Boris KUZMAN, PhD (corresponding author)
kuzmanboris@yahoo.com
Institute of Agricultural Economics, Belgrade, Serbia

How to Reduce Extreme Risk in Portfolios with Developed and Emerging Stock Indices?

Abstract. *This study constructs diversified portfolios incorporating equities from both emerging and developed markets to assess which group demonstrates reduced exposure to downside risk. This is evaluated by using both parametric and semiparametric Conditional Value at Risk (CVaR) models. An additional analysis explores return-adjusted risk efficiency through the STAR Ratio metric. The semiparametric CVaR (mCVaR) model yields notably higher risk estimates than the parametric CVaR, due to its sensitivity to distributional asymmetries such as excess kurtosis and negative skewness. Interestingly, the portfolio of emerging markets shows lower downside risk compared to its developed market counterpart, not because of inherently lower tail risk, but rather due to weaker financial integration among emerging economies. Furthermore, results from the STAR Ratio reveal that the emerging market portfolio outperforms in return-to-risk terms, largely driven by the exceptional average daily returns of Indian SENSEX index, which surpass those of any developed market index included. These findings offer practical insights for international investors and portfolio strategists allocating assets across both market categories.*

Keywords: *stock markets, extreme risk, multi-asset portfolios, robust quantile regression.*

JEL Classification: C21, D53, G32.

Received: 24 July 2025	Revised: 19 January 2026	Accepted: 4 March 2026

1. Introduction

In today's increasingly unpredictable world, global events have amplified financial market volatility, bringing international portfolio diversification into sharper focus. From a theoretical standpoint, diversifying across borders allows investors to mitigate overall risk, largely because returns on international assets are not perfectly correlated. This principle has become especially critical in light of two major disruptions to the global economy: the COVID-19 pandemic and the war in Ukraine. The widespread lockdowns and restrictive public health measures implemented to contain the virus led to severe economic contractions and heightened market instability (e.g., Höhler and Lansink, 2020; Akdeniz et al., 2021; Salas-Fumás, 2021). Albulescu (2021) highlighted a notable surge in the U.S. market volatility during the pandemic, while Baig et al. (2021) found that rising infection and mortality rates undermined both market liquidity and stability. Similarly, Shang

DOI: 10.24818/18423264/60.1.26.10
© 2026 The Authors. Published by Editura ASE. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

et al. (2021) observed that pandemic-induced fear in the U.S. quickly spilled over to international markets, particularly during the early waves. According to Belhassine and Karamti (2021), the global spread of COVID-19 triggered an intense rise in market risk aversion, rivalling levels seen during the Global Financial Crisis. Compounding these challenges, the Russian invasion of Ukraine has triggered a global energy crisis, driving inflation in energy-dependent economies and further straining financial systems (Chishti et al., 2023). Together, these crises have redefined the landscape for investors and risk managers, underscoring the urgent need for resilient portfolio strategies capable of withstanding elevated market risks.

Based on the above considerations, this paper empirically examines the comparative performance of two distinct multivariate portfolios, with the aim of reducing extreme risk. Specifically, the paper constructs two seven-asset portfolios. The first consists of traditional stock indices from developed economies (DEC) within the G7: the U.S., Japan, Germany, the U.K., France, Canada, and Italy. The second includes stock indices from seven emerging market economies (EMEC) within the G20: China, India, Brazil, Russia, South Korea, Mexico, and Indonesia. The deliberate choice to compare developed and emerging markets stems from their fundamentally different characteristics, which can significantly influence portfolio construction and performance. According to the Markowitz (1952) Modern Portfolio Theory, two key factors play a crucial role in portfolio design: the individual risk levels of assets and the degree of correlation among them. From this perspective, emerging markets may offer advantages in both respects (Mirović et al., 2017). As noted by Bruner et al. (2008) and Akbari and Ng (2021), emerging markets are typically less integrated with global markets, which enhances diversification potential. Additionally, their generally lower trading volumes tend to result in lower volatility (see Nishimura, 2016; Tissaoui et al., 2021).

The primary objective of this paper is to determine which multi-asset portfolio exhibits lower extreme risk and which offers superior return-to-risk performance. In this paper, extreme risk is treated as downside risk, that is, the risk of losses. Unlike variance or standard deviation, which treat positive and negative deviations symmetrically, downside risk focuses only on unfavourable outcomes, making it especially relevant for investors concerned with capital preservation. Downside risk is commonly measured using the Value at Risk (VaR) model, which estimates the potential loss of an asset or portfolio at a given confidence level (Živkov et al., 2020). However, VaR has several theoretical limitations, including the lack of subadditivity and non-convexity, which may result in multiple local optima and unstable portfolio rankings (Li et al., 2012). More critically, a major drawback of VaR is its inability to account for losses exceeding the threshold level, potentially leading to flawed investment decisions (Chai and Zhou, 2018). To address this issue, Rockafellar and Uryasev (2002) introduced Conditional Value at Risk (CVaR), which captures the expected magnitude of losses beyond the VaR threshold.

