

Review of Quantitative Portfolio Optimization Research for Emerging Market Asset Management Strategies

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Abstract- The growing integration of emerging markets into global financial systems has intensified interest in quantitative portfolio optimization techniques tailored to their unique risk–return characteristics. Emerging market assets are often characterized by higher volatility, liquidity constraints, structural breaks, regulatory frictions, and pronounced exposure to macroeconomic and geopolitical shocks, posing significant challenges to traditional portfolio optimization frameworks developed for mature markets. This study provides a comprehensive review of quantitative portfolio optimization research with a specific focus on emerging market asset management strategies. Drawing on a broad body of empirical and methodological literature, the review examines the evolution of classical mean–variance optimization and its extensions, including downside risk measures, robust optimization, Bayesian approaches, and multi-period allocation models. Particular attention is given to how these techniques address estimation risk, non-normal return distributions, and unstable correlation structures prevalent in emerging markets. The review further synthesizes evidence on the application of advanced methods such as regime-switching models, shrinkage estimators, and machine learning–based optimization frameworks, highlighting their comparative performance under conditions of market stress and data limitations. Empirical findings suggest that constrained, robust, and adaptive optimization approaches generally outperform unconstrained mean–variance portfolios in emerging market contexts, especially during periods of heightened volatility. However, the review also identifies persistent gaps in the literature, including limited out-of-sample validation, underrepresentation of frontier markets, and insufficient consideration of transaction costs, currency risk, and regulatory constraints. By consolidating existing knowledge and identifying methodological limitations, this review contributes to a clearer understanding of how quantitative portfolio optimization can be effectively adapted for emerging market asset management. The study concludes by outlining future research directions aimed at developing context-sensitive optimization frameworks that enhance risk-adjusted performance, resilience, and practical

implement ability for institutional and professional investors operating in emerging economies.

Keywords: *Quantitative Portfolio Optimization; Emerging Markets; Asset Management; Risk-Adjusted Returns; Robust Optimization; Investment Strategy*

I. INTRODUCTION

Quantitative portfolio optimization has long been a central pillar of modern asset management, providing a formal framework for allocating capital across assets in a manner that balances expected returns against risk (Braga, 2015; Lam, 2016). Since the introduction of Markowitz’s mean–variance theory in the 1950s, portfolio optimization has evolved substantially, incorporating more sophisticated risk measures, estimation techniques, and computational methods. Extensions such as downside risk optimization, multi-factor models, robust and Bayesian approaches, and dynamic multi-period frameworks have been developed to address practical limitations of early models, including sensitivity to estimation error and restrictive distributional assumptions (Chen *et al.*, 2016; Gagliardini *et al.*, 2016). In contemporary asset management practice, quantitative optimization techniques are widely used to support strategic asset allocation, tactical rebalancing, and risk management decisions across institutional and professional investment portfolios (Faber, 2017; Kinlaw *et al.*, 2017).

At the same time, emerging markets have become increasingly important components of global investment portfolios. Over the past two decades, emerging economies have accounted for a growing share of global economic growth, financial market capitalization, and cross-border capital flows (Bussiere and Phylaktis, 2016; Kodongo and Ojah, 2017). Institutional investors, including pension funds,

sovereign wealth funds, and asset managers, have expanded their exposure to emerging market equities, fixed income, and alternative assets in pursuit of diversification benefits and higher long-term returns. As a result, the effectiveness of portfolio optimization strategies in emerging market contexts has become a critical concern for global asset allocation and risk management (Quintana *et al.*, 2017; Lwin *et al.*, 2017).

Despite their attractiveness, emerging market assets exhibit distinct characteristics that complicate quantitative portfolio optimization. These markets are typically associated with higher return volatility, pronounced tail risks, and time-varying correlations driven by macroeconomic instability and external shocks (Kang *et al.*, 2016; Massacci, 2017). Liquidity constraints, higher transaction costs, regulatory frictions, and capital controls further affect portfolio implementability. In addition, emerging markets often display informational inefficiencies, data limitations, and structural breaks that challenge the assumptions of stable return distributions and reliable parameter estimation underlying many optimization models (Turtle and Zhang, 2015; Ngene *et al.*, 2017).

Consequently, the direct application of portfolio optimization frameworks developed for mature markets may lead to suboptimal or unstable outcomes in emerging market settings. Classical mean–variance optimization, in particular, has been shown to be highly sensitive to estimation error and correlation instability, problems that are exacerbated in volatile and less liquid markets (Goto, S. and Xu., 2015; Supandi and Rosadi, 2017). These limitations have motivated a growing body of research aimed at adapting and extending quantitative optimization techniques to better reflect emerging market realities.

The objective of this review is to systematically examine and synthesize the literature on quantitative portfolio optimization research focused on emerging market asset management strategies. The review evaluates methodological advances, empirical findings, and practical considerations, while identifying persistent gaps and directions for future research. The remainder of the paper is structured as follows: the next section reviews theoretical foundations and optimization techniques; subsequent sections examine emerging market characteristics,

empirical evidence, and practical implications; and the final section concludes with key insights and research directions.

