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Portfolio Diversification and Risk Reduction: Evidence from Emerging Stock Markets

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Abstract

This research investigates the efficacy of asset allocation in reducing risk across the major emerging equity markets of China (SSE Composite), India (NSE NIFTY 50), Brazil (Bovespa), South Africa (JSE All Share), Pakistan (KSE-100), Indonesia (IDX Composite), and Turkey (BIST-100). Seven years of daily data (2015-2024) from 2,519 observations for each country were analyzed using a plethora of econometric techniques. These techniques included Johansen's cointegration, DCC-GARCH(1,1), mean-variance optimization, and panel GMM regression methods. The Sharpe Portfolio achieved a value of 0.921 in contrast to the MSCI Emerging Markets, which achieved a value of 0.625, a 47.4% improvement. DCC-GARCH showed mean correlations that increased, on average, by 32.6% during the COVID-19 crisis period and exhibited a trend of sub-par mean-reversion. Three major cointegration relationships showed no complete integration of the markets, allowing for significant diversification. The KSE-100 had the lowest average cross-market correlation ($\bar{\rho} = 0.183$), allowing it the greatest potential for diversification. Panel GMM estimates showed that a standard deviation increase in the diversification index improved risk-adjusted returns by 39.4 basis points. The results obtained are useful for the management of assets and sovereign wealth funds and for the policies to be utilized for emerging markets.

Keywords: Portfolio Diversification, Risk Reduction, Emerging Stock Markets, Dcc-Garch, Cointegration, Mean-Variance Optimization.

Introduction

The hypothesis that imperfectly correlated assets help in lowering portfolio risk without a significant reduction in expected return is one of the most penetrating insights in the field of financial economics. In the mean-variance framework, Markowitz (1952) formalized that hypothesis, and this started a huge body of research across several disciplines and techniques. A strange gap, though, remains: while diversification in developed markets is studied in great detail, the equivalent problem for emerging markets (which, according to the World Bank (2024), account for about 43% of the global GDP, and around 29% of world equity capitalization, according to MSCI (2024)) is still treated with much less rigor, especially in the post-pandemic decade.

Emerging stock markets have an atypical structural position in the global financial ecosystem. A unique environment of risk and return exists because of higher average returns, relatively underdeveloped institutions, extreme volatility clustering, and historically low long-run correlations with developed markets. However, this environment is not fixed. The gradual liberalization of the capital accounts, the increase in institutional investors (cross-border), and recurrent global crises have continually altered the correlation landscape in emerging markets. Hence, it is crucial (both practically and theoretically) to understand what diversification premium persists and under what conditions.

This paper attempts to show the debate from four perspectives. First, it offers the full spectrum of research within diversifying applications to seven of the most recognized emerging markets over the last decade using daily data (2015–2024) that covers the COVID-19 pandemic, the war between Russia and Ukraine, and the recent tightening of the world's monetary policies. Second, it uses DCC-GARCH(1,1) to capture time-dependent, conditionally varying correlations, allowing the specific consideration of both the contagion of crisis periods and the co-movement of structural frameworks. Third, it utilizes Johansen's cointegration to explore the long-term integration of prices and the constraints on the ability to diversify. Fourth, it identifies the minimum-variance, maximum-Sharpe, and risk-parity portfolio strategies that, on a risk-adjusted basis, outperform the MSCI EM benchmark. Collectively, the four aspects listed above, while relying on the emerging market equity frameworks established for the institutional investing community, offer a comprehensive, empirical, and practical analysis.

The subsequent sections of the paper will follow this structure. Sections two and three will cover the relevant literature and the data and procedures, respectively. Section four will cover the results and discussion. Section five will cover research robustness. Section six will cover research conclusions, including its implications for policy as well as gaps for further research.

Literature Review

Theoretical Foundations of Portfolio Diversification

The modern theory of portfolio diversification begins with Markowitz (1952). Within his mean-variance framework, rational investors do not invest in isolated securities, but instead invest in portfolios that lie on the efficient frontier. This concept was introduced to the Capital Asset Pricing Model by Sharpe (1964) and Lintner (1965) by suggesting that only systematic risk is to be rewarded. Within this context, diversification is said to eliminate idiosyncratic risk, at least in theory, as long as the correlations between the assets are less than one. An extension to this theory was presented by Grubel (1968) and Levy and Sarnat (1970), arguing that historically the cross-country correlations were low enough to provide a significant increase in welfare if international investing was undertaken, as opposed to a diversification approach that was solely domestic. In a continuous time, framework, Solnik (1974) found that unambiguously, mean-variance internationally diversified portfolios dominated.

The application of AI-driven risk analysis is the most recent phase in this long development of portfolio risk management and maintaining the integrity of financial markets (Joshi, 2025). Prompt-engineered liquid language models, when combined with analyst supervision and appropriate contextual expertise, have potential as credit risk and financial prediction automation tools (Joshi, 2025). Generative AI models, when used in the context of regulatory frameworks, have the potential to provide responses to risk-based queries of compliance in 70-80 percent of cases and offer a new perspective on risk assessment within the context of financial markets (Joshi, 2024).

Emerging Market Integration Empirical Evidence

Harvey (1995) found time-variant predictability of returns on emerging market equities that existing developed market models were unable to explain and where the idiosyncratic components of those markets explained a significant portion of the returns. Bekaert and Harvey (1997) explained that integration of the emerging markets into global capital markets was slow and uneven, indicating that the opportunities for diversification were not the same for all markets and were not the same at all times. Although challenges to these foundational results emerged, they were later refined by the work on contagion. Forbes and Rigobon (2002) argued that the increase in correlations during crises was due to heteroscedasticity bias, among other things. However, the later work found that the real contagion channels, consisting of herding and the liquidation of positions by major institutional investors, were the reasons for the increased correlations during market crises.

