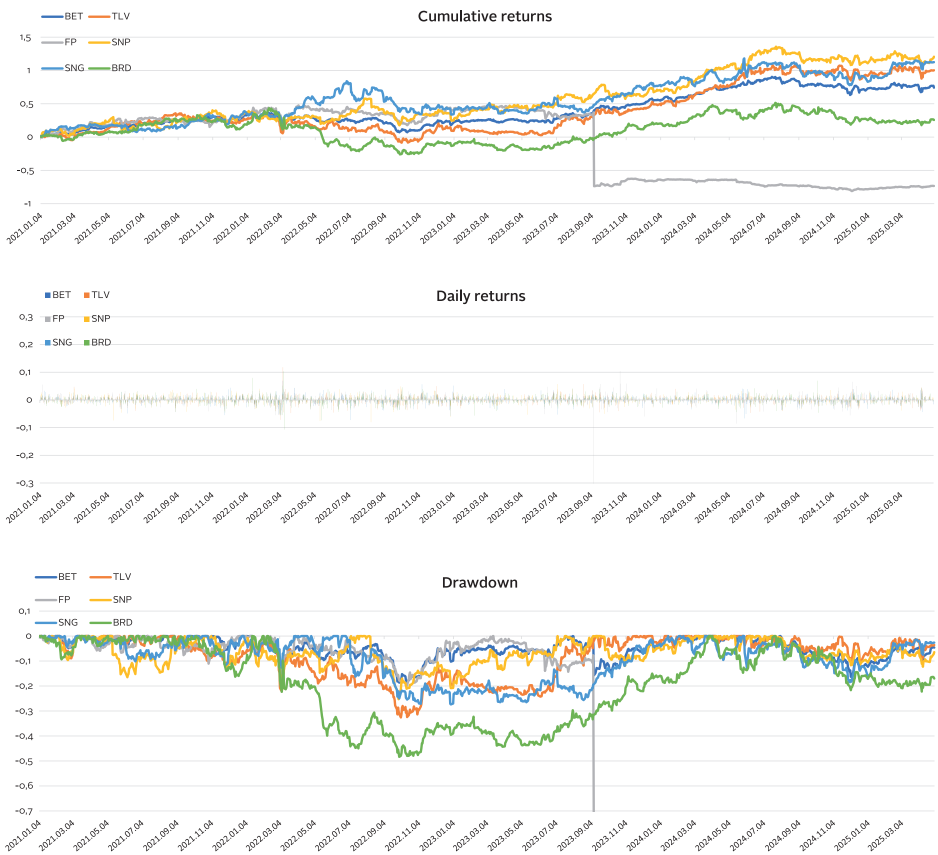


Source: Authors' calculations

Figure 3. depicts a more abrupt trajectory in BET cumulative returns, with notable declines in March 2022, likely attributable to unfavourable broader global economic conditions. Drawdown, which tracks the decline from a return's peak to its subsequent trough, provides valuable insight into portfolio risk. While the Hungarian portfolio's drawdown trend broadly follows its cumulative return, the Romanian portfolio shows sharper fluctuations. Analysis of individual component stocks (especially those with higher index weights) reveals that most follow the respective index trend, except for a few notable exceptions (e.g., MASTERPLAST in Hungary and FP in Romania). During the first third of the study period, BET and its

principal stocks moved closely together; in the last third, divergences became more pronounced, due to global economic conditions. Notably, in this period, the Fondul Proprietatea (FP) underperformed the BET index in terms of cumulative returns. As shown in the graph, the price of FP declined by approximately 27% due to selling pressure from the pension funds. The most pronounced drawdowns are observed during the second and third quarters of the investigated period, which reflects the severe adverse effects of the energy crisis and geopolitical tensions on stock market prices.

