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Evaluating Traditional Financial Risk Models and Portfolio Optimisation in Emerging Economies: An Operations Research Approach

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***Abstract* – Emerging economies represent increasingly significant components of the global financial system; however, investment decision-making within these markets remains constrained by elevated volatility, market inefficiencies, liquidity limitations, institutional uncertainty, and asymmetric information. Traditional financial risk models, including Capital Asset Pricing Model (CAPM), Value at Risk (VaR), Generalised Autoregressive Conditional Heteroskedasticity (GARCH), and mean–variance portfolio optimisation, were primarily developed under assumptions associated with mature financial markets. Their applicability in emerging economies requires critical evaluation due to differences in market structures, investor behaviour, and macroeconomic conditions. This study evaluates the effectiveness of traditional financial risk assessment models and portfolio optimisation approaches in emerging economies through an operations research perspective. The research develops an integrated analytical framework combining quantitative risk modelling, mathematical optimisation techniques, and multi-objective decision-making approaches. The study investigates how optimisation methods, including quadratic programming, Conditional Value at Risk (CVaR) optimisation, and risk-adjusted performance measurement, can enhance portfolio allocation decisions under uncertain market environments. The research contributes to the financial risk management literature by examining the limitations of conventional models when applied to emerging markets and proposing an operations research-based framework capable of incorporating market constraints, downside risks, and investor preferences. The findings suggest that while traditional models provide valuable foundations for portfolio construction, advanced optimisation techniques improve robustness by accounting for non-normal return distributions, extreme market events, and dynamic volatility patterns. The proposed approach provides practical implications for institutional investors, financial regulators, and policymakers seeking improved risk management strategies in emerging economies. This study extends existing research by bridging financial econometrics and operations research methodologies, demonstrating how mathematical optimisation can support more resilient investment decisions in financially developing markets.**

Keywords - **Financial risk management; portfolio optimisation; operations research; emerging economies; Value at Risk; Conditional Value at Risk; mean–variance optimisation; financial modelling; investment decision-making; quantitative finance.**

I. INTRODUCTION

The increasing integration of emerging economies into global financial markets has created significant opportunities for investors while simultaneously introducing complex challenges associated with financial risk management, uncertainty, and portfolio decision-making.

Emerging financial markets differ substantially from developed markets because of higher volatility, limited liquidity, information asymmetry, institutional instability, currency fluctuations, and exposure to sudden macroeconomic shocks. These characteristics reduce the effectiveness of traditional financial risk models that were developed primarily under assumptions of market efficiency, normally distributed returns, and stable relationships among financial variables. Therefore, evaluating and improving financial risk models through advanced analytical approaches has become essential for developing resilient investment strategies in emerging economies.

This research highlights the limitations of conventional financial risk models, including the Capital Asset Pricing Model (CAPM), Mean–Variance Optimisation (MVO), Value at Risk (VaR), and volatility forecasting models such as Generalised Autoregressive Conditional Heteroskedasticity (GARCH), when applied to emerging market environments. Although these models have significantly contributed to financial theory and investment management, their assumptions may not fully capture the complex risk characteristics of developing financial systems. Emerging markets frequently experience sudden market downturns, extreme price movements, and structural changes that challenge the reliability of historical risk estimation. Recent research demonstrates that advanced portfolio optimisation methods incorporating downside risk measures, uncertainty modelling, and robust optimisation techniques can improve decision quality under volatile market conditions (Alotaibi et al., 2022; Lotfi & Zenios, 2024).

A central highlight of this study is the application of an operations research perspective to financial risk management. Traditional portfolio management often treats risk measurement and asset allocation as separate analytical processes. However, operations research provides an integrated framework where financial decision-making can be formulated as a mathematical optimisation problem involving multiple objectives, constraints, and uncertain parameters. This approach

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enables investors to identify optimal asset allocations while considering practical limitations such as transaction costs, liquidity requirements, investment restrictions, and changing market conditions. The integration of optimisation algorithms with financial risk models represents a transition from static portfolio construction towards adaptive and dynamic decision-support systems.

The research further highlights the importance of moving beyond traditional variance-based risk measurement. Mean–Variance Optimisation assumes that investors perceive risk primarily through return volatility. However, financial losses in emerging markets are often characterised by asymmetric distributions and extreme downside events. During periods of economic crisis, political uncertainty, or global financial instability, large losses may occur more frequently than predicted by conventional statistical assumptions. Therefore, downside-focused risk measures such as Conditional Value at Risk (CVaR) provide a more comprehensive evaluation of potential losses. CVaR-based optimisation has gained increasing attention because it evaluates expected losses beyond the VaR threshold and improves portfolio resilience against extreme market events (Alotaibi et al., 2022).