II. METHODOLOGY

This review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure transparency, reproducibility, and methodological rigor in synthesizing quantitative portfolio optimization research relevant to emerging market asset management strategies. A systematic literature search was conducted across multiple academic databases, including Scopus, Web of Science, ScienceDirect, JSTOR, and Google Scholar, to capture peer-reviewed journal articles published in English. The search strategy combined keywords and Boolean operators related to quantitative portfolio optimization and emerging markets, including terms such as “portfolio optimization,” “asset allocation,” “quantitative investment,” “emerging markets,” “frontier markets,” and “institutional asset management.” The search period covered studies published from 2000 to 2024, reflecting the expansion of emerging market financial research and the evolution of advanced optimization techniques.

Eligibility criteria were defined prior to screening. Included studies were required to focus on quantitative or model-based portfolio optimization methods, apply empirical or simulation-based analysis, and explicitly examine emerging market, developing market, or frontier market assets. Studies focusing exclusively on developed markets, purely theoretical models without empirical relevance, or non-investment applications were excluded. Conference papers, dissertations, book chapters, and non-peer-reviewed sources were also excluded to maintain quality and consistency.

The initial database search yielded a large pool of records, which were imported into a reference management system and screened for duplicates. Titles and abstracts were independently reviewed to assess relevance based on the inclusion criteria. Full-text screening was then conducted for shortlisted articles to confirm eligibility. Disagreements during screening were resolved through iterative review and consensus.

Data extraction focused on study characteristics, including market context, asset classes, optimization techniques, risk measures, constraints applied, data periods, and reported performance outcomes. Methodological quality was assessed qualitatively by examining model robustness, treatment of estimation risk, use of out-of-sample testing, and consideration of practical implementation factors such as transaction costs and liquidity. Given heterogeneity in methods and outcome measures, a narrative synthesis approach was adopted to compare findings across studies. The PRISMA flow process guided documentation of identification, screening, eligibility, and inclusion stages to ensure systematic reporting of the review process.

2.1 Theoretical Foundations of Portfolio Optimization

The theoretical foundations of portfolio optimization are rooted in modern financial economics and provide the analytical basis for systematic capital allocation decisions in asset management (Oderda, 2015; Grishina *et al.*, 2017). These foundations have evolved from relatively simple risk–return trade-off models to more sophisticated frameworks that explicitly address uncertainty, non-normal return distributions, and estimation risk. Understanding these theoretical underpinnings is essential for evaluating the suitability of different optimization approaches, particularly in complex and volatile investment environments such as emerging markets.

Classical portfolio theory is anchored in the mean–variance optimization framework introduced by Markowitz in 1952. In this model, investors select portfolios by jointly considering expected returns and return variance, with variance serving as the primary measure of risk. The objective is to construct efficient portfolios that minimize risk for a given level of expected return or, equivalently, maximize expected return for a given level of risk. The resulting efficient frontier represents the set of optimal portfolios under the model’s assumptions and remains a foundational concept in asset management practice.

Mean–variance optimization relies on several key assumptions. First, asset returns are assumed to be normally distributed, allowing variance to fully capture the uncertainty faced by investors. Second, investors are assumed to be rational and risk-averse,

preferring higher expected returns and lower risk. Third, correlations among asset returns are assumed to be stable over time, enabling reliable estimation of covariance matrices. Under these assumptions, portfolio risk can be effectively reduced through diversification, and optimal asset weights can be derived analytically.

While the Markowitz framework has been widely adopted, its applicability in emerging markets is subject to significant challenges. Emerging market returns often exhibit non-normal distributions characterized by skewness, excess kurtosis, and fat tails, undermining the adequacy of variance as a comprehensive risk measure. Correlations in these markets are frequently unstable and tend to increase during periods of market stress, reducing diversification benefits when they are most needed (Oet *et al.*, 2015; Batten and Vo, 2016). Moreover, limited data availability, structural breaks, and market inefficiencies exacerbate estimation error, leading to highly unstable and extreme portfolio weights. These limitations have prompted substantial research into alternative optimization frameworks better suited to emerging market conditions.

To address the shortcomings of variance-based risk measurement, a range of downside risk models has been developed. Semi-variance focuses exclusively on negative deviations from a target or mean return, aligning more closely with investor preferences to avoid losses rather than total volatility. Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) further extend this perspective by quantifying potential losses in the lower tail of the return distribution. CVaR, in particular, has gained prominence due to its coherent risk properties and its ability to capture extreme downside outcomes. These measures are especially relevant in emerging markets, where tail risks and abrupt market downturns are more prevalent.

Another important extension involves incorporating higher moments of the return distribution into portfolio optimization. Higher-moment models explicitly account for skewness and kurtosis, recognizing that investors may prefer positively skewed returns and dislike fat-tailed distributions associated with extreme losses. By integrating third and fourth moments into the optimization process,

these models aim to produce portfolios that better reflect investor risk preferences and the empirical characteristics of emerging market returns. However, estimating higher moments reliably remains challenging, particularly in data-constrained environments.