Figure 3. The cumulative daily drawdown of main Romanian stocks and BET

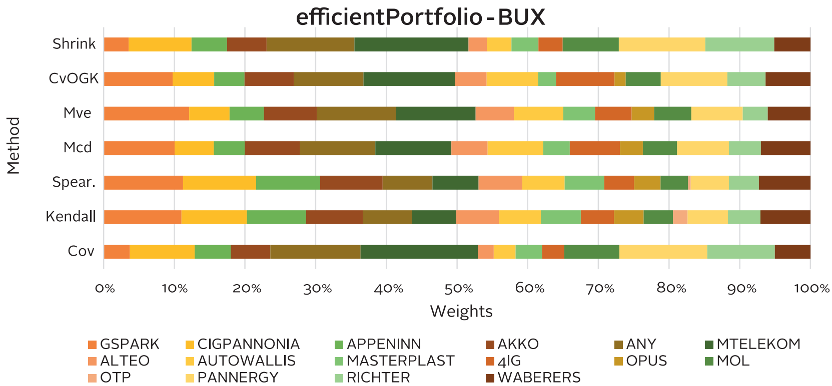


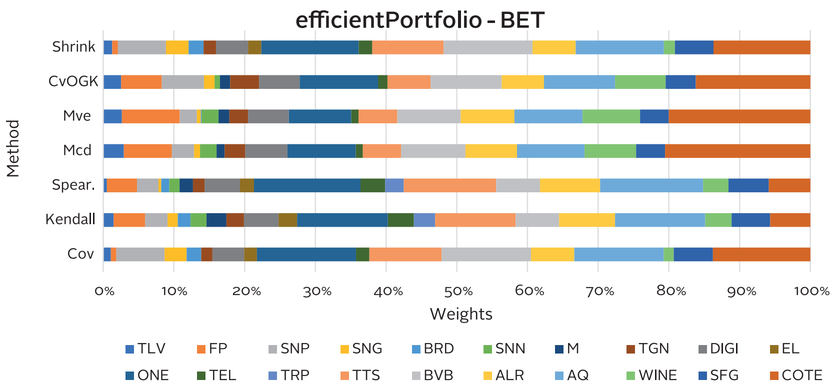
Source: Authors' calculations

Subsequently, we used the *efficientPortfolio* module to construct a portfolio on the efficient frontier, where the optimal portfolio lies at the intersection of the investor's indifference curve and the frontier itself. The analysis involved various functions in R to estimate stock returns and covariance, including the default product moment estimator (*covEstimator*), non-parametric rank estimators

(*Kendall's and Spearman's*), robust estimators (*mcdEstimator* for minimum covariance determinant and *mveEstimator* for minimum volume ellipsoid), the Orthogonalised Gnanadesikan–Kettenring estimator (*covOGKEstimator*), and a shrinkage estimator (*shrinkEstimator*). Each method aims to maximise expected return for a specified VaR level while also controlling risk.

Figure 4. Portfolio obtained with module 'efficientPortfolio'- BET and BUX





Source: Authors' calculations

The resulting efficient portfolios for the Hungarian BUX stocks are presented in Figure 4. and Table 6. In particular, 7–9 stocks dominate the portfolio under Kendall's and Spearman's estimators, jointly accounting for over 68% of the portfolio's weight. These key stocks are GSPARK, CIGPANNONIA, APENINN, AKKO, ANY, MTELEKOM, ALTEO, AUTOWALLIS, and MASTERPLAST (with minor differences across estimators). Under the robust approaches (*mcdEstimator* and *mveEstimator*), the portfolios are more diversified, encompassing a larger number of stocks.

Table 6. Efficient Portfolio obtained with module *'efficientPortfolio'* – BUX stocks weights