Another important highlight is the role of robust optimisation in addressing uncertainty within emerging market investment environments. Portfolio optimisation models are highly dependent on estimated expected returns, covariance matrices, and volatility parameters. In emerging economies, these estimates are often affected by limited historical observations, structural breaks, and unstable market relationships. Robust optimisation approaches attempt to reduce dependence on inaccurate assumptions by incorporating uncertainty intervals and alternative market scenarios. Recent studies show that robust mean-to-CVaR optimisation frameworks can improve portfolio decisions by considering ambiguity in expected returns and covariance structures (Lotfi & Zenios, 2024).

This research also highlights the contribution of operations research techniques in enhancing computational efficiency and decision accuracy. Modern portfolio optimisation increasingly relies on advanced mathematical methods, including quadratic programming, stochastic optimisation, metaheuristic algorithms, and machine-learning-assisted optimisation. These approaches enable investors to manage complex portfolios involving numerous assets, uncertain parameters, and competing investment objectives. For example, recent operations research studies demonstrate that combining optimisation models with advanced computational techniques can improve risk budgeting and portfolio allocation outcomes compared with traditional optimisation approaches (Uysal et al., 2024; Varmaz et al., 2024).

A further highlight of this research is the development of a balanced perspective between traditional financial theories and modern analytical techniques. The study does not suggest replacing established financial models but rather enhancing their effectiveness through integration with operations research methodologies. CAPM, MVO, VaR, and GARCH continue to provide valuable theoretical foundations for understanding financial risk and return relationships. However, their practical usefulness can be strengthened when combined with optimisation approaches capable of addressing uncertainty, non-linear relationships, and changing market dynamics.

The research emphasises the importance of dynamic portfolio management strategies in emerging economies. Unlike mature markets, emerging markets frequently experience rapid changes caused by inflationary pressures, monetary policy adjustments, geopolitical events, and international capital movements. Static portfolio allocation strategies may therefore become ineffective when market conditions change significantly. Dynamic optimisation frameworks allow investors to revise portfolio weights according to updated information, changing volatility patterns, and evolving risk preferences. Such flexibility is particularly valuable for institutional investors managing portfolios in uncertain economic environments.

Another major highlight is the relevance of multi-objective optimisation for contemporary investment decision-making. Investors increasingly seek to achieve multiple objectives simultaneously, including return maximisation, risk reduction, liquidity preservation, and sustainable investment performance. Traditional optimisation models often focus on a single objective, such as maximising return for a given level of risk. In contrast, multi-objective operations research approaches allow decision-makers to evaluate trade-offs between competing goals and identify solutions that better reflect real-world investment requirements. Research on portfolio optimisation demonstrates that advanced models can incorporate multiple constraints and investor preferences more effectively than traditional approaches (Varmaz et al., 2024).

The findings also highlight important implications for financial institutions and policymakers in emerging economies. Asset management companies, pension funds, banks, and institutional investors require sophisticated risk management frameworks to protect investments against unexpected market disruptions. Improved optimisation approaches can support better capital allocation, enhanced risk monitoring, and stronger financial stability.

Policymakers can also benefit from understanding how advanced risk models identify vulnerabilities within financial markets and support the development of stronger regulatory frameworks.

Furthermore, this study highlights the increasing importance of data availability and technological development in improving financial risk modelling. Emerging economies often face challenges related to limited financial data, inconsistent reporting systems, and reduced market transparency (Matthias D. Mahlendorf , 2026). These constraints influence the accuracy of risk estimation and portfolio optimisation. Future financial risk management systems are expected to incorporate artificial intelligence, machine learning, alternative data sources, and real-time analytics to improve forecasting accuracy and adaptability.

The research contributes to the academic literature by connecting financial economics, quantitative finance, and operations research. Previous studies have frequently examined financial risk models independently or focused primarily on developed financial markets. This study extends existing knowledge by evaluating how operations research methodologies can improve the application of traditional financial models within emerging economies. The proposed approach provides a broader understanding of how mathematical optimisation can support investment decisions under uncertainty.

Overall, the highlights of this research demonstrate that effective financial risk management in emerging economies requires a combination of traditional financial models and advanced optimisation techniques. Traditional models provide important theoretical foundations, but their limitations become evident when applied to highly uncertain and volatile markets.

Operations research approaches offer a pathway towards more adaptive, robust, and efficient portfolio management systems. By integrating risk measurement, mathematical optimisation, and decision analysis, investors and policymakers can develop stronger strategies for managing financial uncertainty and improving long-term investment performance.