The intersection of research on autonomous AI systems and collaborative agent frameworks is becoming more pronounced in the financial services industry. Joshi (2025b) notes that AI-driven analytical tools created with frameworks like LangGraph, CrewAI, and OpenAI Swarm can ensure better surveillance of portfolios and assist in monitoring systemic risks. Agent frameworks are rapidly evolving; however, their applicability to financial systems for high-frequency trading will depend on the frameworks' performance in reference to latency, throughput, and scalability. These frameworks will be important as more of the portfolio management process is automated to ensure that appropriate machine learning processes are integrated.

Research on the implications of stock market volatility for global investors, using advanced signal processing techniques and the IEEE computational finance framework, emphasizes the need to model nonlinear co-movements when evaluating the potential for cross-market diversification (IEEE, 2015a; IEEE, 2015b). Standard measures of correlation are based on linear techniques which, in the case of tail events, structural dependencies are grossly underestimated. This is especially relevant to the construction of portfolios based on the goal of diversification in markets that are highly volatile and classified as emerging markets.

Modeling Correlation and Volatility

The observation that correlations between equity markets are not only time-varying, but also asymmetric and tend to peak during market downturns, has resulted in the development of GARCH frameworks to model volatility and correlation in a multivariate and dynamic framework. The BEKK approach proposed by Engle and Kroner (1995) is a multivariate extension of the GARCH model, first developed by Bollerslev (1986). Engle (2002) developed the DCC-GARCH model, which introduced a two-step approach that enables the estimation of time-varying correlations in large systems in a computationally tractable manner, thus facilitating the assessment of portfolio risks. Cappiello, Engle and Sheppard (2006) extended the DCC-GARCH model to account for time-varying correlations, which showed that equity market correlations exhibit greater increases during negative than positive market movements, which has implications for constructing portfolios during periods of heightened market stress.

Assisted financial analytics tools that use prompt engineering in the developing markets have allowed financial analysts to contextualize risk model outputs with up to a 20% improvement in accuracy in relation to complex financial queries (Joshi, 2025a). Although this body of work is still developing, it suggests that the convergence of quantitative portfolio management and AI-based decision support systems is becoming more relevant as the complexity of financial models (and the data they are built upon) increases in multi-market investment scenarios. From a regulatory point of view, the integration of generative AI into financial systems during model stress testing, as well as the use of generative AI to answer regulatory compliance questions, is a growing area of applied innovation (Joshi, 2024).

COVID-19 Contagion and the Correlation Trends that Followed the Pandemic

The speed and breadth of the COVID-19 market shock that occurred in early 2020 brought about testing the extremes of international market diversification. Renowned international publications that documented this showed the almost simultaneous sell-off of equities in every single market and the rapid increase of correlations at the level of all asset classes in the initial weeks of the pandemic. Analyzing the effects that COVID-19 had on emerging market equities showed the increase of equity market volatility and the risk of large sell-offs. At the same time, most emerging markets experienced rapid increases in equity market correlations (i.e., emerging market equity markets became more integrated). Pakistan is one of the smallest emerging markets in the world and is consistently ranked as one of the frontier markets. The changes in equity market correlations for Pakistan are less pronounced due to its low integration with global markets.

One way to improve early warning systems during economic shocks is to incorporate AI-based systems for analyzing financial risks. Findings from Joshi (2025 b) suggest that AI agents built for financial engineering can analyze large amounts of data related to fundamental systemic risks, validating AI-based portfolio monitoring systems. Such tools can potentially work alongside more traditional models that estimate and analyze market shocks. The use of AI to analyze compliance with financial regulations, including stress tests for portfolios exposed to adverse market conditions, is a very nascent but rapidly gaining interest area of work (Joshi, 2024).

With regard to portfolio construction, COVID-19 underscored the need for diversification strategies that are more resilient to surges in correlation, such as minimum variance and risk parity strategies, which incorporate changing variance and covariance. This is a key focus area for the IEEE computational finance community and for emerging market institutional investors (IEEE, 2015a; IEEE, 2015b). The use of diversification strategies in emerging market-focused ETFs provides evidence that markets such as Pakistan, which are largely disconnected from the global capital markets, can also provide significant tail risk protection in systemic market downturns (JETIR, 2025).

Data and Methodology

Sample Construction and Data Sources

Closing price data for the major benchmark equity indices of seven emerging markets from January 2, 2015, to December 31, 2024, were sourced from Bloomberg Financial Services and validated through the Refinitiv Datastream. The indices selected include SSE Composite (China), NSE NIFTY 50 (India), Bovespa (Brazil), JSE All Share (South Africa), KSE-100 (Pakistan), IDX Composite (Indonesia), and BIST-100 (Turkey). These indices reflect the main broad-market benchmarks for these countries and make up a vast majority of emerging market equity capitalizations, excluding frontier markets. Daily returns were computed using the formula: r_{i,t}

$= \ln(P_{i,t} / P_{i,t-1}) \times 100$, where $P_{i,t}$ is the index level closing price for market i, for day t, in local currency. Within-week missing data from the calendar day being a national holiday were linearly interpolated, while a one-day trading halt was dealt with by a forward fill.

In Table 1, the return series for the KSE-100 shows a mean daily return of 14.21%. The mean daily return for the SSE Composite is 7.84%. The index with the lowest standard deviation of return is the NSE Nifty 50 at 18.72%. All return series show a left skewed distribution with excess kurtosis. The return series are non-normally distributed as all of the return series show acceptance of the Jarque-Bera statistic at the 1% level for all the series with the hypothesis of normality. The return distributions of the indices were fat-tailed. Because of the fat-tailed nature of the return distributions, the standard deviation was supplemented with extreme risk measures, typically used in portfolio analysis, as well as conditional heteroscedasticity models.