However, both parametric VaR and CVaR are considered reliable risk measures only under the assumption of normality. This implies that they rely solely on the first two moments, mean and variance, for risk estimation, while ignoring higher-order moments such as skewness and kurtosis. To address this limitation, the present study takes a step forward by adopting a solution that overcomes this two-moment bias. Specifically, the paper draws on the work of Favre and Galeano (2002), who introduced the semiparametric or modified VaR (mVaR), based on the Cornish-Fisher expansion (Cornish and Fisher, 1938), which incorporates the third and fourth moments into the calculation of downside risk. Since the two-moment limitation also applies to parametric CVaR, the paper employs semiparametric CVaR, commonly referred to as modified CVaR (mCVaR), in the portfolio optimisation process. This approach penalises unfavourable distributional characteristics such as negative skewness and excess kurtosis, while rewarding favourable traits such as positive skewness and low kurtosis (see, e.g., Bredin et al., 2017). All downside risks in portfolios are assessed using a 99% confidence level, implying that actual losses are expected to exceed the estimated threshold in only 1% of cases. To assess the accuracy of these risk estimates, I apply the coverage test proposed by Kupiec (1995), which evaluates how well the theoretical Value at Risk (VaR) models align with observed outcomes. This statistical method enables the identification of the VaR model that most accurately captures the extreme downside risk in practice.

To the best of my knowledge, this paper is among the few studies to construct multivariate portfolios comprising both developed and emerging stock markets with the objective of reducing extreme risk, as measured by CVaR and mCVaR. Additionally, the paper aims to identify which portfolio offers superior return-to-risk performance by calculating modified Sharpe ratios.

Besides the introduction, the remainder of the paper is structured as follows. Section 2 presents the literature review. Section 3 describes the construction of the CVaR and mCVaR portfolios. Section 4 introduces the descriptive statistics and preliminary findings. Section 5 reports the results of the constructed portfolios. Section 6 provides the complementary STAR Ratio analysis. Section 7 discusses the findings, and the final section concludes the paper.

2. Literature review

This section reviews studies that construct multi-asset portfolios incorporating both developed and emerging stock markets. For example, Meriç et al. (2016) apply Principal Components Analysis (PCA) to examine global diversification opportunities for international investors. Their findings suggest that emerging markets offer strong diversification potential due to their relatively low correlations both among themselves and with developed markets. In a related study, Harrathi et al. (2016) analyse volatility spillovers among equity indices from Islamic and non-Islamic emerging economies using a VAR-BEKK-MGARCH framework. Their sample includes daily returns from six countries – Turkey, Indonesia, Egypt, Mexico, China, and Brazil. The authors calculate optimal portfolio weights to construct minimum-risk, cross-country portfolios, along with hedge ratios and measures of hedging effectiveness. More recently, Bekaert et al. (2023) investigate portfolio allocation strategies that integrate emerging markets into global multi-asset portfolios. They compare various weighting approaches – such as equal weighting, valuation-based, and GDP-based schemes, and assess their impact on risk-adjusted portfolio performance.

Huang et al. (2025) analyse more than two decades of data to evaluate how U.S. investors may gain from global portfolio diversification. The study constructs portfolios using both equal weighting and mean-variance optimisation, with performance primarily assessed through the Sharpe ratio. Findings reveal that prior to 2009, international equity diversification provided notable advantages for the U.S. investors. However, in the period following 2009, the effectiveness of such globally diversified portfolios diminished, offering limited benefits to theU.S.-based investors. Shimizu and Shiohama (2020) explore risk-oriented allocation methods within the context of factor investing by developing a multifactor portfolio using an inverse volatility weighting scheme. Utilising daily return data from global equity markets spanning 2002 to 2017, their empirical analysis focuses on the performance of inverse factor volatility strategies across the Japanese, Eurozone, and U.S. markets. The findings demonstrate that these portfolios consistently outperformed traditional market-cap-weighted benchmarks, largely due to their ability to effectively capture and leverage factor-based risk premiums. Lang et al. (2024) apply a time-varying parameter vector autoregression (TVP-VAR) model to investigate how tail risk propagates among the G7 stock markets over the period from January 2000 to September 2022. Their study emphasises key financial crises, including the dot-com bubble burst, the 2008 Global Financial Crisis, the European sovereign debt turmoil, and the COVID-19 pandemic along with its subsequent variants. Their findings reveal that tail risk connectedness within the G7 fluctuated notably during the pandemic, driven by factors such as lockdown measures, disruptions in supply chains, policy interventions, and shifts in investor sentiment. They highlight that analysing these spillover effects enhances the understanding of intermarket dependencies, which is crucial for investors aiming to optimise portfolio diversification and implement robust risk management strategies.