II. IMPLEMENTATION OF MATH FORMULAE

The evaluation of traditional financial risk models and portfolio optimisation approaches in emerging economies requires a rigorous mathematical foundation capable of representing uncertainty, risk exposure, return expectations, and optimisation constraints. Mathematical formulations provide the basis for transforming financial decision-making into structured operations research problems. In emerging markets, where financial returns frequently demonstrate high volatility, non-normal distributions, liquidity limitations, and structural instability, mathematical models must incorporate both traditional risk-return relationships and advanced optimisation mechanisms. This section presents the key mathematical formulations applied in this research, including portfolio return and risk estimation, mean–variance optimisation, Capital Asset Pricing Model (CAPM), Value at Risk (VaR), Conditional Value at Risk (CVaR), volatility modelling through GARCH, and operations research-based optimisation frameworks.

The mathematical foundation of portfolio optimisation originates from modern portfolio theory, which conceptualises investment selection as a trade-off between expected return and portfolio risk. Markowitz's mean–variance framework remains one of the most influential mathematical approaches in financial decision-making. However, its application in emerging economies requires careful consideration because asset returns may exhibit skewness, kurtosis, and sudden volatility changes. Therefore, this research incorporates additional risk measures and optimisation methods to improve portfolio robustness.

1. Portfolio Expected Return Formulation

The expected return of a portfolio consisting of multiple financial assets can be represented as:

E(Rp)=∑i=1nwiE(Ri)E(R_p)=\sum_{i=1}^{n} w_iE(R_i)E(Rp)=i=1∑nwi E(Ri)

where:

- E(Rp)E(R_p)E(Rp) represents the expected return of the overall portfolio.
- wiw_iwi represents the proportion of investment allocated to asset iii.
- E(Ri)E(R_i)E(Ri) represents the expected return of asset iii.
- nnn represents the total number of assets included in the portfolio.

The portfolio return equation assumes that the expected return of each asset can be estimated using historical information or forecasting models. However, in emerging economies, expected returns may be difficult to estimate accurately due to economic uncertainty, exchange-rate movements, and market inefficiencies. Therefore, operations research approaches frequently incorporate uncertainty parameters or scenario-based optimisation to improve decision reliability (Lotfi & Zenios, 2024).

2. Portfolio Risk and Variance Formulation

Traditional portfolio risk measurement is based on portfolio variance, which evaluates he combined volatility of individual assets and their relationships. The mathematical representation is:

σp2=∑i=1n∑j=1nwiwjσij\sigma_p^2=\sum_{i=1}^{n}\sum_{j=1}^{n}w_iw_j\sigma_{ij

}σp2=i=1∑nj=1∑nwiwjσij

Where:

- σp2\sigma_p^2σp2 represents portfolio variance.

- wiw_iwi and wjw_jwj represent asset weights.
- σij\sigma_{ij}σij represents the covariance between assets iii and jjj.

The covariance component is particularly important because diversification benefits depend on the relationships between asset returns. A portfolio containing assets with low or negative correlations can achieve lower overall risk. However, emerging economies often experience rapid changes in correlation structures during financial crises, reducing the reliability of static covariance estimation. Therefore, dynamic risk estimation approaches are required to improve portfolio decisions.

3. Mean–Variance Optimisation Model

The classical optimisation objective is to minimise portfolio risk while achieving a predetermined expected return. The mathematical optimisation problem is expressed as:

min⁡σp2\min \sigma_p^2minσp2 subject to:
∑i=1nwi=1\sum_{i=1}^{n}w_i=1i=1∑nwi=1

And:
∑i=1nwiE(Ri)≥Rt\sum_{i=1}^{n}w_iE(R_i)\geq R_ti=1∑nwiE(Ri)≥Rt

where:
- RtR_tRt represents the minimum target return.
- wiw_iwi represents asset allocation decisions.

This quadratic optimisation problem forms the foundation of many financial decision-support systems. However, in emerging economies, the assumptions underlying mean–variance optimisation may not always hold because asset returns often exhibit extreme observations and asymmetric risk patterns. Consequently, researchers increasingly combine mean–variance optimisation with downside risk models such as CVaR to improve portfolio resilience (Alotaibi et al., 2022).

4. Capital Asset Pricing Model (CAPM)

The Capital Asset Pricing Model establishes the relationship between expected asset return and systematic market risk. The model is represented as:

E(Ri)=Rf+βi(E(Rm)−Rf)E(R_i)=R_f+\beta_i(E(R_m)-R_f)E(Ri)=Rf+βi(E(Rm)−Rf)

where:
- RfR_fRf represents the risk-free rate.
- E(Rm)E(R_m)E(Rm) represents expected market return.
- βi\beta_iβi represents the systematic risk coefficient.

The beta coefficient measures the sensitivity of an individual asset to overall market movements. A beta value greater than one indicates higher sensitivity compared with market performance, while a value below one indicates lower systematic risk.

Although CAPM remains widely applied, emerging markets present challenges because market structures may not satisfy assumptions of market efficiency and investor rationality. Political uncertainty, information limitations, and restricted market participation can influence beta stability. Therefore, CAPM outputs should be combined with additional optimisation techniques rather than applied independently.