Stocks	Cov	Kendall	Spear.	Mcd	Mve	CvOGK	Shrink
MTELEKOM	16.59%	6.29%	6.52%	10.77%	11.30%	12.96%	16.13%
ANY	12.77%	6.92%	7.07%	10.71%	11.16%	9.84%	12.44%
PANNERGY	12.43%	5.72%	5.42%	7.33%	7.27%	9.44%	12.23%
RICHTER	9.56%	4.58%	4.24%	4.53%	3.54%	5.39%	9.74%
CIGPANNONIA	9.17%	9.26%	10.33%	5.55%	5.73%	5.89%	8.89%
MOL	7.80%	4.16%	3.90%	4.86%	5.25%	4.96%	7.96%
AKKO	5.62%	8.04%	8.82%	7.76%	7.50%	7.00%	5.60%
APPENINN	5.09%	8.36%	9.06%	4.39%	4.85%	4.30%	5.01%
WABERERS	5.04%	7.08%	7.28%	7.00%	6.05%	6.35%	5.13%
MASTERPLAST	3.74%	5.66%	5.61%	3.77%	4.49%	2.52%	3.82%
GSPARK	3.71%	11.01%	11.25%	10.03%	12.09%	9.75%	3.56%
4IG	3.14%	4.70%	4.24%	7.10%	5.19%	8.30%	3.43%
AUTOWALLIS	3.10%	5.90%	5.98%	7.86%	6.97%	7.28%	3.48%
ALTEO	2.24%	6.07%	6.18%	5.11%	5.43%	4.45%	2.58%
OPUS	0.00%	4.19%	3.73%	3.23%	3.18%	1.57%	0.00%
OTP	0.00%	2.05%	0.36%	0.00%	0.00%	0.00%	0.00%
Main statistics							
Mean	0.0008	0.0007	0.0007	0.0008	0.0008	0.0008	0.0008
Covariance	0.0069	0.0079	0.0079	0.0076	0.0078	0.0008	0.0008
VaR	0.0093	0.0092	0.0092	0.0084	0.0083	0.0083	0.0093
CVAR	0.0157	0.0176	0.0173	0.0740	0.0175	0.0171	0.0158

Source: Authors' calculations

Across all estimation methods, the mean return is positive, while the covariance differs only marginally. CVaR (Conditional Value at Risk) generally lies within a narrow range for most estimators, although Kendall's and Spearman's estimators yield higher CVaR and thus higher risk. By contrast, *covEstimator*, *covOGKEstimator*, and *shrinkEstimator* tend to produce lower CVaR values.

Table 7. Efficient Portfolio obtained with module *'efficientPortfolio'* – BET stocks weights

Stocks	Cov	Kendall	Spear.	Mcd	Mve	CvOGK	Shrink
ONE	14.00%	12.84%	15.08%	9.65%	8.83%	11.06%	13.78%
COTE	13.80%	5.68%	5.88%	20.54%	20.01%	16.19%	13.69%
BVB	12.66%	6.16%	6.19%	9.11%	8.98%	10.06%	12.59%
AQ	12.65%	12.76%	14.56%	9.56%	9.63%	10.05%	12.48%
TTS	10.23%	11.40%	13.07%	5.39%	5.48%	6.10%	10.08%
SNP	6.85%	3.16%	3.03%	3.12%	2.41%	5.98%	6.81%
ALR	6.14%	7.89%	8.49%	7.29%	7.59%	5.98%	6.08%
SFG	5.55%	5.44%	5.69%	4.08%	4.06%	4.26%	5.46%
DIGI	4.51%	4.89%	5.00%	5.97%	5.76%	5.74%	4.54%
SNG	3.10%	1.45%	0.38%	0.85%	0.57%	1.50%	3.21%
BRD	2.06%	1.81%	1.15%	0.00%	0.11%	0.00%	2.11%
TEL	1.90%	3.67%	3.47%	1.00%	1.02%	1.34%	1.93%
EL	1.81%	2.63%	1.98%	0.00%	0.00%	0.00%	1.88%
TGN	1.59%	2.49%	1.65%	2.93%	2.65%	4.11%	1.74%
WINE	1.41%	3.75%	3.61%	7.30%	8.14%	7.17%	1.57%
TLV	1.09%	1.46%	0.53%	2.92%	2.65%	2.52%	1.27%
FP	0.76%	4.47%	4.26%	6.80%	8.17%	5.76%	0.80%
SNN	0.00%	2.27%	1.45%	2.34%	2.41%	0.74%	0.00%
M	0.00%	2.79%	1.88%	1.13%	1.52%	1.44%	0.00%
TRP	0.00%	3.00%	2.64%	0.00%	0.00%	0.00%	0.00%
Main statistics							
Mean	0.0004	0.0004	0.0003	0.0003	0.0003	0.0004	0.0004
Covariance	0.0058	0.0062	0.0062	0.0064	0.0065	0.0062	0.0058
VaR	0.0088	0.0095	0.0092	0.0094	0.0092	0.0096	0.0088
CVAR	0.0137	0.0150	0.0145	0.0162	0.0165	0.0155	0.0138