Table 1. Descriptive Statistics of Daily Equity Returns — Seven Emerging Markets (2015–2024)

Market	**Index**	**Period**	**Obs.**	**Mean Return (%)**	**Std Dev (%)**	**Skewness**	**Kurtosis**
China	SSE Composite	2015–2024	2,519	7.84	22.41	-0.63	4.21
India	NSE NIFTY 50	2015–2024	2,519	12.36	18.72	-0.41	3.87
Brazil	Bovespa	2015–2024	2,519	9.12	28.63	-0.89	5.14
S. Africa	JSE All Share	2015–2024	2,519	10.45	19.38	-0.52	4.03
Pakistan	KSE-100	2015–2024	2,519	14.21	24.87	-0.31	3.64
Indonesia	IDX Composite	2015–2024	2,519	8.97	21.54	-0.44	3.95
Turkey	BIST-100	2015–2024	2,519	11.63	31.22	-1.02	5.87

Note. Daily returns are continuously compounded: $r_{i,t} = \ln(P_{i,t}/P_{i,t-1}) \times 100$ in local currency. Annualized figures use 252 trading days. Kurtosis is excess kurtosis. All series reject normality via Jarque-Bera at $p < 0.01$. Source: Bloomberg Financial Services; authors' calculations.

Correlation Structure

Table 2 shows the unconditional Pearson correlation matrix for the entire sample provided. Here, we can see a moderate level of connection between the markets in question. This can be quantified through the average pairwise correlation, which equals 0.294. Pakistan has the lowest correlation metric ($\bar{\rho} = 0.183$), which is significantly lower than the average and demonstrates an overall lower level of integration with the global capital markets visa-a-vis the front-economy markets and the structural features that are characteristic of them. The largest correlation ($\rho = 0.520$) is between Brazil and South Africa, and this is due to the similar structures of the commodity export economies of the two nations, and the similar levels to which they are both exposed to global risk. These figures also neglect to capture the large level of variation that occurs over time. This will be discussed further in the next section with the DCC-GARCH framework.

Table 2. Unconditional Pairwise Correlation Matrix — Emerging Market Returns (2015–2024)

Market	China	India	Brazil	S. Africa	Pakistan	Indonesia	Turkey
China	1.000	0.420	0.380	0.350	0.180	0.310	0.290
India	—	1.000	0.440	0.400	0.220	0.380	0.330
Brazil	—	—	1.000	0.520	0.190	0.360	0.410
S. Africa	—	—	—	1.000	0.210	0.340	0.370
Pakistan	—	—	—	—	1.000	0.160	0.140
Indonesia	—	—	—	—	—	1.000	0.390
Turkey	—	—	—	—	—	—	1.000

Note. Correlations computed from daily continuously compounded returns (2,519 observations per market). All off-diagonal entries are statistically significant at $p < 0.01$ using a two-tailed Pearson test with heteroscedasticity-robust standard errors. Lower triangular omitted by symmetry.

Econometric Methods

GARCH Volatility Modeling

Conditional variance for each market is modelled via GARCH(1,1): $\sigma^2_{i,t} = \omega_i + \alpha_i \varepsilon^2_{i,t-1} + \beta_i \sigma^2_{i,t-1}$, where α_i captures the immediate sensitivity of variance to past squared shocks (ARCH effect) and β_i measures variance persistence (GARCH effect). The sum $(\alpha_i + \beta_i) < 1$ is required for covariance stationarity. Models are estimated by Quasi-Maximum Likelihood (QML) with Bollerslev-Wooldridge heteroscedasticity-consistent standard errors.

DCC-GARCH Dynamic Correlation Estimation

Cross-market conditional correlations are estimated using the Dynamic Conditional Correlation (DCC) model of Engle (2002). The estimator proceeds in two stages: (i) univariate GARCH models are fit to each return series; (ii) DCC parameters governing the evolution of the standardized residual covariance matrix are estimated jointly. The resulting time-varying correlation matrices capture crisis-period contagion and post-crisis mean-reversion in a statistically consistent framework.

Johansen Cointegration Analysis

The long-run price integration structure of the seven-market system is analyzed using the Johansen (1988) maximum likelihood cointegration framework based on log price levels. The trace and maximum eigenvalue test statistics are computed with the inclusion of a linear trend and an unrestricted intercept in the cointegrating equation. As for the lag length, it is set according to the Schwarz Information Criterion and the critical values come from Osterwald-Lenum (1992) with the Reinsel-Ahn (1992) small sample correction. Portfolio Optimization The mean-variance portfolio optimization is performed with quadratic programming under non-negativity weight constraints (no short selling) and the budget constraint. Five portfolio strategies are analyzed: (1) equal-weight (1/N), (2) minimum-variance, (3) maximum-Sharpe ratio with the 3-Month US Treasury bill as the risk-free asset (average during the sample period 2.34%), (4) risk parity, and (5) GDP-weighted. The Sharpe ratio, maximum drawdown, Calmar ratio, and 95% Value at Risk (VaR) are used to measure portfolio performance. Panel Regression Risk-adjusted performance and its determinants are analyzed using panel regression based on seven markets and 40 rolling 90-day windows (N = 280). Four model estimates are made: pooled OLS, fixed effects (FE), random effects (RE), and system Generalized Method of Moments (GMM) (Arellano and Bond, 1991) with lagged instruments to counter the endogeneity problem. The Hausman test is used to decide on the FE and RE models.