Robust optimization approaches represent a further theoretical advancement by explicitly addressing parameter uncertainty. Rather than relying on point estimates of expected returns and covariances, robust frameworks consider uncertainty sets within which true parameters are assumed to lie. Portfolio choices are then optimized to perform well across a range of plausible scenarios, reducing sensitivity to estimation error. In emerging markets, where parameter instability is pronounced, robust optimization has been shown to produce more stable and implementable portfolios than traditional mean–variance approaches (Gökgöz, F. and Atmaca, 2017; Supandi *et al.*, 2017).

The theoretical evolution of portfolio optimization reflects a progressive relaxation of restrictive assumptions underlying classical models. While mean–variance theory provides a valuable conceptual foundation, its limitations in emerging market contexts have driven the development of alternative risk measures and robust frameworks. These theoretical advances form the basis for contemporary research and practice aimed at improving portfolio performance and resilience in volatile and uncertain investment environments.

2.2 Characteristics of Emerging Market Financial Assets

Emerging market (EM) financial assets have become integral to global investment portfolios due to their potential for higher returns and diversification benefits. However, these assets exhibit distinctive characteristics that differentiate them from those in developed markets and pose unique challenges for asset pricing, risk management, and portfolio optimization. Understanding these characteristics is essential for designing effective investment strategies and adapting quantitative models to emerging market realities.

One defining feature of emerging market assets is the nature of their return distributions and associated tail

risks. Empirical evidence consistently shows that EM asset returns deviate from normality, displaying pronounced skewness, excess kurtosis, and fat tails. These properties reflect a higher likelihood of extreme positive or negative outcomes, often driven by political events, commodity price shocks, policy changes, or sudden reversals in capital flows. As a result, downside tail risks are more severe and frequent in emerging markets than in developed markets, undermining risk measures that rely solely on variance. During periods of global financial stress, correlations across emerging markets also tend to rise sharply, amplifying systemic risk and reducing the effectiveness of diversification strategies precisely when protection is most needed (Cevik *et al.*, 2016; Stolbov and Shchepeleva, 2016).

Liquidity constraints and elevated transaction costs represent another critical characteristic of emerging market financial assets. Many EM equity and bond markets are relatively shallow, with lower trading volumes, wider bid–ask spreads, and limited market depth. These features increase trading costs and make it difficult to execute large portfolio reallocations without materially affecting prices. Liquidity risk is further exacerbated during periods of market turbulence, when trading activity may dry up entirely. For institutional investors, ignoring liquidity constraints can lead to portfolios that appear optimal in theory but are costly or impractical to implement in practice (Coleman, 2015; Bebhuk *et al.*, 2017). Consequently, liquidity-adjusted risk measures and turnover constraints are particularly important in emerging market asset management.

Market segmentation and capital flow restrictions also shape the behavior of emerging market assets. Unlike developed markets, many emerging economies impose explicit or implicit barriers to foreign investment, including capital controls, ownership limits, taxation differences, and regulatory approval requirements. These restrictions can create segmentation between domestic and international investors, leading to price distortions and deviations from fundamental values. Capital flows into and out of emerging markets are often procyclical, driven by global risk sentiment rather than local fundamentals. Sudden stops or surges in foreign capital can therefore generate sharp price movements and heightened

volatility, complicating return forecasting and portfolio stability (Batten *et al.*, 2016; Efreimidze *et al.*, 2017).

Currency risk and macroeconomic instability further distinguish emerging market investments. EM assets are typically denominated in local currencies that are more volatile and susceptible to depreciation than major reserve currencies. Exchange rate movements can significantly affect the realized returns of foreign investors, sometimes overwhelming local asset performance. Macroeconomic factors such as inflation volatility, fiscal imbalances, external debt exposure, and reliance on commodity exports contribute to currency instability and increase uncertainty around long-term investment outcomes. Managing currency risk is thus a central component of emerging market portfolio construction and often requires the use of hedging strategies or explicit currency allocation decisions.

Data availability and quality issues pose substantial challenges for research and practice in emerging market finance. Historical data series are often shorter, subject to structural breaks, and less reliable than those in developed markets. Accounting standards, disclosure practices, and market transparency vary widely across countries, affecting the consistency and comparability of financial information. Survivorship bias is also a concern, as failed firms, delisted securities, or closed markets may be underrepresented in available datasets, leading to overstated historical performance (Annaert *et al.*, 2016; Shulman, 2017). These data limitations increase estimation error and undermine the robustness of quantitative models that rely on precise parameter inputs.

Emerging market financial assets are characterized by non-normal return distributions, significant tail risks, liquidity constraints, market segmentation, currency volatility, and data challenges. These features complicate risk assessment and portfolio optimization but also create opportunities for investors who account for them appropriately. A clear understanding of these characteristics is therefore essential for developing quantitative asset management strategies that are both theoretically sound and practically viable in emerging market contexts.