3. Portfolio optimisation with CVaR and mCVaR minimising goals

This paper optimises a portfolio comprising seven indices with the aim of minimising CVaR and modified CVaR (mCVaR). Specifically, the paper integrates two advanced risk algorithms with the portfolio optimisation framework of Markowitz (1952). The starting point for constructing minimum-CVaR and minimum-mCVaR portfolios is the Markowitz minimum-variance portfolio, obtained by solving equation (1). The Markowitz portfolio serves only as a working framework, as the optimisation objective is subsequently replaced by CVaR and mCVaR measures.

$$min\, \sigma_p^2 = min\, \sum_{i=1}^{N} w_i^2 \sigma_i^2 + \sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j \rho_{i,j}, \quad (1)$$

$$\sum_{i=1}^{N} w_i = 1\, ; \quad 0 \leq w_i \leq 1 \quad (2)$$

$$\bar{r}_p = \sum_{i=1}^{N} w_i r_i \quad (3)$$

In equation (1), σ_p^2 represents the total variance of the portfolio, while σ_i^2 refers to the variance associated with individual asset i. The term w_i denotes the portfolio weight assigned to asset i. The correlation coefficient between any two distinct assets i and j is indicated by $\rho_{i,j}$. Equation (2) indicates a fundamental constraint in multivariate portfolio optimisation, which means that the aggregate of all asset weights must equal one, with each individual weight constrained within the range [0, 1]. Every portfolio with minimum variance has the corresponding mean value, which is weighted average portfolio return (r_p), and it can be calculated as in equation (3).

First and second moments (r_p and σ_p) from equations (1) and (2) are used for calculating parametric VaR: $VaR_p = r_p + Z_\alpha \sigma_p$, which serves for calculating CVaR. Z_α is the left quantile of the normal standard distribution.

$$CVaR_\alpha = -\frac{1}{\alpha}\int_0^\alpha VaR(x)dx \tag{4}$$

Expression (5) shows how minimum CVaR portfolio can be optimised.

$$\min CVaR_p(w),\ \sum_{i=1}^n w_i r_i \tag{5}$$

Nonetheless, relying on the two-moment CVaR can lead to distorted or inaccurate risk assessments when the portfolio return distribution deviates from normality (Wang et al., 2016). This limitation arises because traditional CVaR considers only the mean and the variance. To address this, one must account for all four statistical moments – mean, variance, skewness, and kurtosis, which is precisely the strength of the modified CVaR (mCVaR). mCVaR incorporates higher-order moments by integrating the modified Value at Risk (mVaR), defined as: $mVaR_\alpha = r_p + Z_{CF,\alpha}\sigma_p$, where $Z_{CF,\alpha}$ represents the Cornish–Fisher adjusted quantile that corrects for skewness and excess kurtosis.

$$Z_{CF,\alpha} = Z_\alpha + \frac{1}{6}(Z_\alpha^2 - 1)S + \frac{1}{24}(Z_\alpha^3 - 3Z_\alpha)K - \frac{1}{36}(2Z_\alpha^3 - 5Z_\alpha)S^2 \tag{6}$$

S and K are measures of skewness and kurtosis of a portfolio. Similar to expression (5), minimum semiparametric CVaR portfolio can be optimised as in expression (7):

$$\min mCVaR_p(w),\ \sum_{i=1}^n w_i r_i \tag{7}$$

4. Dataset and preliminary findings

This paper utilises daily data from seven DEC and seven EMEC indices to construct minimum modified CVaR (mCVaR) portfolios. The DEC indices include the S&P 500 (U.S.), NIKKEI 225 (Japan), DAX (Germany), FTSE 250 (U.K.), CAC (France), TSX (Canada), and FTSE MIB (Italy). The EMEC indices consist of SHCOMP (China), SENSEX (India), BOVESPA (Brazil), MOEX (Russia), KOSPI (Korea), IPC (Mexico), and JCI (Indonesia). The dataset spans five and a half years, from January 2020 to June 2025. This period is intentionally chosen because it includes the COVID-19 pandemic, an unprecedented crisis that was even deeper than the Global Financial Crisis of 2008. This inevitably implies the presence of downside risk, as illustrated by the S&P500 index in Figure 1.[1] All index data were sourced from the website stooq.com. Each group of indices are synchronised separately, and all time-series are converted to log returns (r_i) using the formula: $r_i = 100 \times log(P_{i,t}/P_{i,t-1})$, where P_i represents the price of a given index. Table 1 presents descriptive statistics of the selected assets.

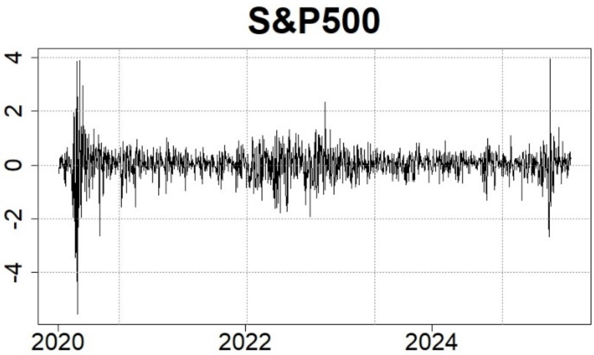

Figure 1. S&P500 returns

Source: Author's own creation.

According to Table 1, the Italian FTSE MIB index exhibits the highest variance among the DEC indices, while the Russian MOEX index shows the highest variance within the EMEC group. All selected indices, except for NIKKEI 225 and SHCOMP, display negative skewness, indicating that the majority of returns are concentrated to the left of the mean. Additionally, all indices have high kurtosis values, suggesting the presence of outliers or extreme risk. These findings suggest that CVaR and mCVaR yield significantly different risk estimates, as confirmed by the results in Table 2. In particular, the relatively high levels of skewness, and especially kurtosis, lead to mCVaR values that are substantially higher than their CVaR counterparts.