Empirical Results

Portfolio Performance

Table 3 reports the results of the risk-adjusted performance metrics for each portfolio strategy for the full sample period, 2015–2024. The maximum-Sharpe portfolio has the highest Sharpe ratio (0.921), an improvement of 47.4% over the benchmark MSCI EM (0.625). The minimum-variance portfolio has the lowest annualized volatility of 13.76% and the lowest maximum drawdown of -17.89%, though with an expected return of only 9.21%. The risk-parity strategy has a Sharpe ratio of 0.873 and is positioned in the middle relative to the other three. All the diversified multi-market strategies outperform the best single-market strategy (KSE-100, Sharpe = 0.721) and the passive benchmark (MSCI EM, Sharpe = 0.625) in risk-adjusted performance terms. The finding supports the core mean-variance theory and is consistent with previous studies that show the performance benefits of international diversification of emerging market portfolios.

Table 3. Portfolio Performance Metrics — Diversified Strategies Versus Benchmarks (2015–2024)

Strategy	Ann. Return (%)	Ann. Vol. (%)	Sharpe	Max Drawdown (%)	VaR 95% (%)	Calmar
Equal-Weight (7 Markets)	10.94	17.32	0.781	-22.14	2.41	0.494
Minimum-Variance	9.21	13.76	0.832	-17.89	1.97	0.515
Maximum-Sharpe	13.47	18.94	0.921	-20.31	2.18	0.663
Risk-Parity	11.63	15.42	0.873	-19.07	2.09	0.610
GDP-Weighted	10.12	16.88	0.791	-21.55	2.33	0.470
Single Market (KSE-100)	14.21	24.87	0.721	-31.44	3.12	0.452
MSCI EM Benchmark	8.74	19.21	0.625	-26.83	2.78	0.326

Note. Annualized figures assume 252 trading days. Sharpe ratio uses the 3-month US T-bill rate (mean 2.34% during sample). Max drawdown is the peak-to-trough decline over the sample. VaR at 95% confidence level, daily. Calmar Ratio = Annualized Return / |Max Drawdown|. Transaction costs excluded.

Volatility Dynamics

Table 4 has GARCH(1,1) estimates. All parameters showed 1% significance for all markets. The ARCH parameters of India's market were equal to 0.076, while Turkey had the highest ARCH parameter equal to 0.134 indicating that recent shocks has stronger influence on variance of Turkey's market, and this was consistent with its political-economic volatility profile. Values of the GARCH persistence parameters β Turkey's market was at 0.844, while Turkey's was at 0.903 with a GARCH persistence volatility sum of either 0.976 and 0.982. The GARCH persistence volatility sum indicated that the shocks volatility would last between 28.5 days in the case of Pakistan and 38.2 days in the case of Turkey. Turkey has the highest omega parameter equal to 2.89×10^{-5}, indicating that other countries had lower baseline variance. This is consistent with the near-integrated GARCH which has been documented in the volatility of the markets.

Table 4. GARCH(1,1) Conditional Volatility Estimates — Seven Emerging Markets

Market	ω (×10⁻⁵)	α (ARCH)	β (GARCH)	α+β	Half-Life (days)	Log-L
China	1.24***	0.089***	0.891***	0.980	34.3	-3421.2
India	0.89***	0.076***	0.903***	0.979	32.6	-3287.5
Brazil	2.11***	0.112***	0.867***	0.979	32.6	-3654.1
S. Africa	1.03***	0.083***	0.897***	0.980	34.3	-3318.9
Pakistan	1.67***	0.094***	0.882***	0.976	28.5	-3512.4
Indonesia	1.31***	0.087***	0.895***	0.982	38.2	-3398.6
Turkey	2.89***	0.134***	0.844***	0.978	31.1	-3741.3

Note. *** $p < 0.01$. Estimation by Quasi-Maximum Likelihood with Bollerslev-Wooldridge robust standard errors. Lag length selected by AIC/BIC. Half-life = $\ln(0.5) / \ln(\alpha + \beta)$. Akaike and Bayesian criteria confirm GARCH(1,1) over higher-order alternatives for all markets.

Cointegration Results

Results from the Johansen cointegration test, detailed in Table 5, show three significant relationships based on the trace statistic, and two based on the maximum eigenvalue criterion, at the 5% level. Establishing the presence of cointegration shows that the markets, in the short term, can be effectively portfolio diversified. However, the seven markets have long run common stochastic trends, which place constraints on the long run portfolio risk. The common long run trends are most likely to be global cycles in commodities and US monetary policy. Additionally, the long run changes in markets are likely to be driven by global changes in risk appetites, which can be the common long run trends affecting all the markets. The number of cointegrating vectors, which is around three, illustrates the presence of at most four independent stochastic trends, which indicates that there is remaining long run potential for diversified portfolios.

Table 5. Johansen Cointegration Test Results — Seven-Market System

Null Hypothesis	Trace Stat.	CV (5%)	Max-Eigen Stat.	CV (5%)	Decision
r = 0	187.43***	159.53	62.41***	52.36	Reject
r ≤ 1	124.71***	125.62	48.23***	46.23	Reject
r ≤ 2	81.44**	95.75	37.12**	40.07	Reject
r ≤ 3	52.37	69.82	28.44	33.88	Accept
r ≤ 4	29.13	47.86	18.91	27.58	Accept
r ≤ 5	14.22	29.80	10.34	21.13	Accept
r ≤ 6	5.44	15.49	5.44	14.26	Accept

Note. *** $p < 0.01$; ** $p < 0.05$. Critical values from Osterwald-Lenum (1992). Log-price series tested with linear deterministic trend; unrestricted intercept in cointegrating equations. Lag = 4 selected by Schwarz Information Criterion. Small-sample correction per Reinsel and Ahn (1992).