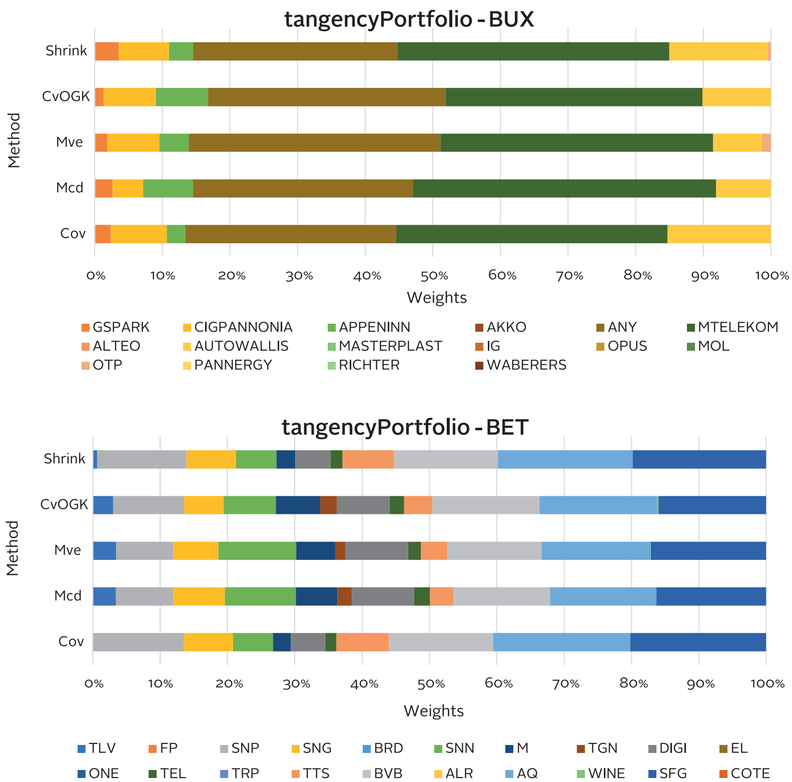
Source: Authors' calculations

Turning to the Romanian BET stocks, the efficient portfolio similarly holds 9 stocks (Figure 4.) for the default and robust estimators, as well as 9 for Kendall's and Spearman's estimators Table 7. Among the most significant holdings are Banca Transilvania (TLV), Fondul Proprietatea (FP), DIGI, ONE, COTE, AQ, and BVB, SFG with ALR also included under certain robust estimators. Portfolios constructed using Kendall's and Spearman's methods appear well diversified, whereas those produced by other estimators concentrate their allocations in fewer stocks.

Similar to the Hungarian results, the portfolio's average return is positive but consistent across most methods, while covariance remains relatively stable. McdEstimator and MveEstimator methods produce the highest VaR and CVaR (hence higher risk), whereas covEstimator, Spearman's estimators and shrinkEstimator yield the lowest values, signifying a smaller risk profile. Overall, this supports the conclusion that a suitable combination of risk estimation methods can substantially alter the composition and risk levels of the efficient portfolio.

In the final phase of the portfolio optimisation, we employed the *tangencyPortfolio* function, designed to maximise the return–risk ratio. Because this method specifically targets the steepest slope in mean–variance space, relatively few stocks receive substantial weights in the final basket Figure 5.

Figure 5. Portfolio obtained with module '*tangencyPortfolio*' – BET and BUX



Source: Authors' calculations

Table 8. presents the tangency portfolio results for BUX stocks. Under used methods (*covEstimator, mcdEstimator*, *mveEstimator, covOGKEstimator* and *shrinkEstimator*) four stocks – MTELEKOM, ANY, AUTOWALLIS, CIGPANNONIA – together account for over 90% of the Hungarian tangency portfolio. The mean return and covariance

estimates remain fairly consistent across all methods, although *covEstimator* and *mcdOGKEstimator* approach produce higher CVaR, indicating greater risk exposure. By contrast, *mveEstimator*, and *shrinkEstimator* produce the lowest CVaR values.