Table 1. Descriptive statistics

Assets	Mean	S.D.	Skew.	Kurt.	Assets	Mean	S.D.	Skew.	Kurt.
S&P500	0.020	0.602	-0.603	17.377	SHCOMP	0.007	0.433	0.489	9.281
NIKKEI225	0.015	0.599	0.242	9.201	SENSEX	0.031	0.515	-1.947	29.096
DAX	0.014	0.575	-0.774	16.906	BOVESPA	0.015	0.653	-1.088	25.121
FTSE250	-0.003	0.528	-0.627	12.066	MOEX	0.003	0.895	-6.782	150.661
CAC	0.006	0.565	-1.095	16.660	KOSPI	0.010	0.548	-0.452	11.149
TSX	0.011	0.520	-1.606	35.939	IPC	0.015	0.469	-0.267	6.041
FTSE-MIB	0.014	0.631	-2.310	30.450	JCI	0.009	0.465	-0.280	15.206

Source: Author's calculation.

[1] For reasons of brevity, the remaining index plots are available upon request.

Table 2. Downside risk measures of the selected assets

Assets	CVaR	mCVaR	Assets	CVaR	mCVaR
S&P500	-1.583	-6.054	SHCOMP	-1.148	-2.194
NIKKEI225	-1.581	-3.234	SENSEX	-1.341	-7.566
DAX	-1.517	-5.659	BOVESPA	-1.724	-9.004
FTSE250	-1.409	-3.954	MOEX	-2.382	-43.691
CAC	-1.500	-5.444	KOSPI	-1.450	-3.824
TSX	-1.374	-9.680	IPC	-1.235	-2.044
FTSE-MIB	-1.667	-9.239	JCI	-1.230	-4.132

Source: Author's calculation.

Table 3. Pairwise Pearson correlations

	S&P500	**NIKKEI**	**DAX**	**FTSE250**	**CAC**	**TSX**	**FTSE-mib**	**Average**
S&P500	1	0.178	0.567	0.521	0.561	0.845	0.543	0.536
NIKKEI	0.178	1	0.372	0.390	0.365	0.218	0.317	0.307
DAX	0.567	0.372	1	0.819	0.935	0.639	0.901	0.705
FTSE250	0.521	0.390	0.819	1	0.823	0.619	0.761	0.655
CAC	0.561	0.365	0.935	0.823	1	0.647	0.904	0.706
TSX	0.845	0.218	0.639	0.619	0.647	1	0.636	0.601
FTSE-mib	0.543	0.317	0.901	0.761	0.904	0.636	1	0.677
	SHCOMP	**SENSEX**	**BOVESPA**	**MOEX**	**KOSPI**	**IPC**	**JCI**	**Average**
SHCOMP	1	0.216	0.105	0.127	0.324	0.159	0.123	0.176
SENSEX	0.216	1	0.311	0.274	0.461	0.263	0.368	0.315
BOVESPA	0.105	0.311	1	0.191	0.165	0.479	0.176	0.238
MOEX	0.127	0.274	0.191	1	0.165	0.220	0.130	0.184
KOSPI	0.324	0.461	0.165	0.165	1	0.251	0.379	0.291
IPC	0.159	0.263	0.479	0.220	0.251	1	0.206	0.263
JCI	0.123	0.368	0.176	0.130	0.379	0.206	1	0.230

Source: Author's calculation.

Table 3 presents the pairwise Pearson correlations for the DEC and EMEC portfolios, revealing that developed stock markets are more highly integrated, which may reduce the effectiveness of diversification. In other words, the results in Tables 2 and 3 help explain the structure of the constructed portfolios.

5. Empirical findings

5.1 Portfolio construction

This section presents the results of the constructed CVaR and mCVaR portfolios, while Table 4 shows their composition. It is evident that the structures of the CVaR and mCVaR portfolios differ significantly, indicating that the third and fourth moments play an important role in the construction of the mCVaR portfolio.

As for the composition of the portfolios, the Canadian TSX holds the highest weight in the DEC CVaR portfolio (38.22%) due to its lowest CVaR value (-1.374). The NIKKEI 225 has the second-highest share (34.35%), despite its relatively high downside risk (-1.581), because it exhibits very low interdependence with the other indices in the portfolio, which justifies its relatively high allocation. The FTSE 250 ranks third, supported by its relatively low downside risk (-1.409).

Regarding the modified CVaR portfolio, only the NIKKEI 225 and the S&P 500 are included, with weights of 78.15% and 21.85%, respectively. The Japanese index has the largest share due to its lowest mCVaR risk and very low correlation with the other indices. The S&P 500 also holds a relatively high share, despite its higher risk level (-6.054), as it shows a very low pairwise correlation with the dominant NIKKEI 225, which drives its inclusion in the portfolio.

In the EMEC CVaR portfolio, the Chinese SHCOMP has the highest share (34.49%) due to its lowest CVaR value (-1.148), followed by JCI and IPC, which also exhibit relatively low risk levels of -1.230 and -1.235, respectively.

SHCOMP again holds the highest share (46.44%) in the mCVaR portfolio due to its low mCVaR risk (-2.214), although this is the second-lowest risk value, the Mexican IPC has the lowest (-2.044). However, the Chinese index receives a larger weight because it has a lower average correlation with the other indices (0.176), compared to the IPC (0.263).