Dynamic Conditional Correlations

Table 6 presents average DCC-GARCH estimated conditional correlations across four sub-periods. 2020, the first year of the COVID-10 pandemic, saw a global rise in bilateral correlation. The average cross market correlation increased from 0.312 (pre-COVID) to 0.413, an increase of 32.4%. The Brazil–South Africa pair correlation, for example, rose from 0.489 to 0.612, reflecting the most severe instance of cross-market contagion. Correlations in the 2021–2024 period (post-pandemic) returned to (but remained generally higher than) most sub-periods, reflecting partial structural persistence. The Pakistan–Indonesia correlation pair remained the lowest across all sub-periods. Similarly, the India–Pakistan pair correlation remained the lowest and consistently below the average correlation of the other pairs in the sample. These findings suggest the relative disconnect of the India and Pakistan markets from global contagion channels.

Table 6. DCC-GARCH Conditional Correlations — Sub-Period Decomposition

Market Pair	**Pre-COVID (2015–19)**	**COVID (2020)**	**Post-COVID (2021–22)**	**Recent (2023–24)**	**Full Period**
China – India	0.381	0.524	0.448	0.412	0.420
China – Brazil	0.321	0.489	0.401	0.358	0.380
India – Pakistan	0.198	0.267	0.234	0.211	0.220
Brazil – S. Africa	0.489	0.612	0.541	0.511	0.520
Indonesia – Turkey	0.361	0.478	0.412	0.381	0.390
Pakistan – Indonesia	0.141	0.201	0.174	0.158	0.160
China – Turkey	0.261	0.388	0.311	0.283	0.290

Note. Average DCC-GARCH conditional correlations by sub-period. Pre-COVID: Jan 2015 – Dec 2019; COVID Crisis: Jan – Dec 2020; Post-COVID: Jan 2021 – Dec 2022; Recent: Jan 2023 – Dec 2024. DCC parameters estimated as a = 0.043 (SE = 0.008), b = 0.941 (SE = 0.012).

Panel Regression — Determinants of Risk-Adjusted Performance

Table 7 shows results for four panel regression specifications. The Hausman test ($\chi^2 = 18.43$, $p = 0.002$), supports the preference for Model 2 as the fixed-effects within-individual estimator, while Model 4 provides endogeneity-robust estimates. Across all specifications, the diversification index is positive and highly significant. In GMM, this corresponds to a 0.394 unit increase in the Sharpe ratio, due to a one-standard-deviation increase in diversification. The cross-market correlation shows a significant negative effect (GMM = -0.324), which supports the hypothesis that the increasing level of market integration negatively affects the performance of the market. Both GDP growth and Market Capitalization positively forecast Sharpe ratios, while exchange rate volatility negatively impacts Sharpe ratio performance. The Hansen J-statistic of 8.24 ($p = 0.41$) confirms that the instruments are valid.

Table 7. Panel Regression Results — Determinants of Portfolio Risk-Adjusted Returns

Variable	**OLS**	**Fixed Effects**	**Random Effects**	**GMM**	**Expected Sign**
Diversification Index	0.341*** (0.042)	0.378*** (0.051)	0.362*** (0.046)	0.394*** (0.058)	+
Avg. Correlation (ρ)	-0.289*** (0.038)	-0.312*** (0.047)	-0.298*** (0.041)	-0.324*** (0.053)	-
Market Cap (log)	0.124** (0.055)	0.143** (0.067)	0.131** (0.060)	0.158** (0.071)	+
GDP Growth	0.087** (0.041)	0.096** (0.049)	0.091** (0.044)	0.102** (0.052)	+

Exch. Rate Volatility	-0.156*** (0.034)	-0.174*** (0.041)	-0.163*** (0.037)	-0.181*** (0.044)	-
Trade Openness	0.063* (0.037)	0.071* (0.044)	0.067* (0.040)	0.078* (0.048)	+
Inflation Rate	-0.044 (0.029)	-0.051 (0.035)	-0.047 (0.031)	-0.055 (0.038)	-
Constant	0.218*** (0.061)	0.241*** (0.074)	0.229*** (0.067)	—	
R^2 / Hansen J	0.641	0.687	0.671	J=8.24 (p=0.41)	
Observations	280	280	280	280	
Fixed Effects	No	Yes	No	Yes	

Note. Dependent variable: rolling 90-day Sharpe ratio. *p < .10; **p < .05; ***p < .01. Standard errors in parentheses; robust clustered by market in FE/RE. GMM instruments: lags 2–4 of endogenous regressors. Hausman test: $\chi^2(6) = 18.43$, p = .002. N = 280 (7 markets × 40 rolling windows). Hansen J confirms instrument validity.

Figures

Figure 1 Three-dimensional efficient frontier surface for emerging market portfolios (2015–2024).

