Mahalanobis distance and Stutzer ratio modelling in emerging markets portfolios

Dejan Zivkov[1], Boris Kuzman[2], Jonel Subic[3]

[1] *University of Novi Sad, Novi Sad School of Business, Serbia, ORCID: 0000-0003-2357-3250, dejanzivkov@gmail.com (corresponding author);*
[2] *Institute of Agricultural Economics, Serbia, ORCID: 0000-0002-8661-2993, kuzmanboris@yahoo.com;*
[3] *Institute of Agricultural Economics, Serbia, ORCID: 0000-0003-1342-1325, jonel_s@iep.bg.ac.rs.*

***Abstract:** This study examines the performance of multi-asset portfolios in global emerging markets, emphasizing their exposure to systemic risk and risk-adjusted returns. The analysis encompasses portfolios from regions such as Southeast Asia, the Middle East and Central Asia, Central and Eastern Europe, Africa, and Latin America. The research uses daily data, covering a 10 years period. Two advanced methodologies are applied in the portfolio construction – the Mahalanobis distance and the Stutzer ratio. The financial turbulence index constructed for the systemic risk measurement reveals a pronounced allocation bias toward a single asset, driven by its distinctive attributes. Interestingly, the asset with the highest weight in the portfolio originates from frontier markets, which are less integrated into the global financial system and thus more insulated from global economic shocks. The Stutzer ratio, through its calculation of the decay parameter theta, provides insights into whether an emerging market portfolio is characterized by high volatility and frequent market fluctuations or is more aligned with long-term investment strategies that emphasize stability and consistent performance. The results indicate that all emerging markets portfolios have higher Stutzer ratio than the developed portfolio, which indicates better risk-adjusted results. However, the theta parameter is mostly lower in the emerging markets portfolios, suggesting higher risk in these markets. The highest Sharpe ratio is found in the African countries portfolio, while the best portfolio, when using the more advanced Stutzer ratio, is with Latin American countries. This study provides insightful guidance for international investors exploring opportunities in emerging markets, focusing on systemic risk and evaluating returns through a risk-adjusted lens.*

***Keywords:** Mahalanobis distance, risk-adjusted performance, multi-asset portfolio optimization.*

***JEL classification:** C61, G32, D53.*

APA Style Citation: Zivkov, D., Kuzman., B, Subic, J. (2025). Mahalanobis distance and Stutzer ratio modelling in emerging markets portfolios. *E&M Economics and Management*, *28*(4), 148–162. https://doi.org/10.15240/tul/001/2025-4-010

Introduction

Over the last couple of decades, emerging markets have implemented numerous reform measures, making them more appealing to global investors. Several reasons make them favourable for investment. First, emerging markets often experience faster economic growth compared to developed economies, driven by industrialization, urbanization, and increasing consumer demand (Časni & Vizek, 2014). Younger and growing middle-class populations lead to rising consumption, creating opportunities for companies to expand and generate higher profits (Eshun et al., 2023). Many emerging markets are investing heavily in infrastructure projects (Babucea et al., 2017), leading to opportunities in construction, real estate, and related sectors, while government-led reforms aimed at liberalizing markets or improving governance can spur economic growth and attract more foreign investment. Some emerging markets are leapfrogging traditional technologies and adopting cutting-edge solutions, creating unique investment opportunities.

On the other hand, emerging markets often face various vulnerabilities due to their developing nature and structural characteristics. They commonly struggle with issues such as inflation, exchange rate fluctuations, and heavy debt burdens (Rocha & Moreira, 2010). From a stock market perspective, these markets are often characterized by a lack of liquidity (Urban, 2017), which makes executing large trades challenging. According to Salisu et al. (2022), stock prices in emerging markets also tend to be more volatile, influenced by speculative behaviour and external shocks. Moreover, emerging markets are particularly sensitive to geopolitical risks, as many of them are heavily reliant on commodity exports (Pitterle et al., 2015). Geopolitical risks can disrupt commodity markets, adversely affecting the revenues and economic stability of these countries. In addition, geopolitical tensions or conflicts can heighten uncertainty, leading global investors to withdraw funds from emerging markets and shift to safer assets in developed economies.

All emerging markets have their own pros and cons when it comes to investment, and the performance of these investments differs significantly between countries due to varying economic, political, social, and structural factors. The goal of the paper is to identify which emerging markets portfolio offers the best opportunities for investors, analysing two perspectives – the level of systemic risk each portfolio is exposed to and its risk-adjusted performance. We construct six-asset portfolios comprising stock indices from emerging markets across five global regions: Southeast Asia, the Middle East and Central Asia, Central and Eastern Europe, Africa, and Latin America. For comparison, we also examine a portfolio consisting of developed G7 countries. While this topic is not new in the literature (Alqahtani et al., 2020; Liu, 2019; Salisu et al., 2020; Zhao et al., 2019), this paper seeks to contribute by employing two unconventional and sophisticated methodological approaches – the Mahalanobis distance (MD) as a measure of systemic risk and the Stutzer ratio as a significant improvement over the classical Sharpe ratio.

Examining systemic risk in emerging markets is important for investors because emerging markets are sensitive to global economic conditions, such as changes in interest rates, commodity prices, or investor sentiment (Mensi et al., 2021). Investors who effectively analyse and manage systemic risks can better navigate volatility in these markets, while taking advantage of their growth potential. On the other hand, the analysis of risk-adjusted performance is equally important because it helps balance the higher growth potential of these markets with the significant risks they pose. Specifically, this calculation enables investors to make informed decisions, optimize portfolios, and avoid excessive risks while capitalizing on growth opportunities.

The Mahalanobis distance is used to calculate the level of systemic risk in each portfolio. It was originally developed as a statistical tool to classify human skulls into distinct groups based on their physical characteristics (Mahalanobis, 1927). In the realm of finance, this concept can be adapted to analyse features such as the statistical moments of assets in a portfolio or the characteristics of portfolios held by investors. When portfolio weights are optimized using outdated or shifting distributions, they can become highly suboptimal, while trading strategies relying on past market patterns that no longer exist are likely to incur losses. To address this issue, Kritzman and Li (2010) introduce the concept of “financial turbulence,” measured using the Mahalanobis distance. The financial turbulence index (FTI) captures the degree of multivariate irregularity or unexpected behaviour in financial market data. In other words, the Mahalanobis distance can be characterized as a statistical measure used to determine the distance between a point and a distribution, taking into account the correlations among variables (Stöckl & Hanke, 2014). In finance, this measure can identify unusual observations in multivariate datasets, such as outliers in portfolio returns or economic indicators (Kanga et al., 2023). Giglio et al. (2016) assert that this methodology has several useful characteristics that make it superior to other methods in detecting turbulence and systemic risk. First, it incorporates the covariance structure of the variables, making it effective in financial systems where variables are highly correlated. Second, it adjusts for different scales of the variables, ensuring that no single variable disproportionately influences the results. Third, it detects extreme deviations from the norm, which indicates stress or vulnerability in financial systems.