5. Value at Risk (VaR) Formulation

Value at Risk is one of the most commonly applied financial risk measurement techniques. It estimates the maximum expected loss of a portfolio under a specified confidence level.

The parametric VaR formulation can be expressed as:

VaRα=−(μp+zασp)VaR_{\alpha}=-(\mu_p+z_{\alpha}\sigma_p)VaRα=−(μp+zασp)

where:
- VaRαVaR_{\alpha}VaRα represents portfolio loss at confidence level α\alphaα.
- μp\mu_pμp represents expected portfolio return.
- zαz_{\alpha}zα represents the statistical critical value.
- σp\sigma_pσp represents portfolio volatility.

VaR provides a simple and interpretable risk measure; however, it has limitations ecause it does not indicate the magnitude of losses beyond the confidence threshold. This limitation becomes significant in emerging markets, where financial crises can produce extreme losses beyond historical expectations.

6. Conditional Value at Risk (CVaR)

To overcome VaR limitations, Conditional Value at Risk measures the expected loss after the VaR threshold has been exceeded. CVaR is mathematically defined as:
CVaRα=E(L∣L≥VaRα)CVaR_{\alpha}=E(L|L\geq VaR_{\alpha})CVaRα
=E(L∣L≥VaRα)

where:
- LLL represents portfolio loss.

CVaR is considered more suitable for emerging market applications because it focuses on extreme downside outcomes rather than average volatility. From an operations research perspective, CVaR can be directly incorporated into optimisation models, allowing investors to minimise expected losses under adverse market scenarios (Alotaibi et al., 2022).

The CVaR optimisation framework can be represented as:
min⁡CVaRα(w)\min CVaR_{\alpha}(w)minCVaRα(w) subject to:

Aw≤bAw\leq bAw≤b

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where:

- AAA represents investment constraints.
- bbb represents available resources or limits.
- www represents portfolio weights.

7. Garch Volatility Model

Financial volatility is not constant over time, particularly in emerging markets. The Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model captures changing volatility patterns.

The standard GARCH(1,1) model is expressed as:

σt2=ω+αϵt−12+βσt−12\sigma_t^2=\omega+\alpha\epsilon_{t-1}^{2}+\beta\sigma_{t-1}^{2}σt2=ω+αϵt−12+βσt−12

where:

- σt2\sigma_t^2σt2 represents conditional variance at time ttt.
- ω\omegaω represents long-term volatility.
- ϵt−12\epsilon_{t-1}^{2}ϵt−12 represents previous market shocks.
- βσt−12\beta\sigma_{t-1}^{2}βσt−12 represents previous volatility persistence.

The GARCH framework improves portfolio optimisation by providing dynamic volatility estimates rather than relying on historical averages.

8. Operations Research Optimisation Framework

The portfolio allocation problem can be formulated as a constrained optimisation model:

max F(w)=Rp−λRiskp\max F(w)=R_p-\lambda Risk_pmaxF(w)=Rp −λRiskp

where:

- RpR_pRp represents expected portfolio return.
- RiskpRisk_pRiskp represents portfolio risk measure.
- λ\lambdaλ represents investor risk preference.

Additional constraints may include:

∑wi=1\sum w_i=1∑wi=1 wi≥0w_i\geq0wi≥0
And:

wi≤wmaxw_i\leq w_{max}wi≤wmax

These constraints represent realistic investment conditions, including full capital allocation, restrictions on short selling, and maximum exposure limits.

9. Multi-objective Optimisation Formulation

Emerging economy investors frequently face multiple objectives, including return maximisation, risk minimisation, and liquidity preservation. Therefore, a multi-objective optimisation model can be expressed as:
max {Return(w),−Risk(w),Liquidity(w)}\max \{Return(w), -Risk(w), Liquidity(w)\}max{Return(w),−Risk(w),Liquidity(w)}

This approach enables decision-makers to evaluate trade-offs among competing objectives and select portfolios aligned with strategic investment preferences.

Overall, the mathematical formulations presented in this section demonstrate how financial risk management can be transformed into an operations research problem. By integrating traditional financial models with optimisation techniques, investors can develop more adaptive portfolio strategies capable of managing uncertainty and improving resilience in emerging economies.