Table 4. Structure of the constructed portfolios

DEC portfolio			EMEC portfolio		
Assets	**CVaR**	**mCVaR**	**Assets**	**CVaR**	**mCVaR**
S&P500	6.10	21.85	SHCOMP	34.49	46.44
NIKKEI225	34.35	78.15	SENSEX	10.44	0.00
DAX	0.00	0.00	BOVESPA	3.91	0.00
FTSE250	21.33	0.00	MOEX	1.99	0.00
CAC	0.00	0.00	KOSPI	1.31	0.00
TSX	38.22	0.00	IPC	22.68	39.27
FTSE-MIB	0.00	0.00	JCI	25.18	14.29

Source: Author's calculation.

Table 5 presents the first four moments, as the well as CVaR and mCVaR risk measure of the constructed portfolios. It can be seen that the CVaR risk measures are lower in the CVaR portfolio than in the mCVaR portfolio, while mCVaR risks are lower in the mCVaR portfolio than in the CVaR portfolio. This is a clear indication the portfolio optimisation is effective in all portfolios. Also, it should be noted that the standard deviation is lower in the CVaR portfolio than in the mCVaR portfolio because it is the main fact that determines the level of CVaR. On the other hand, it is obvious that the third and fourth moments are significantly lower in the mCVaR portfolios than in the CVaR portfolios. This is because the mCVaR portfolio puts a greater emphasis on the higher moments.

Table 5. Descriptive statistics of the constructed portfolios

	DEC portfolio		EMEC portfolio	
	CVaR	**mCVaR**	**CVaR**	**mCVaR**
Mean	0.010	0.016	0.012	0.010
Standard deviation	0.423	0.508	0.295	0.315
Skewness	-1.092	0.112	-0.833	-0.138
Kurtosis	20.505	6.140	6.561	2.207
CVaR	-1.116	-1.338	-0.774	-0.828
mCVaR	-5.472	-2.803	-1.828	-1.209

Source: Author's calculation.

Comparing the risk levels between the DEC and EMEC portfolios, it is evident that the EMEC portfolio exhibits lower CVaR and mCVaR risk, which is in line with Li and Rose (2009). According to Berger et al. (2011), the likely reason for the EMEC portfolio's dominance lies in the fact that emerging markets are significantly less integrated than developed markets (see Table 3). In other words, the correlation matrix appears to play an important role in determining both the level of extreme risk and the structure of the portfolios.

Table 6 provides additional evidence that portfolio optimisation is effective. In other words, all individual assets within the portfolios exhibit lower extreme risk than the portfolio as a whole, resulting in positive HEI values.

Table 6. HEI values of the selected indices

	S&P500	**NIKKEI225**	**DAX**	**FTSE250**	**CAC**	**TSX**	**FTSE-MIB**
CVaR	0.295	0.294	0.264	0.208	0.256	0.187	0.331
mCVaR	0.537	0.133	0.505	0.291	0.485	0.710	0.697
	SHCOMP	**SENSEX**	**BOVESPA**	**MOEX**	**KOSPI**	**IPC**	**JCI**
CVaR	0.325	0.422	0.551	0.675	0.466	0.373	0.370
mCVaR	0.449	0.840	0.866	0.972	0.684	0.409	0.707

Source: Author's calculation.

Finding that the EMEC portfolio has lower extreme risk than the DEC portfolio is not sufficient to claim that the EMEC portfolio is better. In other words, all calculated downside risk measures need to be back-tested, as this helps validate the accuracy and reliability of the VaR model. Back-testing is important because it compares predicted VaR values with realised losses to determine whether the model accurately estimates risk. If the actual losses exceed the predicted VaR too frequently, the model may be flawed.

Table 7. Back-testing results

	DEC portfolio		EMEC portfolio	
	CVaR	**mCVaR**	**CVaR**	**mCVaR**
N	19	0	12	3
Z-score	1.876	-3.542	0.449	-2.336
Prob.	0.061	0.000	0.654	0.019

Notes: N is the number of failures. Bolded values indicate the highest probability and the best model in terms of accuracy.

Source: Author's calculation.

From this perspective, Table 7 presents the results of the Kupiec test, which counts how often actual losses exceed the VaR estimate. The Z-score in Table 7 indicates how much the actual number of VaR exceptions (i.e. days when actual losses exceed the VaR estimate) deviates from the expected number based on the model. Both positive and negative Z-scores can be observed in Table 7. A positive Z-score means that the actual number of exceptions is greater than expected, suggesting that the model underestimates risk and is therefore too optimistic. Conversely, a negative Z-score indicates that the number of exceptions is lower than expected, suggesting that the model overestimates risk and is too conservative.

It is evident that both mCVaR models have relatively large negative Z-scores, indicating that their theoretical risk estimates are too high. In other words, the semiparametric CVaR model does not provide a good assessment of empirical downside risk. On the other hand, both CVaR models exhibit positive Z-scores, implying that they underestimate empirical extreme risk. However, the EMEC portfolio appears to perform significantly better than the DEC portfolio, as the probability of model accuracy is substantially higher for the EMEC portfolio (0.654) compared to the DEC portfolio (0.061).