There is substantial evidence in the literature indicating that stock returns in emerging markets often deviate from a normal distribution (Dridi & Boughrara, 2023; Li et al., 2021; Tanos et al., 2024; Yiming et al., 2024). This challenges the practical applicability of the Sharpe ratio because it is based on the variance, assigning equal weight to deviations both above and below the mean (Sharpe, 1966). This assumption, however, may not align with real-world investor preferences, particularly when the focus is on protecting against losses. The Stutzer ratio, introduced by Stutzer (2000), redefines the concept of risk by focusing on the likelihood of failing to meet a specified target return. Unlike the Sharpe ratio, which views all volatility as risk, the Stutzer ratio emphasizes downside risk. As Stutzer (2000) demonstrates, when a portfolio is expected to outperform a benchmark over time, the probability of underperformance diminishes exponentially as the sample period grows. This decay rate, represented mathematically as theta, is proposed as a performance measure, and Stutzer (2000) provides a method to construct portfolios that maximize this decay rate. The Stutzer ratio has several advantages over the traditional Sharpe measure, according to Haley and McGee (2006). First, it is not constrained by the assumption of normally distributed returns, making it a more flexible and robust performance metric. Second, it accounts for investor preferences for positive skewness, which are overlooked in the mean-variance paradigm. Third, it discourages strategies that generate high returns at the cost of taking extreme risks.

The main contribution of the paper lies in the methodologies employed. First, it evaluates the level of systemic risk in emerging market portfolios using the elaborate Mahalanobis distance approach. Second, it assesses the risk-adjusted performance of the portfolios using the advanced, but rarely used Stutzer ratio metric. To the best of our knowledge, neither methodology has been applied in this context, which provides the motivation for this research.

Apart from the introduction, the paper is organized as follows. The second section provides a review of the existing literature. The third section outlines the methodologies used, focusing on Mahalanobis distance and Stutzer ratio-optimized portfolios. The fourth section presents the dataset and descriptive statistics. Section five is dedicated to presenting the research findings in two subsections. The final section offers the conclusions.

1 Theoretical background

This section presents studies that use emerging equity markets in global portfolios. For instance, Christoffersen et al. (2014) analyse trends and changes in correlations over time using weekly return data from both developed and emerging markets. They argue that including emerging markets alongside developed markets enhances diversification opportunities. Abuaf et al. (2019) conducted an empirical analysis to determine if emerging-market portfolios lie on the mean-variance efficient frontier and assessed which specific markets offer superior diversification benefits. Their findings highlighted Mexico and China as the most significant contributors to portfolio diversification. Gupta and Donleavy (2009) found that, even with rising correlations, Australian investors can still gain advantages by including international emerging markets in their portfolios. Guidi and Ugur (2014) examine the integration of South-Eastern European (SEE) stock markets, specifically those in Bulgaria, Croatia, Romania, Slovenia, and Turkey, with developed markets in Germany, the UK, and the USA. Their study reveals that, despite dynamic cointegration observed during much of the global financial crisis (September 2008 to May 2010), investors could still achieve diversification benefits between September 2007 and June 2013. Jayasuriya and Shambora (2009) build upon existing research regarding enhancements to the efficient portfolio frontier within globally diversified portfolios. Their findings indicate that, over the past eight years, a U.S. investor could have achieved superior returns at the same level of risk by including emerging and frontier markets in their portfolio. Hadhri and Ftiti (2019) explore the profitability of investing in emerging markets. Beyond the traditional first and second moments considered in asset allocation, their analysis emphasizes the third moment: realized skewness. Their results suggest that emerging markets tend to outperform developed markets over various time horizons, particularly during periods of financial crises.

Thomas et al. (2022) explore how frontier markets contribute to enhancing the diversification benefits of international portfolios, particularly in the Asia-Pacific and European regions. Their findings show that while frontier markets provide greater diversification potential than emerging markets, they are more suitable for investors with a higher tolerance for risk. Buchanan et al. (2011) demonstrate that adding emerging markets to a global portfolio offers the combined advantage of lowering risk while boosting returns. Ngene et al. (2018) present detailed findings on the interactions of shocks and volatility between the stock markets of 24 frontier markets and the U.S. They contend that the conditional correlation between the U.S. and each of these frontier markets is typically low or negative, suggesting that U.S. investors can benefit from diversification by including frontier markets in their portfolios. Chan-Lau (2012) contends that allocating a larger portion to emerging markets may enable investors to surpass their benchmarks in growth phases, while keeping the potential for downside risks relatively low. Berger et al. (2013) conclude that emerging markets provide diversification advantages by reducing risk. Their analysis reveals that the volatility in emerging markets is mostly driven by idiosyncratic factors, reinforcing their capacity to mitigate overall portfolio risk. Kohlert (2011) concludes that emerging markets can offer valuable diversification benefits, though their effectiveness largely depends on the specific composition of frontier market indices. If an inappropriate index is selected, its return patterns and correlations may fail, leading to unexpectedly poor performance during turbulent times.

From the perspective of Mahalanobis distance and Stutzer ratio portfolios, few papers have utilized these methodologies. Shi and Weidong (2022) introduce an innovative approach named weighted turbulence, which integrates a dynamic network framework with a weighted Mahalanobis distance to assess systemic risk across global energy markets. According to their findings, this technique effectively captures sharp increases in systemic risk while remaining resilient to distortions caused by noisy data. Their model demonstrates strong practical value for real-world applications in systemic risk analysis. Stöckl and Hanke (2014) explore both current and prospective uses of the Mahalanobis distance within financial contexts. They organize these applications based on the characteristics and origins of the input variables involved. Their analysis highlights how this statistical measure can offer valuable insights and practical benefits for actors operating in financial markets. On the other hand, Benson et al. (2008) utilize the Stutzer ratio framework to examine optimal portfolio design and assess the performance of Australian equity funds. Through a comparative analysis of the Stutzer and Sharpe ratios, they reveal how deviations from normal return distributions carry meaningful economic implications. Their findings underscore the influence of return non-normalities on both portfolio formation and performance assessment methodologies. Alcock et al. (2013) investigate potential manipulation within U.S. REITs by contrasting performance assessments derived from the manipulation-proof performance measure (MPPM) with those based on conventional metrics such as the Sharpe ratio, Jensen's alpha, the information ratio, and the Stutzer index. Their analysis uncovers indications that certain manipulation tactics may exploit leverage in a strategic and opportunistic manner.

2 Research methodologies

2.1 Mahalanobis distance

Kritzman and Li (2010) suggest that the Mahalanobis distance can serve as an effective measure of unusualness in financial markets. Considering an asset return (r_t) at a given day *t*, the deviation of how much this return deviates from the norm is to calculate the standardized squared deviation: $(r_t - \mu)^2/\sigma^2$, where: μ – the expected return; σ^2 – the return variance. A higher ratio indicates a more "unusual" return, implying that the instantaneous return variance surpasses its long-term average. Notably, this ratio corresponds to the squared Mahalanobis distance for a single asset. To extend this concept to a portfolio with *n* assets, one could sum the Mahalanobis distances of all individual assets, yielding the squared Euclidean distance, as in Equation (1):

$$Eu_t^2 = \sum_{i=1}^{n} \frac{\left(r_{t,i} - \mu_i\right)^2}{\sigma_i^2} \quad (1)$$

However, this approach disregards the dependencies between assets, which are crucial for assessing the systemic risk of a group of assets in a portfolio, according to Stöckl and Hanke (2014). The direction of deviations in asset returns from their means holds critical information about their interrelationships, which requires a multivariate distance measure to capture. The squared Mahalanobis distance incorporates this consideration, as in Equation (2).

$$MD_t^2 = (r_t - \mu)'\Sigma^{-1}(r_t - \mu) \quad (2)$$

In cases where the covariance matrix is diagonal (with zero off-diagonal elements), *MD* simplifies to the squared Euclidean distance. Yet, its key advantage lies in its ability to account for joint deviations in asset returns, r_i and r_j (for $i, j = 1, \ldots, n$ and $i \neq j$). When calculating the Mahalanobis distance, demeaned returns are taken into account, ensuring that the calculation reflects how far a data point is from the centre of the distribution. Without demeaning, the Mahalanobis distance would measure the distance from the origin, which is not meaningful when analysing data that naturally clusters around its mean. Using demeaned returns allows the Mahalanobis distance to identify unusual returns relative to the expected behaviour (mean and covariance structure), and also to detect outliers or anomalies (e.g., extreme deviations from normal returns).