Table 8. Portfolio obtained with module 'tangencyPortfolio'- BUX stocks weights

Stocks	Cov	Mcd	Mve	CvOGK	Shrink
MTELEKOM	40.12%	44.86%	40.34%	38.01%	40.20%
ANY	31.19%	32.49%	37.24%	35.12%	30.22%
AUTOWALLIS	15.29%	8.09%	7.21%	10.10%	14.57%
CIGPANNONIA	8.28%	4.49%	7.72%	7.72%	7.47%
APPENINN	2.74%	7.39%	4.28%	7.69%	3.55%
GSPARK	2.38%	2.68%	1.89%	1.36%	3.52%
IG	0.00%	0.00%	0.00%	0.00%	0.00%
AKKO	0.00%	0.00%	0.00%	0.00%	0.00%
ALTEO	0.00%	0.00%	0.00%	0.00%	0.00%
MASTERPLAST	0.00%	0.00%	0.00%	0.00%	0.00%
MOL	0.00%	0.00%	0.00%	0.00%	0.00%
OPUS	0.00%	0.00%	0.00%	0.00%	0.00%
OTP	0.00%	0.00%	1.32%	0.00%	0.46%
PANNERGY	0.00%	0.00%	0.00%	0.00%	0.00%
RICHTER	0.00%	0.00%	0.00%	0.00%	0.00%
WABERERS	0.00%	0.00%	0.00%	0.00%	0.00%
Main statistics					
Mean	0.0010	0.0013	0.0013	0.0013	0.0014
Covariance	0.0086	0.0083	0.0084	0.0085	0.0085
VaR	0.0107	0.0103	0.0107	0.0105	0.0106
CVAR	0.0181	0.0184	0.0180	0.0186	0.0181

Source: Authors' calculations

Table 9. shows the tangency portfolio for BET stocks, where six stocks – BVB, SFG, TTS, SNG, and AQ – dominate under *covEstimator* estimator, constituting at least 85% of the total. Under *mcdEstimator* and *mveEstimator*, the portfolios are more diversified, including 7 stocks (besides the above SNN and DIGI). Interestingly, under Kendall's and Spearman's estimators, the portfolio optimization collapse which reflects the models' specific assumptions and data sensitivity. Mean returns once again remain largely stable across estimators, while covariance varies only marginally. Notably, *covEstimator* and *mcdEstimator* yield the highest CVaR values, implying elevated risk, whereas *shrinkEstimator* and *covOGKEstimator* produce lower CVaR figures.

Table 9. Portfolio obtained with module '*tangencyPortfolio*' – BET stocks weights

Stocks	Cov	Mcd	Mve	CvOGK	Shrink
AQ	20.33%	15.78%	16.20%	17.47%	20.00%
SFG	20.17%	16.30%	17.13%	15.97%	19.83%
BVB	15.51%	14.37%	13.97%	15.89%	15.43%
SNP	13.40%	8.52%	8.50%	10.56%	13.27%
TTS	7.79%	3.47%	3.95%	4.20%	7.66%
SNG	7.29%	7.66%	6.68%	5.87%	7.38%
SNN	5.92%	10.54%	11.56%	7.73%	5.99%
DIGI	5.11%	9.22%	9.29%	7.82%	5.22%
M	2.67%	6.18%	5.79%	6.60%	2.80%
TEL	1.67%	2.36%	1.90%	2.14%	1.79%
TLV	0.14%	3.43%	3.46%	3.01%	0.63%
FP	0.00%	0.00%	0.00%	0.00%	0.00%
BRD	0.00%	0.00%	0.00%	0.00%	0.00%
TGN	0.00%	2.17%	1.53%	2.49%	0.00%
EL	0.00%	0.00%	0.00%	0.00%	0.00%
ONE	0.00%	0.00%	0.00%	0.00%	0.00%
TRP	0.00%	0.00%	0.00%	0.00%	0.00%
ALR	0.00%	0.00%	0.00%	0.00%	0.00%
WINE	0.00%	0.00%	0.02%	0.23%	0.00%
COTE	0.00%	0.00%	0.00%	0.00%	0.00%
Main statistics					
Mean	0.0008	0.0008	0.0008	0.0008	0.0008
Covariance	0.0072	0.0074	0.0074	0.0073	0.0072
VaR	0.0110	0.0105	0.0105	0.0104	0.0109
CVAR	0.0158	0.0172	0.0171	0.0167	0.0158

Source: Authors' calculations

The outcomes of the efficient and tangency portfolio analyses provide evidence that an optimal portfolio – balanced in terms of return and risk – can be constructed by adjusting the weights of selected stocks. Although each covariance estimation method generates slightly different portfolio compositions and varying risk levels, the general conclusion remains that prudent weighting and diversification can enhance portfolio performance under different risk measures.