5.2 Complementary analysis – STAR Ratio portfolio

To provide a more comprehensive analysis, this section aims to estimate which seven-asset portfolio offers a better return-to-downside-risk ratio. The previous section clearly demonstrates that the CVaR risk measure outperforms the modified CVaR in terms of accuracy and reliability. To this end, the Stable Tail Adjusted Return Ratio (STAR Ratio) is employed. This metric evaluates the attractiveness of an investment by combining expected returns with downside risk (CVaR), specifically accounting for extreme negative outcomes in the return distribution. The STAR Ratio reflects how much return is achieved per unit of tail risk. A higher STAR Ratio is preferable, as it indicates a higher return relative to the risk of substantial losses in worst-case scenarios. This measure is particularly relevant for asymmetric return distributions or in non-normal market conditions, where standard deviation (as used in the Sharpe ratio) may not adequately capture risk. Moreover, the STAR Ratio is more robust than other downside-risk metrics (such as the Sortino ratio). This is because it is based on CVaR, which is a coherent risk measure that satisfies the four desirable properties: monotonicity, translation invariance, subadditivity, and positive homogeneity. Equation (8) presents the formula for calculating the STAR Ratio, while expression (9) defines the optimisation procedure aimed at maximising it.

$$STARR = \frac{r_i}{|CVaR|} \tag{8}$$

$$max\left\{\frac{w^T r}{CVaR(w)}\right\}, \tag{9}$$

where w^T denotes the transposed weight vector of individual assets in the portfolio, aligned with the number of return observations T.

Table 8. Results of optimal STAR Ratio portfolios

DEC portfolio		EMEC portfolio	
S&P500	59.56	SHCOMP	2.60
NIKKEI225	38.47	SENSEX	72.23
DAX	1.97	BOVESPA	0.00
FTSE250	0.00	MOEX	0.00
CAC	0.00	KOSPI	0.00
TSX	0.00	IPC	25.17
FTSE-MIB	0.00	JCI	0.00
STAR Ratio	0.015	STAR Ratio	0.024

Source: Author's calculation.

Table 8 presents the results of the optimal STAR Ratio portfolios, along with the corresponding STAR Ratio estimates. In the DEC portfolio, the S&P 500 holds the largest share (59.56%) due to its highest mean return (0.020), followed by the NIKKEI 225 with a 38.47% share, reflecting its position as the second-highest in average return (0.015). In contrast, the EMEC portfolio is dominated by the SENSEX, which holds a 72.23% share, driven by its notably high average return (0.031). Although both BOVESPA and IPC exhibit relatively high average returns (0.015), IPC secures the second-largest share in the portfolio (25.17%) due to its lower CVaR value (-1.235).

Comparing the two STAR Ratio estimates, the EMEC portfolio exhibits a higher STAR Ratio value (0.024) compared to the DEC portfolio (0.015). This indicates that the EMEC portfolio achieves higher daily returns per unit of extreme downside risk. This result aligns with the findings in Table 5, which show that the EMEC portfolio has both a higher mean return and a lower CVaR.

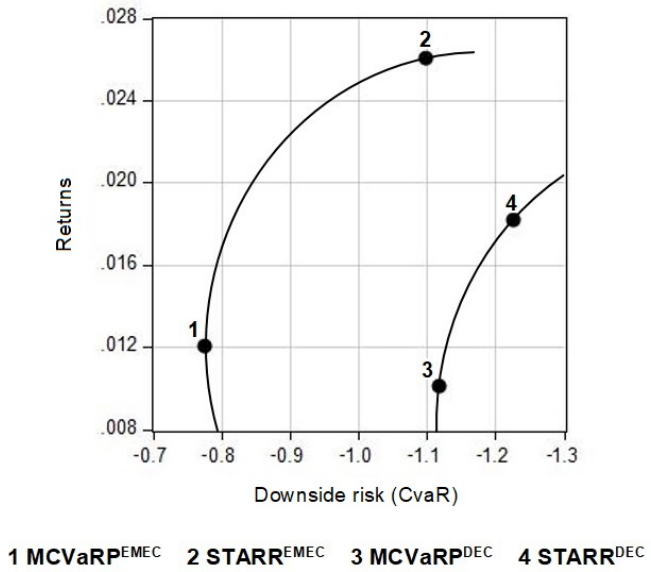

Figure 2. Efficient frontier lines of two portfolios

Source: Author's own creation.

Figure 2 jointly presents efficient frontier lines of the two portfolios, providing a visual perspective of the minimum CVaR and STAR Ratio portfolios. Figure 2 clearly shows that the combination of EMEC indices results in lower extreme risk and a higher STAR Ratio compared to the combination of DEC indices.

5.3 Discussion

The results show that an emerging markets portfolio has a lower extreme risk than a developed markets portfolio, probably because of their lower integration. This has several important implications for investors and portfolio managers. In other words, emerging markets may offer better diversification due to lower correlation and integration with global markets (Patra and Malik, 2025), and investors might reconsider traditional allocations that overweight developed markets for perceived safety. Reallocation of capital could also be a consequence because a lower extreme risk may justify increased exposure to emerging market assets in global portfolios (Bianchi et al., 2022), and investors may shift capital toward EMEC assets, especially in risk-averse or tail-risk-sensitive strategies. The results of the paper could lead to a reassessment of risk perception, where the perception that emerging markets are inherently riskier is called into question. Also, the paper clearly shows that more elaborate downside risk measure is not also the better risk measure.