By summarizing the unusual behaviour of all assets into a single metric, the Mahalanobis distance provides a comprehensive measure of systemic irregularities. Moreover, it does not rely on strict distributional assumptions and is particularly well-suited for elliptically distributed random variables, which can be fully characterized by their location parameter μ and scatter matrix Σ. When this measure is used in the context of portfolios, *MD* is referred to as (squared) financial turbulence index (*FTI*):

$$FTI = \sqrt{\frac{1}{w^2}\left(w_D(r_t - \mu)\right)'\Sigma^{-1}\left(w_D(r_t - \mu)\right)} \quad (3)$$

where: r_t – the vector of asset returns; μ – the mean vector of the distribution; Σ – covariance matrix of the variables and Σ^{-1} – the inverse of the covariance matrix; w_D – the diagonal matrix of weights w_i.

2.2 Stutzer ratio

After calculating the level of systemic risk for each portfolio, we aim to compare their risk-adjusted performance using the Stutzer ratio. The Stutzer ratio offers a refined alternative to the Sharpe ratio, addressing several of its shortcomings. While the Sharpe ratio evaluates risk-adjusted returns by comparing excess returns to volatility, the Stutzer ratio takes a broader perspective by incorporating the full characteristics of return distributions, including skewness and kurtosis (Haley & McGee, 2011). It leverages an exponentially tilted likelihood ratio to account for risks that the Sharpe ratio often overlooks (Bondarenko, 2014). A key limitation of the Sharpe ratio is its sensitivity to outliers, which can distort the assessment of risk-adjusted returns. In contrast, the Stutzer ratio reduces this issue by focusing on the overall distribution of returns rather than solely relying on volatility (Benson et al., 2008). This makes the Stutzer ratio particularly effective in capturing the reliability of long-term returns. Unlike the Sharpe ratio, which can reward portfolios with erratic performance as long as the returns are high, the Stutzer ratio emphasizes consistency. It is specifically designed to favour portfolios that deliver stable returns over time, offering a more accurate representation of risk-adjusted performance for portfolios with non-normal return distributions.

We design portfolios with the objective of maximizing the Stutzer ratio. This metric is calculated in relation to a chosen benchmark asset, where $r_{p,t}$ denotes the return of portfolio at time *T*, adjusted by the benchmark returns. The mean excess return ($\bar{r}_p$) is subsequently defined as:

$$\bar{r}_p(T) = \frac{1}{T}\sum_{t=1}^{T} r_{p,t} \quad (4)$$

Stutzer (2000) explains that when a portfolio has a positive expected excess return, the law of large numbers implies that the probability of observing a negative sample excess return, $\bar{r}_p(T)$, approaches zero as the sample period *T* increases. From this standpoint, an investor aiming to minimize the risk of underperformance might construct a portfolio designed to reduce the likelihood of non-positive average excess returns as quickly as possible. The rate at which this probability diminishes, referred to as I_p, is known as the “portfolio performance index.” This index quantifies how rapidly the chance of underperformance converges to zero and is defined mathematically in Equation (5).

$$I_p = {}^{\max}_{\theta}\left(-\ln E\left(e^{\theta \bar{r}_p(T)}\right)\right) \quad (5)$$

where: θ < 0

For investors aiming to minimize benchmark underperformance, the optimal portfolio is the one with the highest decay rate. Stutzer (2000) shows that if stock returns are normally distributed, I_p is directly linked to the traditional Sharpe ratio, ensuring that portfolio rankings remain identical whether assessed using the Stutzer ratio or the Sharpe ratio. From a portfolio construction perspective, I_p can be utilized as a practical tool for designing portfolios in advance. Consider N potential assets for inclusion in the portfolio, each with a time series of T observed excess returns, $r_{i,t}$ for asset i. The portfolio's excess return at any given time t is then calculated as follows:

$$r_{p,t} = \sum_{i=1}^{N} w_i r_{i,t} \tag{6}$$

where w_i – the weight assigned to asset i within the portfolio. The sample estimate of the expression on the right-hand side of Equation (6) is calculated in the following manner:

$$\hat{I}_p = \max_{\theta} \left(-\ln \frac{1}{T} \sum_{t=1}^{T} e^{\theta \bar{r}_p(T)} \right) \tag{7}$$

The optimal asset weights, according to the portfolio performance index criterion, are found by solving the maximization problem outlined in Equation (8). When optimizing the Stutzer portfolio, it is crucial to choose suitable initial values for both the asset weights and the portfolio performance index. Stutzer (2000) suggests starting with the asset weights that maximize the Sharpe ratio as an initial approximation in Equation (8). Similarly, a reasonable starting value for θ is typically set as the negative of the mean excess return divided by its variance.

$$I_m = \max_{w_1,\dots,w_n} \max_{\theta} \left(-\ln \frac{1}{T} \sum_{t=1}^{T} e^{\theta \bar{r}_p(T)} \right) \tag{8}$$

2.3 Dataset

This study analyses daily closing prices of stock indices from both emerging and developed markets to form six-asset portfolios. The sample includes 30 stock indices representing emerging markets across five global regions: East Asia, the Middle East and Central Asia, Central and Eastern Europe, Africa, and Latin America. For comparison, six indices from G7 countries are incorporated to represent developed markets. The selected indices from East Asia are: JKSE (Indonesia), KLCI (Malaysia), SET (Thailand), VNI (Vietnam), PSEi (Philippines) and STI (Singapore). The Middle East and Central Asia indices are: SENSEX (India), DSEX (Bangladesh), KSI (Pakistan), KASE (Kazakhstan), TADAWUL (Saudi Arabia) and DFM (United Arab Emirates). The emerging European indices are: WIG (Poland), PX (the Czech Republic), BUX (Hungary), BET (Romania), SOFIX (Bulgaria) and SBITOP (Slovenia). The African indices are: EGX (Egypt), MASI (Morocco), NSE (Nigeria), NSX (Namibia), BRVM (Côte d'Ivoire) and JSE (South Africa). The Latin American indices are: BOVESPA (Brazil), IPC (Mexico), IPSA (Chile), COLCAP (Columbia), Lima general (Peru) and JSEAJC (Jamaica). At the end, the G7 indices are: S&P500 (USA), NIKKEI225 (Japan), DAX (Germany), CAC (France), FTSE100 (UK) and FTSE-MIB (Italy). All selected indices are composite stock indices that track the overall performance of multiple stocks across various sectors, providing a broad measure of market performance.