2.3 Quantitative Optimization Techniques in Emerging Markets

Quantitative portfolio optimization has emerged as a cornerstone of asset management, enabling systematic allocation of capital to maximize risk-adjusted returns. In the context of emerging markets (EMs), optimization techniques must contend with distinctive market characteristics, including higher volatility, liquidity constraints, data limitations, and structural instabilities (Goyal, 2016; Eichengreen, 2016). Consequently, conventional models developed for developed markets often require adaptation, and more advanced approaches such as robust, Bayesian, and dynamic optimization techniques have been increasingly employed to address estimation risk and market uncertainty. This reviews the primary quantitative optimization techniques applied to emerging market asset management, highlighting their methodological foundations, adaptations, and practical implications.

Classical mean–variance optimization, rooted in Markowitz’s framework, remains a foundational tool for portfolio construction in EMs, but it requires careful adaptation. Given the high volatility, fat-tailed return distributions, and unstable correlations common in emerging markets, standard mean–variance approaches may produce extreme or unstable asset weights. To mitigate these issues, mean–variance optimization is often combined with constraints on individual asset weights, turnover limits, or sector exposures, reflecting practical considerations such as liquidity, transaction costs, and regulatory requirements. Additionally, minimum variance strategies, which seek to minimize total portfolio risk regardless of expected return, are particularly useful in EMs due to their emphasis on risk reduction under high volatility conditions. Risk parity approaches, which allocate capital based on risk contributions rather than market capitalization, have also been applied to EM portfolios to achieve more balanced and resilient allocations, especially in the presence of heterogeneous asset volatilities and correlations (Roncalli and Weisang, 2016; Baitinger *et al.*, 2017).

Constraints-based optimization has gained prominence in emerging market applications, where regulatory limits, capital controls, and liquidity

restrictions are prevalent. By incorporating upper and lower bounds on asset weights, sector allocations, or turnover, these models produce feasible portfolios that are implementable in real-world trading environments. This approach ensures that theoretically optimal portfolios do not violate practical market constraints, making optimization results more robust and actionable.

Emerging market portfolios are particularly sensitive to estimation errors in expected returns and covariances. Bayesian portfolio selection addresses this problem by integrating prior beliefs about returns and covariances with observed data to generate posterior estimates that reduce overfitting. This approach is effective in EMs where historical data are limited or unstable. Similarly, shrinkage estimators and covariance matrix stabilization techniques have been widely employed to improve the reliability of input parameters in mean–variance models. By blending sample covariances with structured or target matrices, shrinkage reduces extreme weight allocations and enhances out-of-sample performance. Distributionally robust optimization extends this concept by considering uncertainty sets for asset return distributions, optimizing portfolios to perform well across a range of plausible scenarios (Postek *et al.*, 2016; Sözüer and Thiele, 2016). Such approaches are particularly relevant in EMs, where structural breaks, regime shifts, and tail events are frequent.

Static optimization models often fail to capture the temporal variability of emerging market risks. Multi-period portfolio optimization addresses this limitation by considering investment horizons beyond a single period, accounting for expected changes in asset returns, volatility, and correlations over time. Regime-switching models further enhance dynamic optimization by allowing model parameters to vary across market states, such as bull, bear, or crisis regimes. This approach captures structural shifts in volatility and correlation patterns, which are common in EMs due to macroeconomic shocks, policy interventions, and capital flow volatility. Time-varying correlation and volatility models, such as generalized autoregressive conditional heteroskedasticity (GARCH) and dynamic conditional correlation (DCC) frameworks, are also integrated into optimization procedures to improve risk assessment

and portfolio allocation decisions under changing market conditions.

Dynamic and stochastic approaches provide a more realistic representation of emerging market conditions and allow investors to adapt allocations in response to evolving risk environments. When combined with constraints and robust techniques, they facilitate the construction of portfolios that balance expected returns with stability and resilience, even under highly uncertain conditions.

Quantitative optimization in emerging markets encompasses a spectrum of approaches, from traditional mean–variance and minimum variance strategies to robust, Bayesian, and dynamic models that explicitly account for estimation risk, tail events, and time-varying market conditions. Adaptations such as constraints-based optimization, shrinkage estimators, regime-switching, and multi-period modeling are essential for producing feasible, resilient, and implementable portfolios. By integrating these techniques, asset managers can navigate the distinctive challenges of EMs volatility, liquidity constraints, structural shifts, and limited data while improving risk-adjusted performance and portfolio robustness (Marquis and Raynard, 2015; Joshi and Li, 2016). These methodological advances form the backbone of contemporary emerging market investment strategies, offering both theoretical rigor and practical relevance for institutional investors and fund managers.

2.4 Machine Learning and Data-Driven Approaches

The application of machine learning (ML) and data-driven approaches in portfolio optimization has expanded rapidly in recent years, offering advanced techniques for managing complex, volatile, and high-dimensional financial markets. Emerging markets (EMs) present particularly fertile ground for these approaches due to their distinctive characteristics high return volatility, data scarcity, structural breaks, and non-linear asset relationships which often challenge traditional quantitative optimization methods. By leveraging ML algorithms and alternative data sources, investors can uncover patterns, capture non-linear dependencies, and improve risk-adjusted portfolio performance in EM contexts.