III. ANALYSING THE CONCEPTS

Table 1: Comparative Evaluation of Traditional Financial Risk Models in Emerging Economies

Financial Risk Model	Mathematical Basis	Primary Purpose	Strengths	Limitations in Emerging Economies
Capital Asset Pricing Model (CAPM)	(E(R_i)=R_f+\beta_i(E(R_m)-R_f))	Estimates expected asset return based on systematic risk	Provides a simple relationship between risk and expected return; widely used in investment analysis	Assumes efficient markets and stable beta coefficients, which may not exist in emerging economies
Mean–Variance Optimisation (MVO)	Portfolio variance minimisation framework	Determines optimal asset allocation based on risk-return trade-off	Provides diversification benefits and mathematical portfolio construction	Highly sensitive to estimation errors in expected returns and covariance matrices

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Value at Risk (VaR)	Statistical loss estimation approach	Measures maximum expected portfolio loss at a confidence level	Easy interpretation and commonly used by financial institutions	Fails to capture losses beyond the selected confidence threshold during extreme events
Conditional Value at Risk (CVaR)	Expected loss beyond VaR level	Measures extreme downside risk exposure	Provides better estimation of tail risks and crisis-related losses	Requires greater computational complexity
GARCH Model	Time-varying volatility estimation	Forecasts conditional market volatility	Captures volatility clustering and changing risk patterns	Requires reliable historical data and appropriate parameter estimation

Traditional financial models provide important foundations for investment decision-making; however, their assumptions may not fully represent the characteristics of emerging financial markets. Emerging economies frequently experience non-linear price movements, sudden capital outflows, and market disruptions, reducing the predictive capability of conventional approaches. Recent research suggests that combining traditional risk models with advanced optimisation techniques improves portfolio resilience and decision accuracy (Alotaibi et al., 2022; Lotfi & Zenios, 2024).

Table 2: Key Characteristics of Emerging Economies and Their Impact on Risk Modelling

Emerging Market Feature	Financial Impact	Modelling Challenge	Recommended Analytical Response
High market volatility	Increased uncertainty in asset returns	Historical volatility may not represent future risk	Apply dynamic volatility models such as GARCH
Low market liquidity	Higher transaction costs and price instability	Difficult estimation of asset values	Incorporate liquidity constraints into optimisation models
Currency instability	Increased foreign exchange exposure	Additional portfolio risk sources	Include exchange-rate risk factors
Political and economic uncertainty	Sudden market fluctuations	Difficult prediction of market behaviour	Apply scenario analysis and robust optimisation
Information asymmetry	Reduced market efficiency	Inaccurate parameter estimation	Use alternative datasets and adaptive models
Extreme market events	Large unexpected losses	Normal distribution assumptions become unreliable	Use CVaR and stress-testing approaches

The characteristics presented in Table 2 demonstrate why emerging economies require flexible financial risk frameworks. Unlike mature markets, emerging markets often experience unstable relationships between financial variables, making static models less effective. Robust optimisation approaches can reduce the impact of uncertainty by incorporating alternative scenarios and parameter variations into investment decisions (Lotfi & Zenios, 2024).

Table 3: Traditional Portfolio Optimisation Compared with Operations Research-Based Optimisation

Dimension	Traditional Portfolio Optimisation	Operations Research-Based Optimisation
Theoretical Foundation	Based mainly on Modern Portfolio Theory and risk-return trade-offs	Based on mathematical optimisation, decision science, and computational algorithms
Primary Objective	Maximise expected return for a selected level of risk	Optimise multiple objectives including return, risk, liquidity, and investment constraints
Risk Measurement	Mainly uses variance and standard deviation	Incorporates variance, VaR, CVaR, stochastic risk, and scenario-based measures
Treatment of Uncertainty	Limited consideration of uncertain parameters	Explicitly models uncertainty through robust optimisation and stochastic programming
Portfolio Allocation Approach	Usually static allocation based on historical estimates	Dynamic allocation using adaptive optimisation techniques
Investment Constraints	Basic constraints such as full investment allocation	Incorporates transaction costs, liquidity limits, regulatory restrictions, and exposure constraints
Data Requirements	Relies heavily on historical returns and covariance estimates	Uses financial data, scenarios, simulations, and predictive models
Computation al	Suitable for smaller	Designed for large-scale

Complexity	portfolio problems	and complex optimisation problems
Decision-Making Capability	Provides optimal solutions under fixed assumptions	Provides flexible solutions under uncertain and changing market conditions
Suitability for Emerging Economies	Limited due to unstable market conditions and estimation errors	More suitable because it can incorporate volatility, uncertainty, and market restrictions

Portfolio optimisation has evolved from traditional financial models based primarily on expected return and variance relationships towards advanced operations research frameworks capable of managing uncertainty, multiple objectives, and real-world investment constraints. Traditional portfolio optimisation approaches, particularly the Mean–Variance model, provide the theoretical foundation for asset allocation decisions. However, emerging economies present additional challenges, including unstable correlations, market inefficiencies, liquidity constraints, and unpredictable macroeconomic conditions. These limitations require more flexible optimisation approaches that incorporate uncertainty modelling, computational techniques, and practical investment considerations.