The dataset spans a significant period, from January 2015 to December 2024, with all data sourced from the Investing.com platform. Stock prices are converted into log-returns, denoted as $r_{i,t}$, using the formula: $r_{i,t} = 100 \times \log(P_{i,t}/P_{i,t-1})$, where P_i refers to the stock price. To maintain consistency across the dataset, all time-series of a single portfolio are synchronized based on available observations. The MSCI All Country World Index serves as the benchmark asset for constructing the Stutzer portfolio, providing a comprehensive measure of global equity performance across both developed and emerging markets.

Tab. 1 presents the four-moment descriptive statistics of the selected indices. It can be observed that all kurtosis values exceed the benchmark of 3, indicating the presence of extreme risk. The Mahalanobis distance provides a comprehensive measure of systemic risk for each portfolio, accounting for both the mean characteristics of the indices and their correlation interdependencies. Additionally, the third moment also reveals non-normal

Tab. 1: Descriptive statistics

	Mean	Std. dev.	Skew.	Kurt.		Mean	Std. dev.	Skew.	Kurt.
South East Asia portfolio					**Mid Asia portfolio**				
JKSE	0.004	0.413	−0.229	13.043	**SENSEX**	0.016	0.412	−1.372	14.110
KLCI	0.000	0.295	−0.372	14.161	**DSEX**	0.009	0.339	1.115	21.763
SET	−0.007	0.404	−1.992	30.942	**KSI**	0.008	0.414	−0.437	6.949
VNI	0.013	0.495	−0.982	7.411	**KASE**	0.025	0.387	0.147	12.956
PSEi	−0.005	0.522	−1.558	19.449	**TADAWUL**	0.018	0.409	−0.239	9.237
STI	−0.001	0.358	−0.883	12.902	**DFM**	0.016	0.416	−0.710	10.187
CEEC portfolio					**African portfolio**				
WIG	0.009	0.514	−1.132	16.836	**EGX**	0.042	0.592	−0.261	6.879
PX	0.012	0.408	−0.977	14.094	**MASI**	0.001	0.302	−1.671	29.100
BUX	0.027	0.532	−1.437	16.306	**NSE**	0.014	0.440	0.593	9.182
BET	0.013	0.426	−1.902	24.793	**NSX**	0.019	0.656	−0.414	8.417
SOFIX	0.008	0.329	−2.120	33.370	**BRVM**	−0.008	0.306	0.278	7.165
SBITOP	0.012	0.354	−1.699	21.705	**JSE**	0.015	0.487	−0.118	10.444
Latin America portfolio					**DEC portfolio**				
BOVESPA	0.020	0.651	−0.599	15.247	**S&P500**	0.020	0.493	−0.829	19.413
IPC	0.005	0.428	−0.272	5.527	**NIKKEI225**	0.010	0.568	−0.480	12.189
IPSA	0.014	0.492	−0.202	17.361	**DAX**	0.014	0.530	−0.606	14.326
COLCAP	0.010	0.495	0.185	22.730	**CAC**	0.013	0.519	−0.895	15.049
Lima general	0.019	0.487	−0.371	13.254	**FTSE100**	0.004	0.435	−0.918	16.850
JSEAJC	0.022	0.425	0.355	40.537	**FTSE-MIB**	0.013	0.613	−1.666	23.385

Source: own

behaviour, suggesting that the normally-based Sharpe ratio results may diverge from the more complex Stutzer ratio, which takes into account significantly more factors than the classical Sharpe ratio. Both the Mahalanobis distance and the Stutzer ratio incorporate the correlation matrix when optimizing a portfolio, and these results may help explain the portfolio outcomes. Therefore, Tab. 2 presents the pairwise Spearman correlations for each portfolio. The average correlations between indices are: 0.287, 0.119, 0.226, 0.096, 0.240 and 0.589 for SEAC, MEAC, CEEC, AFC, LAC and DEC portfolio, respectively. According to these results, the developed markets have the highest average correlation, while all emerging markets are significantly less integrated. This might affect the performance of the portfolios.

3 Empirical results

3.1 Mahalanobis distance results

This section presents the financial turbulence index results for the six portfolios, calculated using the Mahalanobis distance methodology. The structure of the calculated portfolios is shown in Tab. 3, while the average values of the FTI are presented in Tab. 4. Fig. 1 illustrates the time-varying evolution of the FTI across the sample.

Before finding reasons for the result in Tab. 3, it is worth of knowing that the key factors affecting *MD* are demeaned returns (deviations from the mean), high variance (variables with higher variance contribute less to MD), correlation matrix and outliers. The mean of assets is important in calculating a portfolio because it acts as the centre or reference point from which deviations are

Tab. 2: Pairwise Spearman rank correlation

	JKSE	KLCI	SET	VNI	PSEi	STI		SENSEX	DSEX	KSI	KASE	TADAWUL	DFM
JKSE	1	–	–	–	–	–	SENSEX	1	–	–	–	–	–
KLCI	0.374	1	–	–	–	–	DSEX	0.079	1	–	–	–	–
SET	0.310	0.349	1	–	–	–	KSI	0.124	0.058	1	–	–	–
VNI	0.178	0.185	0.202	1	–	–	KASE	0.192	0.051	0.087	1	–	–
PSEi	0.344	0.372	0.279	0.144	1	–	TADAWUL	0.214	−0.004	0.047	0.137	1	–
STI	0.320	0.395	0.387	0.168	0.306	1	DFM	0.226	0.056	0.079	0.164	0.270	1
	WIG	PX	BUX	BET	SOFIX	SBITOP		EGX	MASI	NSE	NSX	BRVM	JSE
WIG	1	–	–	–	–	–	EGX	1	–	–	–	–	–
PX	0.419	1	–	–	–	–	MASI	0.092	1	–	–	–	–
BUX	0.434	0.390	1	–	–	–	NSE	0.027	0.055	1	–	–	–
BET	0.292	0.310	0.285	1	–	–	NSX	0.133	0.052	−0.018	1	–	–
SOFIX	0.087	0.119	0.114	0.119	1	–	BRVM	0.021	0.043	0.029	−0.004	1	–
SBITOP	0.168	0.180	0.151	0.204	0.118	1	JSE	0.142	0.065	−0.002	0.816	−0.002	1
	BOVESPA	IPC	IPSA	COLCAP	Lima	JSEAJC		S&P500	NIKKEI	DAX	CAC	FTSE100	FTSE−MIB
BOVESPA	1	–	–	–	–	–	S&P500	1	–	–	–	–	–
IPC	0.416	1	–	–	–	–	NIKKEI	0.214	1	–	–	–	–
IPSA	0.367	0.391	1	–	–	–	DAX	0.584	0.319	1	–	–	–
COLCAP	0.349	0.332	0.306	1	–	–	CAC	0.585	0.333	0.934	1	–	–
Lima	0.379	0.381	0.301	0.336	1	–	FTSE100	0.543	0.322	0.820	0.858	1	–
JSEAJC	0.013	−0.005	−0.003	−0.010	0.050	1	FTSE−mib	0.542	0.273	0.863	0.879	0.770	1

Source: own

measured. *MD* measures the distance of each observation from the centre of a multivariate distribution, where the mean represents this centre in multivariate analysis. By calculating demeaned returns, the estimation ensures that the distance is measured relative to the central tendency of the data. Typically, assets with high mean returns are preferred unless their variance or correlation makes them risky.