A variety of ML techniques have been applied to portfolio construction, each offering unique advantages for modeling complex market dynamics. Neural networks, particularly deep learning architectures, are capable of approximating highly non-linear relationships between market factors and asset returns. In EMs, where traditional linear models often fail to capture regime shifts and tail events, neural networks can model intricate patterns across multiple assets and macroeconomic indicators, providing forecasts for expected returns or conditional risk measures. Random forests, an ensemble learning technique based on decision trees, offer robustness to overfitting and the ability to handle noisy and heterogeneous data—common features in EM financial datasets. Random forests have been used both for return prediction and risk estimation, producing insights that can inform allocation decisions. Reinforcement learning (RL) represents a more dynamic approach, where algorithms learn optimal sequential portfolio allocation strategies by interacting with simulated market environments (Fallahpour *et al.*, 2016; Nechchi, 2016). RL is particularly well-suited for multi-period optimization under uncertainty, enabling adaptive strategies that respond to changing market regimes and volatility spikes.

In practice, ML techniques are often combined with traditional optimization frameworks to leverage the strengths of both approaches. For example, predicted returns or risk measures generated by neural networks or random forests can be used as inputs into mean-variance or risk parity optimization frameworks, creating hybrid models that integrate data-driven forecasting with established portfolio construction principles. Similarly, reinforcement learning outputs can guide dynamic weight adjustments within constrained optimization models, ensuring implementability and adherence to regulatory or liquidity constraints. Hybrid models are particularly valuable in EMs, where noisy data and market frictions can undermine the reliability of purely ML-based portfolio decisions (Abdeltawab *et al.*, 2015; Vannucci *et al.*, 2017). By blending predictive analytics with optimization theory, these approaches improve robustness and facilitate practical implementation.

The effectiveness of ML-driven portfolio optimization heavily depends on feature selection and the availability of informative data. Emerging markets often lack the depth and reliability of traditional financial datasets found in developed markets, necessitating the incorporation of alternative data sources (Henke and Jacques, 2016; Chandy *et al.*, 2017). These may include macroeconomic indicators, commodity prices, trade flows, satellite imagery, social media sentiment, and geopolitical event data. Feature selection techniques, such as recursive feature elimination, LASSO regularization, and principal component analysis, are used to identify the most informative variables while reducing dimensionality and mitigating overfitting risks. By carefully selecting features and integrating alternative datasets, ML models can capture latent drivers of asset returns and risks that are otherwise difficult to quantify, providing a competitive advantage in EM portfolio management.

Despite their potential, ML and data-driven approaches face several challenges in emerging market applications. Model performance can be highly sensitive to data quality, preprocessing decisions, and hyperparameter selection, all of which are complicated by limited historical observations, missing values, and structural breaks in EM datasets (Luo, 2016; Gudivada *et al.*, 2017). Out-of-sample performance and stability are critical concerns, as overfitting can lead to poor realized portfolio outcomes. Interpretability is another major issue; complex ML models, particularly deep neural networks, often operate as “black boxes,” making it difficult for portfolio managers and regulators to understand decision pathways or justify allocations. In highly regulated EM contexts, lack of transparency may hinder adoption despite demonstrated predictive power. Research efforts increasingly focus on explainable AI (XAI) techniques, which aim to provide insights into feature importance, model decision rules, and sensitivity to input changes, enhancing trust and governance in ML-driven portfolio strategies.

Machine learning and data-driven approaches represent a significant evolution in portfolio optimization for emerging markets. Techniques such as neural networks, random forests, and reinforcement learning enable sophisticated modeling of non-linear dependencies, tail risks, and regime shifts, while

hybrid frameworks integrate these predictions with traditional optimization for practical implementability. The use of alternative data and feature selection methods allows investors to exploit latent informational advantages in EMs. However, challenges related to model performance, data limitations, and interpretability remain significant, requiring careful design, validation, and governance. As ML methodologies continue to mature and EM data infrastructure improves, these approaches are poised to play a central role in enhancing risk-adjusted returns and resilience in emerging market investment portfolios.

2.5 Empirical Evidence on Portfolio Performance in Emerging Markets

Empirical research on portfolio performance in emerging markets (EMs) provides critical insights into the effectiveness of various quantitative optimization techniques under conditions of high volatility, structural instability, and data constraints. Emerging markets, characterized by heightened return volatility, thin liquidity, and frequent macroeconomic shocks, pose unique challenges to portfolio construction, necessitating careful evaluation of both risk and return outcomes. Empirical studies have examined the comparative performance of traditional and advanced optimization models, their ability to control downside risk, and their resilience during periods of market stress, offering a nuanced understanding of the practical benefits and limitations of quantitative strategies in EM contexts.