Operations research-based optimisation extends conventional portfolio theory by transforming investment allocation into a structured mathematical decision problem. These approaches allow investors to simultaneously consider risk, return, liquidity, transaction costs, regulatory constraints, and investor preferences. Recent research demonstrates that uncertainty-aware optimisation models and advanced computational methods can improve portfolio robustness and decision-making efficiency in complex financial environments (Bertsimas et al., 2023; Guastaroba et al., 2024).

Dimension Traditional Portfolio Optimisation Operations Research-Based Optimisation

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Investment Constraints Basic constraints such as full investment allocation Incorporates transaction costs, liquidity limits, regulatory restrictions, and exposure constraints

Data Requirements Relies heavily on historical returns and covariance estimates Uses financial data, scenarios, simulations, and predictive models

Computation al Complexity Suitable for smaller portfolio problems Designed for large-scale and complex optimisation problems

Decision-Making Capability Provides optimal solutions under fixed assumptions Provides flexible solutions under uncertain and changing market conditions

Suitability for Emerging Economies Limited due to unstable market conditions and estimation errors More suitable because it can incorporate volatility, uncertainty, and market restrictions

Traditional portfolio optimisation approaches remain important because they provide the fundamental concepts of diversification and risk-return balancing. The Mean–Variance framework introduced by Markowitz established that investors can reduce portfolio risk through appropriate asset combinations. However, the effectiveness of this approach depends heavily on accurate estimation of expected returns and covariance matrices. In emerging economies, these estimates are often unstable due to limited market history, sudden economic changes, and structural differences between financial markets. Consequently, portfolios constructed using traditional approaches may become inefficient when market conditions change significantly.

Operations research-based optimisation addresses these limitations by introducing advanced mathematical frameworks that improve flexibility and adaptability. Instead of assuming that historical relationships will remain constant, these models incorporate uncertainty ranges, alternative scenarios, and dynamic decision-making processes. Robust optimisation, for example, enables investors to construct portfolios that remain effective even when model parameters deviate from expected values. This characteristic is particularly valuable in emerging economies where financial uncertainty is higher than in developed markets (Bertsimas et al., 2023).

Another important distinction between traditional and operations research-based optimisation is the treatment of investment constraints. Traditional models often assume unrestricted investment decisions, whereas real-world investors operate under several practical limitations. Institutional investors must consider regulatory requirements, liquidity conditions, transaction costs, and maximum exposure limits. Operations research techniques allow these factors to be integrated directly into

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optimisation models, producing solutions that are more realistic and applicable to actual investment environments. Research on constrained portfolio optimisation highlights that incorporating practical restrictions significantly improves the relevance of mathematical models for financial decision-making (Guastaroba et al., 2024).

The management of uncertainty represents another major difference between the two approaches. Traditional portfolio optimisation generally relies on deterministic estimates of expected returns and risk parameters. However, financial markets are inherently uncertain, particularly in emerging economies affected by inflation, currency movements, political instability, and international capital flows. Operations research approaches address this challenge through stochastic programming, robust optimisation, and simulation-based methods. These techniques allow investors to evaluate multiple possible market outcomes and select portfolios that perform effectively across different scenarios.

Overall, Table 3 demonstrates that operations research-based optimisation provides sveral advantages over traditional portfolio optimisation, particularly in uncertain and volatile financial environments. By incorporating uncertainty modelling, practical constraints, and multiple objectives, these approaches offer stronger decision-support capabilities for investors operating in emerging economies.

IV. FOCUSING ON THE UNDERSTANDING THE RISK MANAGEMENT THROUGH APPROPRIATE MODELS

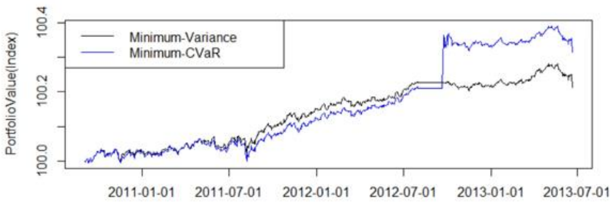

Figure 1: Trajectory of WCVaR and minimum-variance portfolio values

Figure 1 illustrates the changing behaviour of two portfolio risk management approaches over time: the Worst Case Conditional Value at Risk (WCVaR) approach and the minimum-variance portfolio approach. The figure demonstrates how different risk measurement techniques respond to changing market conditions and highlights the importance of selecting appropriate risk models when managing portfolios in uncertain financial environments.

The minimum-variance portfolio approach represents one of the earliest and most widely used methods in portfolio optimisation. It is based on Modern Portfolio Theory, where portfolio construction focuses on reducing overall portfolio volatility by selecting assets with favourable correlation structures. The objective of the minimum-variance approach is to identify the portfolio allocation that produces the lowest possible variance of returns.