Tab. 1 presents the optimized results of the Mahalanobis distance portfolios, revealing a distinct pattern. In other words, it can be seen that in all portfolios, one asset holds a very high share, while all other assets have negligible weights. In all cases, the dominant asset in the portfolio has a relatively high mean, low variance, low correlation and high kurtosis. For example, in the SEAC portfolio, the majority of the investment is concentrated in the Vietnamese index (VNI), which has the highest mean (0.013) and the lowest average correlation with other assets (0.175). The SENSEX index in the MECAC portfolio has relatively high mean (0.016), low variance (0.412) and high kurtosis (14.110). In the CEEC portfolio, the Bulgarian SOFIX has the highest share due to the lowest variance (0.329) and the highest kurtosis (33.370). This is also the case with MASI in the AFC portfolio. The Jamaican JSEAJS index has the highest mean of 0.022 and a very low average correlation of 0.009, which explains its dominance in the portfolio (99.71%). In the DEC portfolio, S&P500 has the share of 83.56%, with the highest mean (0.020) and the second-lowest average correlation (0.411).

Fig. 1 illustrates the dynamic FTI for each optimal portfolio. It is clear that the highest

Tab. 3: Structure of Mahalanobis distance portfolios

SEAC		MECAC		CEEC		AFC		LAC		DEC	
JKSE	0.48	**SENSEX**	95.06	**WIG**	0.10	**EGX**	0.10	**BOVESPA**	0.10	**S&P500**	83.56
KLCI	0.30	**DSEX**	0.09	**PX**	0.40	**MASI**	99.69	**IPC**	0.10	**NIKKEI225**	0.65
SET	0.69	**KSI**	0.42	**BUX**	0.24	**NSE**	0.02	**IPSA**	0.00	**DAX**	4.28
VNI	97.80	**KASE**	0.95	**BET**	0.34	**NSX**	0.06	**COLCAP**	0.06	**CAC**	4.11
PSEi	0.30	**TADAWUL**	1.51	**SOFIX**	98.08	**BRVM**	0.00	**Lima gen.**	0.03	**FTSE100**	3.88
STI	0.43	**DFM**	1.97	**SBITOP**	0.84	**JSE**	0.13	**JSEAJC**	99.71	**FTSE-MIB**	3.53

Note: Acronyms SEAC, MECAC, CEEC, AFC, LAC and DEC denote South East Asian countries, Middle-East and Central Asian countries, Central and Eastern European countries, African countries, Latin American countries and developed countries, respectively.

Source: own

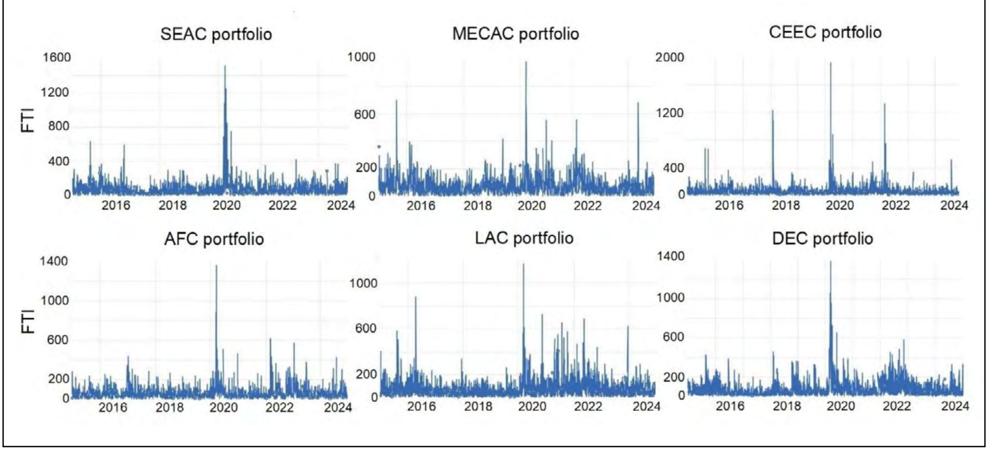

Fig. 1: Calculated financial turbulence index of optimal portfolios

Source: own

impact from systemic risk occurred during the COVID-19 pandemic. The pandemic was a major shock to global stock markets, and these results are consistent with Uddin et al (2021), Hsu and Tang (2022) and Yu and Xiao (2023). Additionally, higher systemic risk is also observed during the Russia-Ukraine war, which triggered an energy crisis and turmoil in global energy commodity markets.

Fig. 1 shows how the level of systemic risk fluctuates over time, but it hardly can be used for accurate comparison to determine which group of countries has experienced the highest impact from global systemic risk. Additionally, the high concentration of a single asset in all portfolios may distort the picture of which group of countries is most affected. Therefore, Tab. 4 calculates the average level of systemic risk for both the optimal portfolios and the equal-weight portfolios. The latter is expected to more realistically reflect which group of countries suffers the most from global systemic risk. It should also be noted that the level of FTI in all optimal portfolios is lower than that in the equal-weight portfolios, indicating the effectiveness of the optimization.

Tab. 4: Financial turbulence index of equal-weight and optimal portfolios

	SEAC	MECAC	CEEC	AFC	LAC	DEC
Optimal portfolios						
FTI (%)	83.13	76.74	77.56	64.87	64.07	82.72
Equal weight portfolios						
FTI (%)	88.91	89.26	88.40	87.94	87.04	88.73

Source: own

According to the optimal portfolio results, the LAC and AFC portfolios experienced the lowest level of global systemic risk. This essentially means that the JSEAJC and MASI indices are highly resistant to global shocks, as these two indices occupy the largest share in the portfolio. These findings align with Kohlert (2011), who asserts that emerging markets can deliver valuable diversification benefits, though their effectiveness largely depends on the composition of frontier market indices. Similarly, Berger et al. (2013) argue that emerging markets offer diversification advantages by lowering risk, as their volatility is predominantly influenced by idiosyncratic factors, further enhancing their ability to reduce overall portfolio risk. The equal-weight portfolio results indicate that all portfolios experienced a relatively equal amount of systemic risk, but the LAC portfolio performed slightly better than the others. In the equal-weighted portfolio, we do not find evidence that developed countries are more susceptible to global crises compared to emerging markets.

3.2 Stutzer ratio results

Identifying extreme turbulence in portfolios suggests that the Sharpe ratio may provide an inaccurate risk-adjusted assessment, as it assumes normality. Therefore, we apply a more complex and sophisticated metric, the Stutzer ratio, which penalizes investments with skewed or heavy-tailed distributions, commonly observed in stock markets. In order to be thorough in the analysis, we estimate both Sharpe and Stutzer portfolios to examine how their structure and performance differ, and Tab. 5 shows these results.

The Sharpe ratio is easy to understand because it favours assets with a high mean return and low risk in a portfolio. All dominant assets in Sharpe portfolios have the highest mean returns, as Tab. 5 indicates. For instance, the VNI index is the only asset in the SEAC portfolio because it has by far the highest mean return (0.013). KASE holds a significant share of 83.02% with a mean return of 0.025, while BUX dominates with 96.10% due to its high mean return of 0.027. EGX has a high mean return of 0.042, followed by JSE with a mean return of 0.015, resulting in respective portfolio shares of 53.07% and 26.67%. JSEAJC, Lima General, and BOVESPA occupy positions in the portfolio based on their risk-adjusted performance. In the DEC portfolio, the S&P500 holds a 100% share, driven by its highest mean return (0.020) and relatively low risk (0.493).