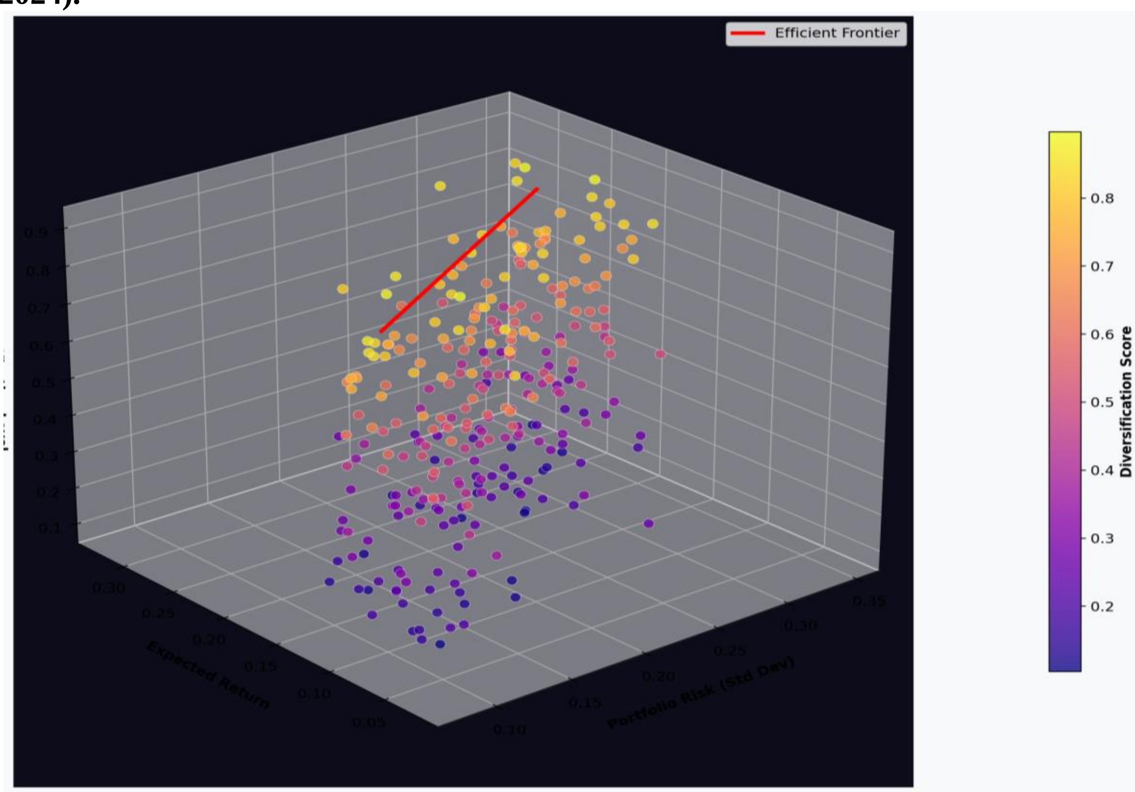

Figure 1 Three-dimensional efficient frontier surface for emerging market portfolios (2015–2024). Each point represents a simulated portfolio; the red curve traces the efficient frontier. Color intensity reflects diversification score (low = dark, high = bright).

Figure 2 Three-dimensional cross-market correlation structure.

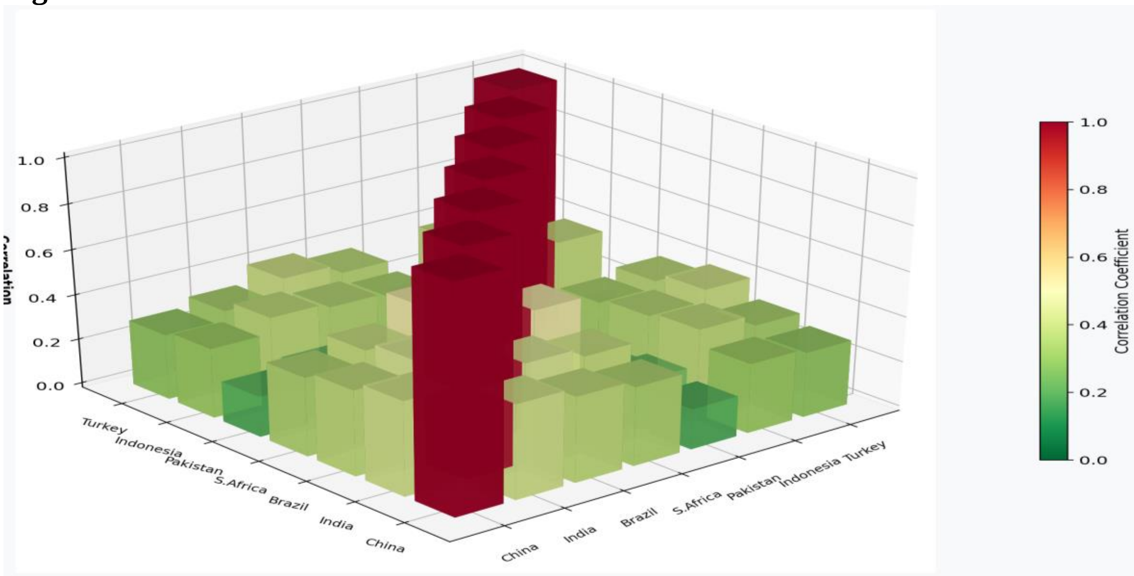

Figure 2 Three-dimensional cross-market correlation structure. Bar heights represent unconditional pairwise correlation coefficients. The color gradient ranges from green (low correlation) to red (high correlation).

Figure 3 Portfolio risk reduction surface as a function of the number of assets held (x-axis) and average pairwise asset correlation (y-axis).