From the aspect of portfolio managers, these results may prompt managers to increase emerging markets weights in long-term portfolios, and enhance potential for risk-adjusted returns through more efficient frontiers. Portfolios incorporating emerging markets might have lower vulnerability to extreme events, enhancing capital preservation strategies.

The higher STAR Ratio of the emerging markets portfolio indicates that these assets may offer superior compensation for tail risk. This suggests that emerging markets could play a more prominent role in tactical asset allocation, particularly in risk-sensitive strategies. Portfolio managers might consider increasing exposure to emerging markets if their objective is to optimise tail-risk-adjusted returns.

However, investors and portfolio managers need to carefully consider investing in EMEC markets because they carry various vulnerabilities. For example, from a political and regulatory perspective, unstable governments, political unrest, or corruption can disrupt markets (Luiz and Barnard, 2022). Sudden policy changes – such as capital controls, nationalisations, or changes in taxation – may negatively impact foreign investors, while weak legal systems can compromise investor protection and property rights. Additionally, emerging economies are often more vulnerable to economic shocks, such as commodity price swings, inflation, or external debt crises. A high dependence on exports or specific sectors (e.g., oil, mining) increases macroeconomic fragility. Exchange rate volatility is also a major concern, as depreciation of the local currency against the investor's base currency can erode returns even if local market performance is positive. Finally, many emerging stock markets have lower trading volumes and fewer institutional investors, leading to wider bid-ask spreads, slippage, and difficulties when exiting positions.

6. Conclusions

This paper constructs multivariate portfolios comprising emerging and developed stock markets, aiming to determine which portfolio exhibits lower downside risk, as measured by the CVaR and modified CVaR models. The considered time period includes the COVID-19 pandemic and the war in Ukraine, implying heightened volatility and extreme risk in the stock markets. Additionally, a complementary analysis examines which portfolio offers superior return-to-risk performance, as measured by the STAR Ratio.

The results indicate that assets with low extreme risk and low pairwise correlations with other indices in the portfolio hold a dominant position. This is evident in the DEC portfolio, where the S&P 500 and NIKKEI 225 indices are prominent, while the SHCOMP, IPC, and JCI indices have a significant share in the EMEC portfolio. The mCVaR model reports significantly higher downside risk than the CVaR model because it accounts for high kurtosis and negative skewness. When comparing the downside risk measures between the two portfolios, the EMEC portfolio exhibits a lower downside risk than the DEC portfolio. However, this result is not due to lower extreme risk in emerging markets, but rather to the lower level of integration among them, which substantially contributes to the reduction of extreme risk. Finally, both extreme risk models are evaluated using the Kupiec test, which clearly indicates that the mCVaR measure is overly strong, as it significantly overestimates extreme risk, potentially leading to misguided investment decisions. However, this does not imply that mCVaR is methodologically inferior to the simpler CVaR model; rather, it indicates that, in this specific sample, it may be overly conservative or less empirically accurate due to its sensitivity to extreme kurtosis.

An additional analysis calculates the STAR Ratio, which measures the return-to-risk performance of the portfolios. The results suggest that the EMEC portfolio has a higher STAR Ratio, primarily due to the Indian SENSEX index, which recorded significantly higher average daily returns than any index in the DEC portfolio.

This paper may provide valuable information for global stock market investors and portfolio managers investing in both developed and emerging markets. It proposes an optimal combination of assets that minimises extreme risk and maximises the STAR Ratio. It also clearly indicates which downside risk model is more suitable for evaluating extreme risk – parametric or semiparametric CVaR.

Acknowledgement: *Paper is a part of research financed by the MSTDI RS, agreed in decision no. 451-03-136/2025-03/200009 from 4.2.2025.*

References

[1] Akbari, A., Ng, L. (2021), *International Market Integration: A Survey*. *Asia-Pacific Journal of Financial Studies*, 49, 161-195.

[2] Akdeniz, C., Catik, A.N., Kisla, G.H. (2021), *The impact of oil prices on oil-gas stock returns: a fresh evidence from the COVID-affected countries*. *Economic Computation and Economic Cybernetics Studies and Research*, 5(3), 221-236.

[3] Albulescu, C.T. (2021), *COVID-19 and the United States financial markets' volatility*. *Finance Research Letters*, 38, 101699.

[4] Baig, A., Butt, H.A., Haroon, O., Rizvi, S.A.R. (2021), *Deaths, panic, lockdowns and US equity markets: The case of COVID-19 pandemic*. *Finance Research Letter*s, 38, 101701.

[5] Bekaert, G., Harvey, C.R., Mondino, T. (2023), *Emerging equity markets in a globalized world. Emerging Markets Review*, 56, 101034.

[6] Belhassine, O., Karamti, C. (2021), *Contagion and portfolio management in times of COVID-19. Economic Analysis and Policy*, 72, 73-86.

[7] Berger, D., Pukthuanthong, K., Yang, J.J. (2011), *International diversification with frontier markets. Journal of Financial Economics*, 101(1), 227-242.