On the other hand, the structure of all Stutzer portfolios differs significantly from that of the Sharpe portfolio, indicating that additional factors, such as higher moments and the decay parameter, play an important role. Assets with the highest share in the Sharpe ratio also tend to have a high share in the Stutzer ratio portfolio. However, it can be noted that in most cases (except the AFC portfolio) assets that have a zero share in the Sharpe portfolio appear in the Stutzer portfolio, suggesting that the latter accounts for more factors than the classical Sharpe ratio.

Tab. 6 presents the Sharpe and Stutzer ratios for their respective portfolios. The results clearly show that the Sharpe ratio is greater in the Sharpe portfolios, whereas the Stutzer ratio is higher in the Stutzer-optimized portfolios. These findings strongly indicate the effectiveness of both portfolio optimization approaches. When comparing Sharpe performance across portfolios, the AFC portfolio stands out with the highest Sharpe ratio, recorded at 0.089. In the Stutzer portfolio, the LAC portfolio achieves the highest ratio, with the JSEAJC index holding the largest share at nearly 67%. The Jamaican index possesses several favourable characteristics that elevate it to the top

Tab. 5: Structure of Sharpe and Stutzer portfolios

SEAC		MECAC		CEEC		AFC		LAC		DEC	
Panel A: Sharpe portfolios											
JKSE	0.00	**SENSEX**	8.47	**WIG**	0.00	**EGX**	53.07	**BOVESPA**	31.37	**S&P500**	100.00
KLCI	0.00	**DSEX**	0.00	**PX**	0.00	**MASI**	0.00	**IPC**	0.00	**NIKKEI225**	0.00
SET	0.00	**KSI**	0.00	**BUX**	96.10	**NSE**	3.60	**IPSA**	0.00	**DAX**	0.00
VNI	100.00	**KASE**	83.02	**BET**	3.90	**NSX**	16.67	**COLCAP**	0.00	**CAC**	0.00
PSEi	0.00	**TADAWUL**	8.51	**SOFIX**	0.00	**BRVM**	0.00	**Lima gen.**	32.23	**FTSE100**	0.00
STI	0.00	**DFM**	0.00	**SBITOP**	0.00	**JSE**	26.67	**JSEAJC**	36.40	**FTSE-MIB**	0.00
Panel B: Stutzer portfolios											
JKSE	8.77	**SENSEX**	8.07	**WIG**	0.00	**EGX**	81.77	**BOVESPA**	12.81	**S&P500**	78.46
KLCI	0.00	**DSEX**	17.18	**PX**	0.00	**MASI**	0.00	**IPC**	0.00	**NIKKEI225**	18.70
SET	0.00	**KSI**	3.41	**BUX**	51.39	**NSE**	0.00	**IPSA**	0.00	**DAX**	2.84
VNI	91.23	**KASE**	43.71	**BET**	11.85	**NSX**	0.00	**COLCAP**	4.49	**CAC**	0.00
PSEi	0.00	**TADAWUL**	16.64	**SOFIX**	9.53	**BRVM**	0.00	**Lima gen.**	15.77	**FTSE100**	0.00
STI	0.00	**DFM**	10.98	**SBITOP**	27.23	**JSE**	18.23	**JSEAJC**	66.93	**FTSE-MIB**	0.00

Source: own

in the LAC portfolio – a high mean return (0.022), low risk (0.425), positive skewness (0.355), and a low average correlation with other LAC indices (0.020).

Tab. 7 provides descriptive statistics comparing the Sharpe and Stutzer ratios across all six portfolios. Interestingly, the Sharpe ratio portfolio exhibits a higher mean than the Stutzer counterpart in four out of six cases, as well as lower negative skewness also in four out of six cases. From a theoretical standpoint, this seems counterintuitive since the Stutzer ratio is designed to favour higher returns and lower negative skewness. However, a critical factor in calculating the Stutzer ratio is the decay factor (theta), which is not considered in the Sharpe ratio. The decay factor determines the weight assigned to historical data when calculating risk-adjusted returns. A lower decay factor places greater emphasis on recent data,

Tab. 6: Values of Sharpe and Stutzer ratios in Sharpe and Stutzer portfolios

	SEAC	MECAC	CEEC	AFC	LAC	DEC
Panel A: Sharpe ratio						
Sharpe portfolio	0.015	0.036	0.043	**0.089**	0.033	0.020
Stutzer portfolio	0.014	0.017	0.023	0.077	0.024	0.016
Panel B: Stutzer ratio						
Sharpe portfolio	0.0002 (−0.0149)	0.0005 (−0.0365)	0.0009 (−0.0432)	0.0020 (−0.0891)	0.0013 (−0.0328)	0.0003 (−0.0199)
Stutzer portfolio	0.0004 (−0.0574)	0.0030 (−0.3147)	0.0014 (−0.1437)	0.0026 (−0.1402)	**0.0115** (−0.4239)	0.0008 (−0.0926)

Notes: The numbers in parentheses denote theta; bold values highlight the larger figure when comparing the six portfolios.

Source: own

Tab. 7: Descriptive statistics of Sharpe and Stutzer portfolios

	SEAC		MECAC		CEEC		AFC		LAC		DEC	
	Sharpe	Stutzer	Sharpe	Stutzer	Sharpe	Stutzer	Sharpe	Stutzer	Sharpe	Stutzer	Sharpe	Stutzer
Mean	0.013	0.012	0.024	0.019	0.027	0.020	0.030	0.037	0.021	0.021	0.020	0.018
Variance	0.495	0.463	0.339	0.239	0.518	0.356	0.423	0.509	0.348	0.325	0.493	0.432
Skew.	−0.982	−1.066	−0.152	−1.024	−1.472	−2.409	−0.705	−0.423	−0.953	−0.149	−0.829	−0.985
Kurt.	7.425	7.803	12.810	12.975	16.587	27.535	8.933	7.573	16.933	27.792	19.412	18.702

Source: own

making the portfolio more responsive to current market trends and changes. This approach is particularly suitable for rapidly changing or volatile markets, as it captures short-term dynamics and adjusts quickly to shifts in risk or return patterns. Conversely, a higher decay factor gives more weight to long-term data, making the portfolio more stable and less sensitive to short-term fluctuations, which is ideal for strategic, long-term portfolios. In addition, the theta parameter is also important in the selection of individual assets in the portfolio. In our case, we maximize theta, which means the optimization reduces weights for assets with significant downside risk or negative skewness, favoring more stable and positively skewed assets.

As shown in Tab. 6, four emerging market portfolios (MECAC, CEEC, AFC, and LAC) have lower theta values compared to portfolios composed of developed market indices. A lower theta indicates that emerging market portfolios are more volatile and operate in rapidly shifting markets where responsiveness is essential. These results are in line with Thomas et al. (2022). On the other hand, the DEC and SEAC portfolios report higher theta values. Higher theta is better suited for long-term portfolios that prioritize stability and reduced sensitivity to short-term noise. Therefore, the selection of theta should align with the investor's time horizon, risk tolerance, and the characteristics of the assets within the portfolio. Emerging markets or highly volatile assets may benefit from a lower theta, while developed markets or more stable assets tend to perform better with a higher theta. Thus, the decay factor probably plays a crucial role in shaping the Stutzer portfolio structures, often taking precedence over lower negative skewness and higher returns. This might explain the somewhat unexpected results observed in the descriptive statistics of the Sharpe and Stutzer portfolios.