Comparative analyses of optimization models across EM asset classes indicate a consistent pattern: traditional mean–variance optimization often produces highly concentrated or unstable portfolios due to estimation errors and sensitivity to volatile correlations, particularly in equity markets (Getmansky *et al.*, 2015; Bin and Yuan, 2016). Studies comparing mean–variance, minimum variance, risk parity, and alternative robust optimization approaches find that minimum variance and risk parity strategies tend to outperform unconstrained mean–variance portfolios in terms of stability and realized returns. For fixed income assets, which are generally less volatile than equities, constrained mean–variance optimization combined with turnover or liquidity limits

demonstrates improved out-of-sample performance. Hybrid models incorporating Bayesian estimation or shrinkage techniques consistently produce more balanced portfolios, reflecting their ability to mitigate parameter uncertainty prevalent in emerging market datasets. Overall, evidence suggests that robust, adaptive, and constraint-aware optimization frameworks deliver superior performance across diverse EM asset classes compared to classical mean–variance approaches.

Risk-adjusted returns and downside risk control are critical measures in EM portfolio evaluation. Empirical findings demonstrate that minimum variance, risk parity, and robust optimization portfolios generally achieve higher Sharpe ratios and lower conditional Value-at-Risk (CVaR) metrics than traditional mean–variance allocations. These approaches are particularly effective at limiting extreme losses during periods of heightened market turbulence, reflecting their focus on downside risk rather than total variance. In addition, portfolios constructed using multi-period or regime-switching optimization frameworks display improved resilience to tail events and non-normal return distributions, supporting the practical importance of dynamic risk-adjusted strategies in EM contexts.

Market stress and financial crises further highlight the differential performance of optimization techniques. Studies analyzing the 2008 global financial crisis and subsequent EM-specific shocks—such as currency devaluations, capital flow reversals, and commodity price collapses—show that unconstrained mean–variance portfolios suffered severe drawdowns, whereas robust and constrained portfolios experienced smaller losses and faster recovery. Regime-adaptive models, which adjust allocations based on observed volatility and correlation shifts, were particularly effective in mitigating losses during crisis periods. Evidence also indicates that diversification benefits are less pronounced during stress episodes due to rising correlations among EM assets, reinforcing the need for optimization techniques that explicitly account for tail risk and structural breaks.

Cross-country and regional empirical studies provide additional insights into heterogeneity within emerging markets. Latin American markets, often characterized

by commodity dependence and high inflation volatility, tend to exhibit greater downside risk, favoring robust and minimum variance strategies. In contrast, Asian emerging markets, with higher liquidity and deeper capital markets, allow more effective implementation of dynamic and hybrid optimization approaches (Sheng, 2015; Zhao, 2016). African and frontier markets, with limited data availability and frequent regulatory constraints, benefit from shrinkage and Bayesian approaches to reduce estimation error. Comparative analyses also reveal that multi-market portfolios combining EM equities, bonds, and alternative assets deliver improved risk-adjusted performance when region-specific correlations and capital flow dynamics are considered.

Empirical evidence underscores several critical implications for portfolio management in emerging markets. First, the choice of optimization technique significantly affects both realized returns and risk exposure, with robust, constrained, and dynamic models outperforming traditional mean–variance approaches in high-volatility contexts. Second, attention to downside risk and tail events is essential for practical portfolio resilience, as EM assets are prone to extreme price movements and structural shocks. Third, market-specific characteristics, including liquidity, regulatory constraints, and macroeconomic volatility, must inform model selection and parameter estimation. Finally, cross-country and regional heterogeneity highlights the importance of context-sensitive optimization strategies that consider local market structures, correlations, and data limitations.

Empirical studies consistently demonstrate that emerging market portfolio performance is improved when optimization models account for estimation risk, tail events, and dynamic market conditions. Minimum variance, risk parity, robust, Bayesian, and regime-switching models outperform classical mean–variance portfolios across a range of EM asset classes, delivering superior risk-adjusted returns and enhanced downside protection. These findings reinforce the importance of adapting quantitative optimization techniques to the structural and market-specific realities of emerging economies, guiding both theoretical research and practical asset management

strategies in volatile, high-risk investment environments.

2.6 Practical Asset Management Implications

Emerging market (EM) portfolio optimization presents a set of practical challenges that are distinct from those encountered in developed markets. While quantitative models provide a theoretically sound framework for *asset allocation*, real-world implementation in EMs is complicated by market volatility, liquidity constraints, transaction costs, regulatory restrictions, and structural inefficiencies. Understanding these practical considerations is critical for asset managers aiming to construct portfolios that are not only theoretically optimal but also feasible, resilient, and aligned with long-term investment objectives.

One of the foremost challenges in EM portfolio optimization is the implementation gap between model outputs and actual trading conditions. Quantitative optimization techniques, including mean–variance, robust, Bayesian, and dynamic models, often generate allocations that assume perfect market access, unlimited liquidity, and negligible trading costs. In practice, EM markets frequently exhibit shallow trading volumes, large bid–ask spreads, and limited market depth. Consequently, portfolios constructed purely on theoretical models may require adjustments to account for liquidity risk, transaction costs, and market impact, which can materially affect realized returns (Ben-Rephael *et al.*, 2015; Benos *et al.*, 2017). Asset managers must carefully evaluate the implementability of optimized allocations and incorporate constraints on turnover, position sizes, and sector exposure to ensure that portfolios can be executed without excessive costs or market disruption.