[8] Bianchi, B., Galstyan, V., Herzberg, V. (2022), *Global risk and portfolio flows to emerging markets: Evidence from irish-resident investment funds. Journal of International Money and Finance*, 123, 102600.

[9] Bredin, D., Conlon, T., Potì, V. (2017), The *price of shelter - Downside risk reduction with precious metals. International Review of Financial Analysis*, 49, 48-58.

[10] Bruner, R.F., Li, W., Kritzman, M., Myrgren, S., Page, S. (2008), *Market integration in developed and emerging markets: Evidence from the CAPM. Emerging Markets Review* 9(2), 89-103.

[11] Chai, S., Zhou, P. (2018), The *Minimum-CVaR strategy with semi-parametric estimation in carbon market hedging problems. Energy Economics*, 76, 64-75.

[12] Chishti, M.Z., Khalid, A.A., Sana, M. (2023), *Conflict vs sustainability of global energy, agricultural and metal markets: A lesson from Ukraine-Russia war. Resources Policy*, 84, 103775.

[13] Favre, L., Galeano, J.A. (2002), *Mean-modified Value-at-Risk optimization with hedge funds. Journal of Alternative Investments*, 5(2), 21-25.

[14] Harrathi, N., Aloui, C., Houfi, M.A., Majdoub, J. (2016), *Emerging equity markets connectedness, portfolio hedging strategies and effectiveness. International Journal of Financial Research* 7(2), 189-201.

[15] Höhler, J., Lansink, A.O. (2020), *Measuring the impact of COVID-19 on stock prices and profits in the food supply chain. Agribusiness*, 37(1), 171-186.

[16] Huang, R., Kambouroudis, D., McMillan, D.G. (2025), *Is portfolio diversification still effective: evidence spanning three crises from the perspective of U.S. investors. Journal of Asset Management,* 26, 115-135.

[17] Kupiec, P. (1995), *Techniques for verifying the accuracy of risk management models. Journal of Derivatives*, 3, 73-84.

[18] Lang, C., Hu, Y., Corbet, S., Hou, Y(G). (2024), *Tail risk connectedness in G7 stock markets: Understanding the impact of COVID-19 and related variants. Journal of Behavioral and Experimental Finance*, 41, 100889.

[19] Li, X-M., Rose, L.C. (2009), *The tail risk of emerging stock markets. Emerging Markets Review*, 10(4), 242-256,

[20] Li, J., Huang, H., Xiao, X. (2012), *The sovereign property of foreign reserve investment in China: A CVaR approach. Economic Modelling*, 29(5), 1524-1536.

[21] Luiz, J.M., Barnard, H. (2022), *Home country (in)stability and the locational portfolio construction of emerging market multinational enterprises. Journal of Business Research*, 151, 17-32.

[22] Markowitz, H. (1952), *Portfolio selection. Journal of Finance*, 7(1), 77-91.

[23] Meriç, I., Ding, J., Meriç, G. (2016), *Global portfolio diversification with emerging stock markets. Emerging Markets Journal*, 6(1), 59-62.

[24] Mirović, V., Živkov, D., Njegić, J. (2017), *Construction of commodity portfolio and its hedge effectiveness gauging – revisiting DCC models. Czech Journal of Economics and Finance*, 67(5), 396-422.

[25] Nishimura, Y. (2016), *Intraday volatility and volume in china's stock index and index futures markets. Asia-Pacific Journal of Financial Studies*, 44, 932-955.

[26] Patra, S., Malik, K. (2025), *Return and volatility connectedness among US and Latin American markets: A QVAR approach with implications for hedging and portfolio diversification. Global Finance Journal*, 65, 101094.

[27] Rockafellar, R.T., Uryasev, S. (2002), *Conditional value-at-risk for general loss distributions. Journal of Banking and Finance*, 26, 1443-1471.

[28] Salas-Fumas, V. (2021), *Spanish non-financial corporations and the COVID pandemic: vulnerability, resilience and transformation. Applied Economic Analysis*, 29(85), 42-57.

[29] Shang, D., Yu, C., Diao, G. (2021), *Study on Impacts of COVID-19 Pandemic Recession Based on Monte Carlo Simulation. Prague Economic Papers*, 30(6), 724-747.

[30] Shimizu, H., Shiohama, T. (2020), *Constructing inverse factor volatility portfolios: A risk-based asset allocation for factor investing. International Review of Financial Analysis*, 68, 101438.

[31] Tissaoui, K., Hkiri, B., Talbi, M., Alghassab, W., Alfreahat, K.I. (2021), *Market volatility and illiquidity during the COVID-19 outbreak: Evidence from the Saudi stock exchange through the wavelet coherence approaches. North American Journal of Economics and Finance*, 58, 101521.

[32] Wang, C-S., Zhibiao Zhao, Z. (2016), *Conditional Value-at-Risk: Semiparametric estimation and inference. Journal of Econometrics*, 195(1), 86-103.

[33] Živkov, D., Kuzman, B., Subić, J. (2020), *What Bayesian quantiles can tell about volatility transmission between the major agricultural futures? Agricultural Economics – Zemedelska Ekonomika*, 66(5), 215-225.