3.3 Discussion

The study finds that certain frontier market indices, such as VNI, MASI or JSEAJC, dominate the optimized Mahalanobis distance portfolios due to their lower integration into the global financial system. This could have various implications for global investors. First, the weak correlations with global stock markets reduces overall portfolio volatility and enhances diversification, especially during periods of global financial turbulence. This is in line with Atipaga et al. (2025), who researched the connection between developed and developing African countries. Second, this could mean that frontier markets are less affected by events like interest rate hikes in developed economies, geopolitical tensions, or global recessions (Talebi et al., 2025). Third, frontier markets are less dependent on foreign portfolio investments, and their economies are more localized and less reliant on global trade or supply chains. According to Harb and Umutlu (2024), this means that frontier markets are typically driven by local factors rather than global trends, which can provide stability in portfolios during global systemic risk events.

However, frontier markets are not without challenges. In other words, frontier markets often characterize political and regulatory instability, limited liquidity and smaller market size as well as underdeveloped financial infrastructure. These factors imply the presence of higher risk in frontier stock markets, as it is suggested by the lower theta parameter in the Stutzer ratio portfolios.

Conclusions

The paper examines the performance of emerging market multi-asset portfolios from the perspective of systemic risk susceptibility and risk-adjusted output. The paper is unique in the literature because two sophisticated methodological approaches are applied in this process – the Mahalanobis distance and Stutzer ratio.

The calculation of the FTI, based on the Mahalanobis distance methodology, reveals that the impact of global systemic risk is lower in optimal portfolios compared to equal-weight portfolios. Furthermore, the optimization process highlights a significant concentration in a single asset within the portfolio, driven by the unique idiosyncratic characteristics of that specific asset. An intriguing finding is that, in four out of five cases, the assets with the highest weight in the portfolio originate from less developed frontier markets. This occurs because frontier markets are less integrated into global financial systems and less dependent on global trade flows. As a result, they serve as a buffer, being less exposed to the volatility of global markets. In four out of five cases, the emerging market portfolios demonstrate lower sensitivity to global systemic risk compared to the developed market portfolio, with Latin American and African countries achieving the best results.

The Stutzer ratio analysis enhances the overall findings by providing insights into the risk-adjusted performance of the selected portfolios. Unlike the traditional Sharpe ratio, the Stutzer ratio offers key advantages, such as relaxing the assumption of normality and incorporating higher moments of the return distribution. A particularly noteworthy feature of this measure is its use of the decay parameter, theta, which highlights subtle portfolio characteristics related to risk and the likelihood of underperformance. The findings reveal that all emerging market portfolios achieve higher Stutzer ratios compared to the developed market portfolio, reflecting superior risk-adjusted performance. However, the theta parameter is generally lower in emerging market portfolios, signaling a higher level of risk associated with these markets. According to the results, the Latin American portfolio has the best Stutzer ratio.

This paper serves as a valuable resource for global investors interested in emerging market investments, offering a detailed analysis from the perspectives of systemic risk and risk-adjusted performance. It presents the precise structure of both the Mahalanobis distance and Stutzer ratio portfolios, providing insights into which emerging markets deliver the best performance. Both individual and institutional investors can leverage the findings to develop asset allocation strategies that optimize the performance of their investment portfolios.

Acknowledgement: *The 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

Abuaf, N., Ayala, T., & Sinclair, D. (2019). Global equity investing: An efficient frontier approach. *International Finance*, *22*(1), 70–85. https://doi.org/10.1111/infi.12146

Alcock, J., Glascock, J., & Steiner, E. (2013). Manipulation in U.S. REIT investment performance evaluation: Empirical evidence. *The Journal of Real Estate Finance and Economics*, *47*(3), 434–465. https://doi.org/10.1007/s11146-012-9378-8

Alqahtani, A., Bouri, E., & Vo, X. V. (2020). Predictability of GCC stock returns: The role of geopolitical risk and crude oil returns. *Economic Analysis and Policy*, *68*, 239–249. https://doi.org/10.1016/j.eap.2020.09.017

Atipaga, U.-F., Alagidede, I., & Tweneboah, G. (2025). Information flow between stock returns of advanced markets and emerging African economies. *Research in International Business and Finance*, *73*, 102603. https://doi.org/10.1016/j.ribaf.2024.102603

Babucea, A. G., Rabontu, C. I., & Balacescu, A. (2017). Analysis of variance of infrastructure for the main categories of public utilities at territorial level in Romania. *Economic Computation and Economic Cybernetics Studies and Research*, *51*(2), 85–102.

Benson, K., Gray, P., Kalotay, E., & Qiu, J. (2008). Portfolio construction and performance measurement when returns are non-normal. *Australian Journal of Management*, *32*(3), 445–462. https://doi.org/10.1177/031289620803200304

Berger, D., Pukthuanthong, K., & Yang, J. J. (2013). Is the diversification benefit of frontier markets realizable by mean-variance investors? The evidence of investable funds. *The Journal of Portfolio Management*, *39*(4), 36–48. https://doi.org/10.3905/jpm.2013.39.4.036

Bondarenko, O. (2014). Variance trading and market price of variance risk. *Journal of Econometrics*, *180*(1), 81–97. https://doi.org/10.1016/j.jeconom.2014.02.001

Buchanan, B. G., English, P. C., & Gordon, R. (2011). Emerging market benefits, investability and the rule of law. *Emerging Markets Review*, *12*(1), 47–60. https://doi.org/10.1016/j.ememar.2010.09.001

Časni, A. Č., & Vizek, M. (2014). Interactions between real estate and equity markets: An investigation of linkages in developed and emerging countries. *Czech Journal of Economics and Finance*, *64*(2), 100–119.

Chan-Lau, J. A. (2012). Frontier markets: Punching below their weight? A risk parity perspective on asset allocation. *The Journal of Investing*, *21*(3), 140–149. https://doi.org/10.3905/joi.2012.21.3.140

Christoffersen, P., Errunza, V., Jacobs, K., & Jin, X. (2014). Correlation dynamics and international diversification benefits. *International Journal of Forecasting*, *30*(3), 807–824. https://doi.org/10.1016/j.ijforecast.2014.01.001

Dridi, I., & Boughrara, A. (2023). Flexible inflation targeting and stock market volatility: Evidence from emerging market economies. *Economic Modelling*, *126*, 106420. https://doi.org/10.1016/j.econmod.2023.106420

Eshun, J., Acheampong, E., Botchway, K. D. K., Guy-Roland N'Drin, M., & Adzove, D. (2023). Labour market flexibility and economic growth in Africa. *Prague Economic Papers*, *32*(3), 320–349. https://doi.org/10.18267/j.pep.828

Giglio, S., Kelly, B., & Pruitt, S. (2016). Systemic risk and the macroeconomy: An empirical evaluation. *Journal of Financial Economics*, *119*(3), 457–471. https://doi.org/10.1016/j.jfineco.2016.01.010

Guidi, F., & Ugur, M. (2014). An analysis of South-Eastern European stock markets: Evidence on cointegration and portfolio diversification benefits. *Journal of International Financial Markets, Institutions and Money*, *30*, 119–136. https://doi.org/10.1016/j.intfin.2014.01.007

Gupta, R., & Donleavy, G. D. (2009). Benefits of diversifying investments into emerging markets with time-varying correlations: An Australian perspective. *Journal of Multinational Financial Management*, *19*(2), 160–177. https://doi.org/10.1016/j.mulfin.2008.10.001