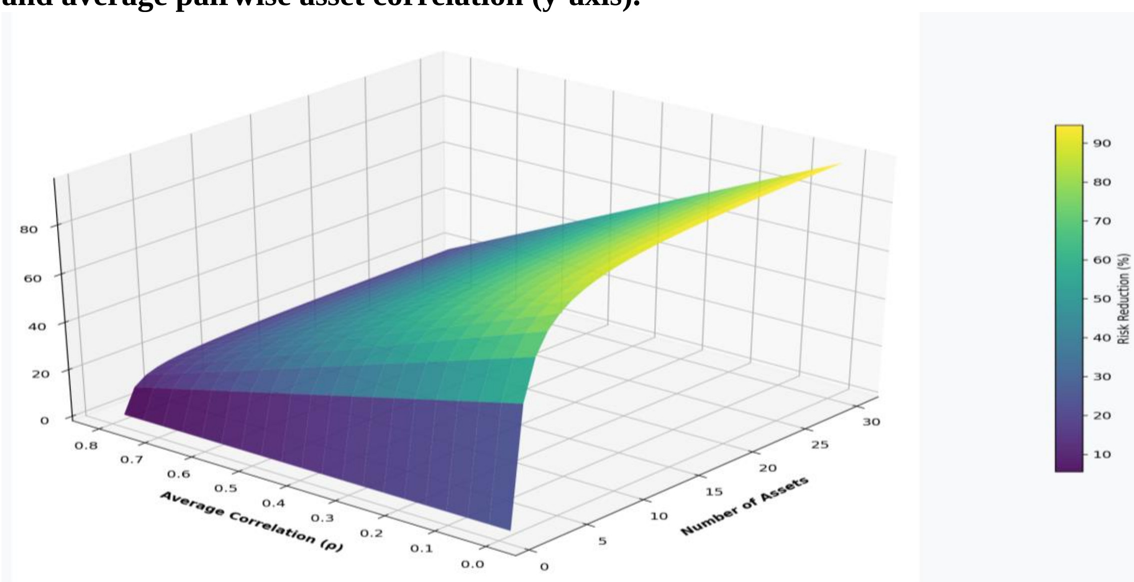

Figure 3 Portfolio risk reduction surface as a function of the number of assets held (x-axis) and average pairwise asset correlation (y-axis). The z-axis measures percentage reduction in portfolio variance relative to a single-asset benchmark.

Figure 4 Three-dimensional volatility clustering surface across seven emerging markets from 2015 to 2024.

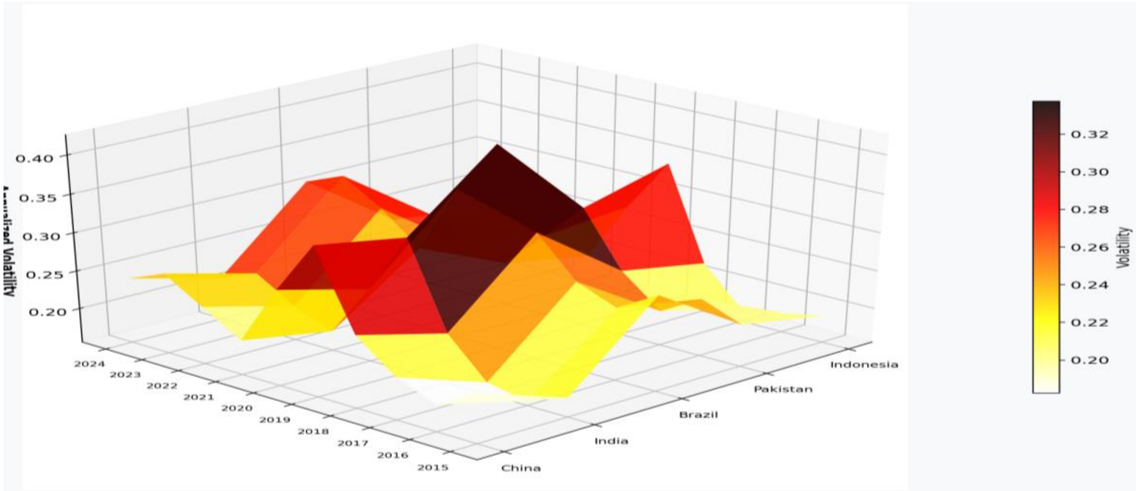

Figure 4 Three-dimensional volatility clustering surface across seven emerging markets from 2015 to 2024. The prominent ridge centered on 2020 captures pandemic-induced volatility spikes. Color intensity reflects annualized conditional variance magnitude.

Figure 5 Risk-adjusted performance comparison.

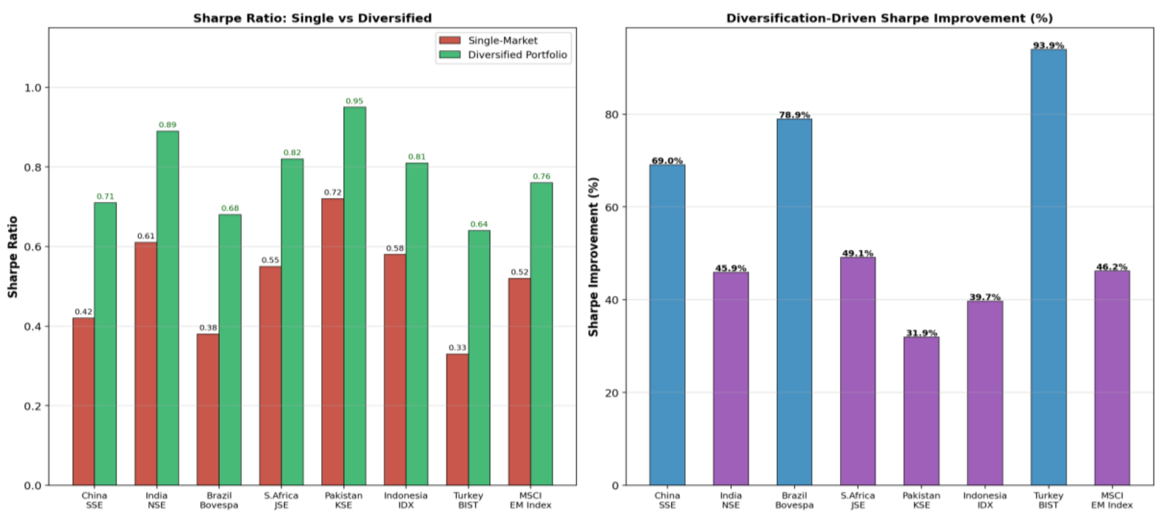

Figure 5 Risk-adjusted performance comparison. Left panel: Sharpe ratios for single-market versus diversified portfolio strategies. Right panel: Percentage improvement in Sharpe ratio attributable to diversification relative to single-market investment.