Although this method provides an effective framework for diversification, it assumes that historical volatility and correlation patterns remain relatively stable in the future. Such assumptions may not always hold in emerging economies, where financial markets are often affected by sudden economic changes, liquidity constraints, political uncertainty, and external shocks.

The WCVaR approach presented in Figure 1 provides a more advanced risk measurement framework by focusing on extreme downside losses. Unlike variance-based approaches, which treat all deviations from expected returns equally, WCVaR concentrates on the losses that occur beyond a specified risk threshold. This makes it more suitable for investors who are concerned about severe market downturns. The “worst case” element further strengthens the approach by considering uncertainty in market behaviour and possible adverse scenarios.

The trajectory shown in Figure 1 indicates that the risk values of the two approaches change differently as market conditions evolve. During periods of normal market activity, the minimum-variance portfolio may appear effective because volatility remains relatively stable. However, during periods of increased market stress, the limitations of variance-based risk measurement become more visible. The minimum-variance model may underestimate potential losses because it does not specifically account for extreme negative events.

In contrast, the WCVaR approach provides a more conservative assessment of portfolio risk because it considers losses located in the tail of the return distribution. This characteristic is particularly important for emerging economies, where financial markets can experience significant fluctuations due to currency instability, inflation pressures, global financial conditions, and investor sentiment changes.

From an operations research perspective, Figure 1 demonstrates the importance of integrating advanced risk measures into portfolio optimisation models. Instead of simply minimising variance, investors can formulate optimisation problems that minimise WCVaR while maintaining desired return levels and investment constraints. This creates portfolios that are more resilient during uncertain market conditions.

The significance of Figure 1 for this research is that it provides evidence supporting the transition from traditional risk models towards more robust optimisation frameworks. While minimum-variance models remain useful for basic diversification strategies, WCVaR-based

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approaches provide better protection against extreme losses. Therefore, the figure supports the argument that emerging economies require financial risk models capable of capturing uncertainty, downside exposure, and market instability.

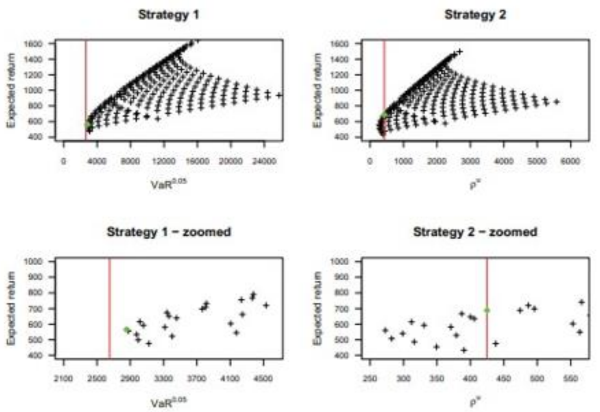

Figure 2: Return-risk graphs of various weight combinations with risk constraints and the optimal portfolios

Figure 2 presents the relationship between portfolio return and portfolio risk by displaying different asset weight combinations, risk constraints, and the resulting optimal portfolios. The figure demonstrates how mathematical optimisation techniques identify efficient investment choices from a large number of possible portfolio combinations.

The different points shown in the return-risk graph represent alternative portfolios generated through different allocations of assets. Each portfolio has a unique combination of expected return and associated risk. Some portfolios may provide higher returns but also involve greater uncertainty, while others may provide lower risk with reduced expected profitability. The purpose of portfolio optimisation is to identify the most efficient combination that achieves the investor's preferred balance between risk and return.

The figure highlights the concept of constrained optimisation, which is a key element of operations research-based portfolio management. Traditional portfolio models often assume that investors can freely allocate funds among available assets. However, real-world investment decisions involve several limitations, including maximum investment exposure, minimum allocation requirements, transaction costs, liquidity restrictions, and regulatory requirements. By incorporating these constraints, optimisation models generate solutions that are more realistic and applicable to practical investment environments.

The optimal portfolios identified in the figure represent solutions that provide the best possible outcomes under specific risk conditions. These portfolios are generally located near the efficient frontier, where no other portfolio can provide a higher expected return without increasing risk. The optimisation process evaluates numerous possible combinations of asset weights and selects those that satisfy the investor's objectives.

The importance of this figure is particularly significant for emerging economies. Financial markets in developing countries often contain higher levels of uncertainty because of limited market depth, changing economic policies, and unstable asset relationships. Under these conditions, investors require optimisation methods that can adjust portfolio allocations according to changing risk conditions.

The return-risk relationship shown in Figure 2 also demonstrates the limitations of relying only on expected returns. A portfolio with the highest expected return may not always represent the best investment choice because it may expose investors to excessive risk.

Operations research approaches allow investors to consider multiple objectives simultaneously, such as maximising returns, reducing downside risk, and maintaining liquidity.