Hadhri, S., & Ftiti, Z. (2019). Asset allocation and investment opportunities in emerging stock markets: Evidence from return asymmetry-based analysis. *Journal of International Money and Finance*, *93*, 187–200. https://doi.org/10.1016/j.jimonfin.2019.01.002

Haley, M. R., & McGee, M. K. (2006). Tilting safety first and the Sharpe portfolio. *Finance Research Letters*, *3*(3), 173–180. https://doi.org/10.1016/j.frl.2006.04.002

Haley, M. R., & McGee, M. K. (2011). "KLICing" there and back again: Portfolio selection using the empirical likelihood divergence and Hellinger distance. *Journal of Empirical Finance*, *18*(2), 341–352. https://doi.org/10.1016/j.jempfin.2010.12.002

Harb, H., & Umutlu, M. (2024). Shock resistors or transmitters? Contagion across industries and countries during the COVID-19 pandemic and the global financial crisis. *Economics Letters*, *244*, 112026. https://doi.org/10.1016/j.econlet.2024.112026

Hsu, Y.-L., & Tang, L. (2022). Effects of investor sentiment and country governance on unexpected conditional volatility during the COVID-19 pandemic: Evidence from global stock markets. *International Review of Financial Analysis*, *82*, 102186. https://doi.org/10.1016/j.irfa.2022.102186

Jayasuriya, S. A., & Shambora, W. (2009). Oops, we should have diversified! *Applied Financial Economics*, *19*(22), 1779–1785. https://doi.org/10.1080/09603100903035947

Kanga, D., Soumaré, I., & Amenounvé, E. (2023). Can corporate financing through the stock market create systemic risk? Evidence from the BRVM securities market. *Emerging Markets Review*, *55*, 101031. https://doi.org/10.1016/j.ememar.2023.101031

Kohlert, D. M. (2011). International diversification in a troubled world: Do frontier assets still improve the efficient frontier? *The Journal of Investing*, *20*(2), 42–49. https://doi.org/10.3905/joi.2011.20.2.042

Kritzman, M., & Li, Y. (2010). Skulls, financial turbulence, and risk management. *Financial Analysts Journal*, *66*(5), 30–41. https://doi.org/10.2469/faj.v66.n5.3

Li, Y., Zhuang, X., Wang, J., & Dong, Z. (2021). Analysis of the impact of COVID-19 pandemic on G20 stock markets. *The North American Journal of Economics and Finance*, *58*, 101530. https://doi.org/10.1016/j.najef.2021.101530

Liu, J. (2019). Impacts of lagged returns on the risk-return relationship of Chinese aggregate stock market: Evidence from different data frequencies. *Research in International Business and Finance*, *48*, 243–257. https://doi.org/10.1016/j.ribaf.2019.01.002

Mahalanobis, P. C. (1927). Analysis of race-mixture in Bengal. *Journal of the Asiatic Society of Bengal*, *23*, 301–333.

Mensi, W., Shafiullah, M., Vo, X. V., & Kang, S. H. (2021). Volatility spillovers between strategic commodity futures and stock markets and portfolio implications: Evidence from developed and emerging economies. *Resources Policy*, *71*, 102002. https://doi.org/10.1016/j.resourpol.2021.102002

Ngene, G., Post, J. A., & Mungai, A. N. (2018). Volatility and shock interactions and risk management implications: Evidence from the U.S. and frontier markets. *Emerging Markets Review*, *37*, 181–198. https://doi.org/10.1016/j.ememar.2018.09.001

Pitterle, I., Haufler, F., & Hong, P. (2015). Assessing emerging markets' vulnerability to financial crisis. *Journal of Policy Modeling*, *37*(3), 484–500. https://doi.org/10.1016/j.jpolmod.2015.03.010

Rocha, K., & Moreira, A. (2010). The role of domestic fundamentals on the economic vulnerability of emerging markets. *Emerging Markets Review*, *11*(2), 173–182. https://doi.org/10.1016/j.ememar.2009.11.004

Salisu, A. A., Ogbonna, A. E., Lasisi, L., & Olaniran, A. (2022). Geopolitical risk and stock market volatility in emerging markets: A GARCH–MIDAS approach. *The North American Journal of Economics and Finance*, *62*, 101755. https://doi.org/10.1016/j.najef.2022.101755

Salisu, A. A., Sikiru, A. A., & Vo, X. V. (2020). Pandemics and the emerging stock markets. *Borsa Istanbul Review*, *20*(1), S40–S48. https://doi.org/10.1016/j.bir.2020.11.004

Sharpe, W. F. (1966). Mutual fund performance. *Journal of Business*, *39*(S1), 119–138. https://doi.org/10.1086/294846

Shi, X., & Weidong, C. (2022). A robust hybrid method using dynamic network analysis and weighted Mahalanobis distance for modeling systemic risk in the international energy market. *Energy Economics*, *109*, 105954. https://doi.org/10.1016/j.eneco.2022.105954

Stöckl, S., & Hanke, M. (2014). Financial applications of the Mahalanobis distance. *Applied Economics and Finance*, *1*(2), 78–84. https://doi.org/10.11114/aef.v1i2.511

Stutzer, M. (2000). A portfolio performance index. *Financial Analysts Journal*, *56*(3), 52–61. https://doi.org/10.2469/faj.v56.n3.2360

Talebi, A., Bragues, G., Hadlul, S., & Sharma, A. (2025). Global stock markets during COVID-19: Did rationality prevail? *Research in International Business and Finance*, *73*, 102610. https://doi.org/10.1016/j.ribaf.2024.102610

Tanos, B. A., Farooq, O., & Ahmed, N. (2024). Secrecy culture and sensitivity of investment to stock prices: Evidence from emerging markets. *Journal of International Financial Markets, Institutions and Money*, *96*, 102045. https://doi.org/10.1016/j.intfin.2024.102045

Thomas, N. M., Kashiramka, S., Yadav, S. S., & Paul, J. (2022). Role of emerging markets vis-à-vis frontier markets in improving portfolio diversification benefits. *International Review of Economics and Finance*, *78*, 95–121. https://doi.org/10.1016/j.iref.2021.11.012

Uddin, M., Chowdhury, A., Anderson, K., & Chaudhuri, K. (2021). The effect of COVID-19 pandemic on global stock market volatility: Can economic strength help to manage the uncertainty? *Journal of Business Research*, *128*, 31–44. https://doi.org/10.1016/j.jbusres.2021.01.061

Urban, D. (2017). The impact of sovereign wealth fund ownership on the financial performance of firms: The evidence from emerging markets. *E&M Economics and Management*, *20*(3), 176–188. https://doi.org/10.15240/tul/001/2017-3-012

Yiming, W., Xun, L., Umair, M., & Aizhan, A. (2024). COVID-19 and the transformation of emerging economies: Financialization, green bonds, and stock market volatility. *Resources Policy*, *92*, 104963. https://doi.org/10.1016/j.resourpol.2024.104963

Yu, X., & Xiao, K. (2023). COVID-19 Government restriction policy, COVID-19 vaccination and stock markets: Evidence from a global perspective. *Finance Research Letters*, *53*, 103669. https://doi.org/10.1016/j.frl.2023.103669

Zhao, S., Chen, X., & Zhang, J. (2019). The systemic risk of China's stock market during the crashes in 2008 and 2015. *Physica A: Statistical Mechanics and Its Applications*, *520*, 161–177. https://doi.org/10.1016/j.physa.2019.01.006