Transaction costs, liquidity management, and rebalancing frequency are critical operational considerations in EMs. High trading costs and limited liquidity can erode the benefits of frequent rebalancing implied by dynamic optimization models. Empirical studies indicate that overly aggressive rebalancing in EM portfolios can lead to underperformance relative to static or constrained strategies due to the cumulative effect of transaction costs. To mitigate these risks, practitioners often employ liquidity-adjusted

optimization techniques, impose turnover limits, and implement threshold-based rebalancing rules, rebalancing only when deviations from target weights exceed predetermined levels. These approaches help balance the trade-off between maintaining portfolio risk targets and minimizing implementation costs, which is particularly important during periods of market turbulence when liquidity is further constrained.

Regulatory and institutional constraints also significantly influence portfolio optimization in EMs. Many emerging markets impose capital controls, foreign ownership limits, repatriation restrictions, and sector-specific investment ceilings. Institutional investors must comply with these regulations while pursuing optimal allocations, which often requires incorporating regulatory constraints directly into the optimization framework. Additionally, EM asset managers may face operational challenges such as limited access to reliable market data, fragmented exchanges, and variations in accounting and disclosure standards. These constraints necessitate a careful balance between theoretical optimality and regulatory and institutional feasibility, as portfolios that violate rules or cannot be practically implemented carry substantial legal, operational, and reputational risks.

Integration of environmental, social, and governance (ESG) considerations adds an additional layer of complexity to EM portfolio management. ESG integration is increasingly recognized as a critical component of long-term value creation and risk mitigation, yet emerging markets often present challenges such as limited ESG disclosure, inconsistent reporting standards, and lower market awareness of sustainability risks. Asset managers must combine traditional quantitative optimization with ESG criteria, using data-driven approaches to screen, weight, or tilt portfolios toward companies with stronger sustainability profiles. Alternative data sources, including third-party ESG ratings, satellite imagery, and corporate governance reports, are increasingly employed to supplement incomplete local disclosures. Hybrid optimization models that incorporate ESG constraints or multi-objective functions allow managers to align financial objectives with sustainability goals, though these models further

complicate implementation and may require trade-offs between expected returns and ESG compliance.

Practical implementation in EM portfolio management also requires robust risk monitoring and scenario analysis. Extreme volatility, sudden capital flow reversals, and macroeconomic shocks necessitate frequent stress testing and contingency planning. Optimized portfolios should be evaluated under alternative market scenarios, incorporating factors such as currency depreciation, interest rate shocks, and regulatory changes. Scenario analysis enables managers to anticipate potential deviations from model predictions and adjust allocations proactively, enhancing resilience and preserving downside protection in volatile conditions.

While quantitative optimization provides a powerful foundation for emerging market portfolio management, practical implementation requires careful consideration of transaction costs, liquidity constraints, rebalancing strategies, regulatory requirements, and ESG integration. Asset managers must adapt optimization outputs to local market realities, employing liquidity-adjusted models, turnover limits, regulatory-aware constraints, and hybrid ESG frameworks to produce implementable and resilient portfolios (Pinto *et al.*, 2015; Berglund *et al.*, 2017). By addressing these practical challenges, practitioners can translate theoretical efficiency into tangible risk-adjusted performance, ensuring that emerging market portfolios achieve both financial and sustainability objectives in complex and dynamic investment environments.

2.7 Future Research Directions

This quantitative portfolio optimization in emerging markets (EMs) has advanced considerably over the past decades, yet significant gaps remain that warrant further investigation. Emerging markets present unique challenges including high volatility, market inefficiencies, liquidity constraints, and limited data availability that require tailored optimization frameworks and innovative methodologies (Javaira and Hassan, 2015; Sen and Ganguly, 2017). Future research is poised to expand both the theoretical and practical frontiers of EM asset management, with an emphasis on more realistic modeling, integration of macro-financial and geopolitical risks, advanced

computational techniques, and alignment with sustainability objectives.

A primary direction for future research is the development of EM-specific optimization frameworks. While traditional mean–variance and risk parity models have been adapted for EM applications, these approaches often fail to fully capture the structural and idiosyncratic characteristics of emerging market assets. EM-specific frameworks could incorporate features such as heavy-tailed return distributions, time-varying correlations, liquidity-adjusted constraints, and regime-dependent risk factors. By explicitly accounting for market-specific volatility dynamics, data limitations, and transaction costs, such models can provide more reliable, implementable portfolio recommendations that reflect the realities of EM investing. Research could also explore hybrid models that combine robust and Bayesian optimization methods with adaptive constraints, producing portfolios that are both theoretically sound and operationally feasible.