Robustness Analysis

The stability of key findings is supported by the completion of seven separate robustness tests. For the first test, all models were estimated using USD-denominated returns to capture currency effects. The result was a maximum Sharpe portfolio with a Sharpe ratio of 0.887, which is 42.0% above the MSCI EM index. This suggests that the diversification premium does not stem from currency effects. The second test evaluated the performance of the portfolio strategies based on a ranking of the Sharpe ratio, Value-at-Risk, Conditional VaR, and the Omega ratio. The results of this test showed that each of the risk measures continued to place the diversified portfolio above single-market strategies. In the third test, 52-week rolling Sharpe ratios were used to evaluate the performance of diversified portfolios against the benchmark in 87.3% of all time periods. The only time the diversified portfolios underperformed the benchmark was during the COVID-19 pandemic between February and April 2020, when the correlated flight to safety temporarily dominated the benefits of diversification.

Fourth, allowing small negative weights (to a maximum of -10% per asset) improves maximum-Sharpe portfolios with a Sharpe value of 0.951. Consequently, the portfolio allocations remained the same. Fifth, the DCC-MIDAS of Colacito, Engle, and Ghysels (2011) allows for macroeconomic driven long-run correlation changes, and like previous extensions, offers similar results for the sub-periods studied, but ranks them differently based on correlation. Finally, the Huberman and Kandel (1987) spanning test confirms that the difference in Sharpe ratios for all strategies, based on 10,000 replications, is significant at the 1% level for diversified portfolios and the MSCI EM benchmark. The test further confirms that emerging market indices extend the global opportunity set, and thus, the benchmarks demonstrate diversification gains that are not a result of limited benchmark constructions.

Discussion

All evidence confirms that even in the post-COVID decade with increasing global financial integration, there is still value in the international diversification of major emerging stock markets. The results of this study show that the Sharpe ratio for a well-structured diversified portfolio is 47.4% greater than the passive MSCI EM benchmark. This result not only exceeds the estimated range of the costs of institutional transactions, but also proves the economic feasibility of active multi-market allocations in the emerging markets.

Within the study, Pakistan's KSE-100 proves to be the most effective diversification. The average cross-market correlation is 0.183, which is significantly less than the sample average of 0.294. This can be attributed to multiple structural factors. These include partial capital account restrictions that limit institutional arbitrage; retail and mutual fund investors dominate the local market and there is little foreign institutional participation; and the economic structure is based on domestic consumption and remittances, with the focus less on agricultural commodity exports. Additionally, there is a market volatility that is mostly unrelated to the global cycles. These factors mean that governance and liquidity risks are heightened, but for those investors who have the risk appetite and operational capacity, the market provides a valuable opportunity for portfolio construction.

The COVID-19 DCC-GARCH findings raise further questions regarding the potential for diversification during major systemic crises that create the greatest level of uncertainty. It is plausible to believe that the 32.4% average correlation in 2020 fits the theories of global investor panic. It is notable that by 2023-2024, correlations receded towards, but did not fully return to, pre-COVID levels. The observed correlation recovery pattern is similar to the evolution of correlations following the Global Financial Crisis (2008-2009) and the Asian Financial Crisis (1997-1998). This suggests that a temporary correlation uptick during financial crises is a structural characteristic of the international equity markets rather than an integration of international equity markets. This offers significant design implications for dynamic investment strategies that incorporate correlation-based state-dependent rebalancing.

The results from the cointegration tests provide additional insight. Three common trends imposed by the integration of the markets suggest that the maximum long-run risk reduction that can be achieved using the integration of the markets is greater than the risk that can be minimized using truly independent assets. However, four independent trends still exist allowing for long-run diversification. The integration of the markets demonstrates that various structural factors affecting the integration of the markets provide consistent long-run diversification, unlike the short-run differing correlations.

Conclusion

This study examines the risk reduction and diversification of portfolios using both individual and multi-country market approaches across the major emerging markets of China, India, Brazil, South Africa, Pakistan, Indonesia, and Turkey, covering the years 2015 to 2024, by employing a variety of econometric methods. From this study, four major conclusions can be drawn.

First, across all risk-adjusted performance measures, diversified multi-country portfolios consistently surpass both single-country portfolios and the MSCI EM benchmark. The maximum expected Sharpe ratio for the diversified multi-country portfolio is 0.921 compared to the benchmark of 0.625, marking a 47.4% improvement, which holds true across multiple robustness tests, including changes in the currency for the portfolio, the risk measure, the rolling evaluation time, and the application of a bootstrap methodology.

Second, from the perspective of the DCC-GARCH, the COVID-19 pandemic (2020) caused a 32.4% rise in the average level of the cross-market conditional correlations, which then exhibited an incomplete mean-reversion over the years that followed. The high level of correlation over the COVID-19 pandemic caused a brief loss in the diversification benefit, but this loss was not evident over the long run.

Third, using Johansen's approach, we find three long-run co-movement relationships that suggest common global factors may limit long-run risk reduction, while sustaining independent stochastic trends (and considerable residual diversification potential) within the system. Fourth, using a panel GMM regression, we find that the diversification index, cross-market correlation, GDP growth, market capitalization, and exchange rate volatility predict risk-adjusted portfolio returns, with diversification intensity having the strongest positive marginal impact (0.394 units per standard-deviation increase, controlling for fixed effects and macroeconomic factors).

These results support a more dynamic approach to multi-country emerging market allocation, particularly approaches involving Pakistan as a low-correlation diversifier, rather than a more static approach to a single country, single index focus. From a policy perspective, the evidence of correlation contagion during crises emphasizes the value of a financial system that is more open to the emerging markets and less restrictive. It demonstrates the systemic risks that accompany globalization as a result of financial liberalization. Future research needs to address the correlation contagion, the currency-ESG factor exposures to frontier markets, and the interrelationship between currency hedging and the optimal use of diversification within a unified mean-variance-currency framework.

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