Conclusions

The primary objective of this study was to perform a comparative analysis of the performance and risk profiles of two neighbouring Central and Eastern European (CEE) stock markets – the Hungarian BUX and Romanian BET indices. Through a comprehensive application of both traditional and advanced performance and risk measures, this research provided empirical evidence regarding the nuances of investment attractiveness and portfolio management in these emerging European markets.

The findings highlighted distinct differences between the two markets. Statistical analysis revealed that the Hungarian portfolio exhibited greater risk, as indicated by its higher standard deviation, interquartile range, semivariance, and total risk compared to the Romanian portfolio. In contrast, the Expected Shortfall (ES) and Value at Risk (VaR) reveal more favourable values for the Hungarian stocks. The skewness/kurtosis ratio confirms non-normal distribution of returns with a tendency toward extreme negative returns. These distribution characteristics significantly influence risk management strategies for investors and portfolio managers.

Performance evaluation using Sharpe, Treynor, and Jensen ratios provided additional insights. Although Hungarian portfolios demonstrated higher "reward-to-variability" measures under certain Sharpe ratio variants (StdDev and VaR-based), these were predominantly negative, reflecting underperformance relative to their respective risk-free benchmarks. Additionally, Jensen's alpha suggested the Romanian market return outperforms CAPM benchmark. The Treynor ratio, which measures return per unit of systematic risk, is higher in the Hungarian case, implying a more favourable risk–return profile when only systematic risk is considered.

Importantly, the analysis of systematic risk showed that both markets are influenced by market-wide movements. Hungary shows a higher overall risk profile and exhibits greater sensitivity to market fluctuations (beta > 1), suggesting that investors in Hungarian stocks must carefully consider broader market dynamics when making investment decisions.

Portfolio optimization further supported the hypothesis that portfolio performance can be enhanced through the careful reallocation of stock weights. Utilising R-based portfolio optimisation techniques, particularly the tangency and efficient frontier methods, the study demonstrated the potential for significant improvements in portfolio risk-return profiles. Among the methods applied, the tangency portfolio approach with the Orthogonalized Gnanadesikan-Kettenring estimator (covOGKEstimator) consistently provided the most favourable risk-return trade-offs for both Hungarian and Romanian portfolios. These results underscore the effectiveness of advanced statistical methods and highlight the benefits of actively managed portfolios in emerging markets.

For investors, understanding the risk-return dynamics and market sensitivities of these indices can inform strategic asset allocation and risk management practices. The results suggest that Hungarian stocks may appeal to investors with a higher risk tolerance, whereas Romanian stocks might suit investors seeking to balance market sensitivity with moderate risk exposure. For policymakers, recognising the differences in market structure and risk profiles can inform regulatory adjustments aimed at enhancing market stability and investor confidence. This is even more important given the ongoing challenges posed by geopolitical tensions and macroeconomic volatility, including energy crises and inflationary pressures prevalent in the CEE region.

This study lays the groundwork for future academic inquiry. Further research might also examine cross-market spillover effects and sector-specific dynamics within these markets, thereby enriching the literature on portfolio management in emerging economies. Considering the limitations of the present study, we intend to further enhance the research by incorporating additional countries' emerging European stock market indices. In addition, dividing the examined period into separate sub-periods could be a useful direction for deepening the analysis.

In conclusion, this analysis underscores the complexity and richness of portfolio management in emerging markets. Through the deliberate application of advanced performance and risk measures, as well as sophisticated portfolio optimisation techniques, investors can achieve improved outcomes, aligning risk exposure with return objectives in a rapidly evolving financial landscape. ■

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