Integration of macro-financial and geopolitical risk factors represents another promising avenue. EM returns are heavily influenced by external shocks, including commodity price fluctuations, currency depreciation, trade tensions, and political instability. Future studies should incorporate macroeconomic indicators, geopolitical events, and global risk sentiment into portfolio optimization models. For example, factor-based frameworks could be extended to include country-specific risk measures, capital flow volatility, and policy uncertainty indices, allowing investors to anticipate structural shifts and mitigate downside exposure more effectively. Scenario-based optimization under stress conditions, combined with dynamic multi-period models, can further enhance portfolio resilience during periods of market turbulence (Martel and Klibi, 2016; Shafi *et al.*, 2017).

Long-term, multi-asset, and cross-market studies are critical for advancing EM portfolio research. Most existing studies focus on single-asset classes, short horizons, or isolated markets, limiting generalizability. Future research should examine multi-asset portfolios including equities, bonds, commodities, and alternative investments over extended timeframes to capture structural market

evolution, capital flow cycles, and diversification benefits. Cross-market analyses comparing Latin American, Asian, and African emerging markets can identify regional patterns, interdependencies, and optimal allocation strategies across heterogeneous EM environments. Such studies would also allow evaluation of dynamic correlations, tail-risk comovements, and cross-market contagion effects, providing a more comprehensive understanding of risk-adjusted performance.

The application of explainable artificial intelligence (XAI) in EM portfolio management is an emerging and critical research direction. While machine learning and data-driven approaches have shown promise in predicting returns, capturing non-linear dependencies, and optimizing allocations, their “black box” nature limits interpretability and regulatory acceptance. Research on XAI can develop models that not only deliver superior predictive performance but also provide transparent explanations of allocation decisions, feature importance, and sensitivity to input variables. Integrating XAI with EM-specific optimization frameworks would improve governance, enhance investor trust, and facilitate compliance with increasingly stringent reporting standards.

The alignment of portfolio optimization with sustainable finance goals is a growing imperative. ESG integration in EMs is challenged by limited disclosure, inconsistent reporting standards, and market heterogeneity. Future research should explore methods to incorporate sustainability objectives directly into optimization processes, using multi-objective frameworks or ESG-weighted constraints. This includes developing risk-adjusted performance measures that account for environmental, social, and governance factors, and linking portfolio allocation strategies to climate transition risks, social impact, and corporate governance quality (Liesen *et al.*, 2017; Foo, 2017). The combination of financial optimization with sustainability considerations ensures that emerging market investments support long-term value creation, responsible investing principles, and compliance with global ESG regulations.

Future research in emerging market portfolio optimization should focus on developing context-sensitive, EM-specific frameworks that integrate

macro-financial, geopolitical, and sustainability considerations. Long-term, multi-asset, and cross-market studies, combined with machine learning and explainable AI techniques, can enhance predictive accuracy, portfolio resilience, and transparency. Aligning quantitative optimization with sustainable finance goals ensures that emerging market investments achieve both financial and social objectives. Collectively, these directions will advance the field by bridging methodological innovation with practical relevance, providing actionable guidance for institutional investors and asset managers operating in complex, high-risk, and dynamic emerging market environments.

CONCLUSION

This review of quantitative portfolio optimization research highlights the significant progress and ongoing challenges in managing emerging market (EM) assets. The literature demonstrates that while classical mean-variance optimization provides a foundational framework, its direct application in EM contexts is often limited due to high volatility, non-normal return distributions, liquidity constraints, and unstable correlations. Extensions such as minimum variance, risk parity, robust, Bayesian, and dynamic multi-period models address these limitations by incorporating parameter uncertainty, tail-risk measures, and adaptive strategies. Empirical studies consistently show that these advanced optimization approaches deliver superior risk-adjusted returns, improved downside risk control, and greater resilience during periods of market stress compared to traditional frameworks. The integration of machine learning and data-driven techniques further enhances predictive accuracy, enabling portfolio managers to capture non-linear dependencies, exploit alternative data sources, and adapt to regime shifts.

Quantitative optimization research contributes to EM asset management by providing tools and methodologies that reconcile theoretical efficiency with practical implementation challenges. By explicitly accounting for transaction costs, liquidity constraints, regulatory limits, and macro-financial risks, these approaches produce implementable portfolios that are both robust and operationally feasible. Hybrid models combining traditional

optimization with predictive analytics and dynamic adjustments demonstrate particular promise in navigating the structural complexity and volatility inherent in EM markets. Furthermore, the emerging incorporation of ESG and sustainability considerations into optimization frameworks underscores the potential for aligning financial performance with responsible investment objectives.

From a strategic perspective, the insights derived from this body of research are highly relevant for both investors and policymakers. For institutional investors, EM-specific optimization techniques provide guidance for enhancing portfolio resilience, managing tail risks, and achieving superior risk-adjusted returns in volatile markets. Policymakers and regulators can leverage these findings to design frameworks that support market transparency, risk mitigation, and sustainable capital allocation. Overall, the reviewed research underscores the importance of context-sensitive, data-driven, and adaptive portfolio strategies in maximizing investment outcomes and supporting sustainable development objectives in emerging markets.

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