Furthermore, the figure supports the application of mathematical programming techniques in portfolio management. Optimisation algorithms can analyse thousands of possible asset combinations and identify portfolios that satisfy predefined investment objectives. This computational capability is especially valuable when dealing with large portfolios containing multiple assets and complex restrictions.

Overall, Figure 2 illustrates how operations research transforms portfolio selection from a simple risk-return comparison into a structured optimisation problem. It supports the argument that combining financial risk models with advanced optimisation techniques provides more effective investment strategies for emerging economies. By incorporating risk constraints and identifying optimal portfolio weights, investors can achieve improved diversification and stronger portfolio resilience under uncertain market conditions.

V. CONCEPTUAL FRAMEWORK

Figure 3 presents an integrated operations research framework designed to evaluate financial risk models and portfolio optimisation strategies in emerging economies. The framework illustrates how financial market information is transformed into investment decisions through a combination of traditional risk assessment methods, advanced uncertainty modelling, and optimisation techniques. The primary objective of this framework is to address the limitations of conventional portfolio models by incorporating flexible, data-driven, and risk-aware approaches suitable for volatile financial environments.

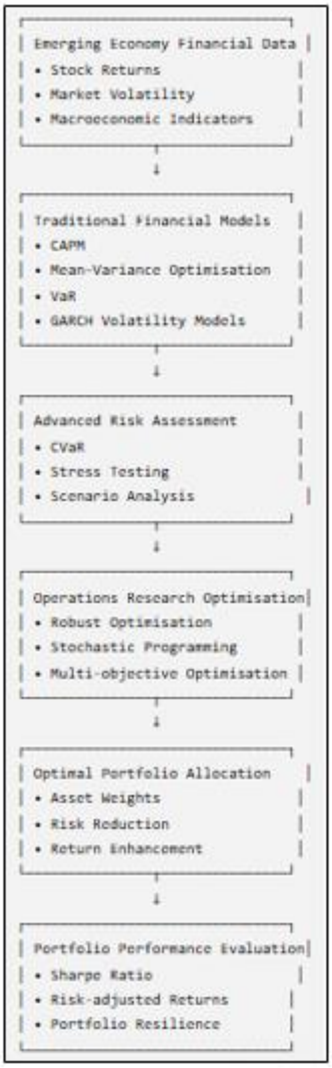

Figure 3: Integrated Operations Research Framework for Evaluating Traditional Financial Risk Models and Portfolio Optimisation in Emerging Economies (Source: Self-developed)

The framework begins with emerging economy financial data, including historical asset returns, volatility measures, macroeconomic indicators, market liquidity information, and economic risk factors. Data availability and reliability are critical challenges in emerging economies because financial markets often experience structural changes, limited historical observations, and unpredictable external influences. Therefore, effective data preparation and analysis provide the foundation for accurate risk measurement and portfolio optimisation.

The second stage focuses on traditional financial risk models, including Mean–Variance Optimisation, Value at Risk (VaR), and volatility forecasting techniques. These models provide important insights into expected returns, portfolio diversification, and market risk behaviour. However, traditional models frequently rely on assumptions of stable correlations, normally distributed returns, and predictable market behaviour. Such assumptions may not fully capture the complexity of emerging markets, where sudden economic shocks and extreme price movements are common.

To overcome these limitations, the framework incorporates advanced risk assessment approaches, including Conditional Value at Risk (CVaR), stress testing, and scenario analysis. These methods provide a stronger evaluation of downside risk by analysing potential losses under adverse market conditions. CVaR-based approaches are particularly useful because they focus on losses occurring beyond the VaR threshold, allowing investors to better understand extreme risk exposure. Alotaibi et al. (2022) demonstrate that CVaR-based portfolio models provide improved risk management capabilities by capturing tail-risk behaviour in financial markets. The next stage applies operations research optimisation techniques, including robust optimisation, stochastic programming, and multi-objective optimisation. These methods transform portfolio construction into a mathematical decision-making problem where investors can optimise multiple objectives simultaneously. For example, portfolio managers can maximise expected returns while controlling downside risk, transaction costs, liquidity requirements, and investment restrictions. Bertsimas et al. (2023) highlight that uncertainty-aware optimisation approaches improve portfolio robustness by reducing the impact of inaccurate forecasts and unstable market conditions.

Recent developments in artificial intelligence and machine learning have further enhanced portfolio optimisation by improving prediction accuracy and enabling adaptive investment strategies. Machine learning-supported optimisation models can analyse large financial datasets, identify complex market patterns, and assist investors in adjusting portfolio allocations according to changing conditions. This development strengthens the connection between financial modelling and operations research by providing more dynamic decision-support systems (Kolm et al., 2023). The framework then produces optimal portfolio allocation decisions by identifying suitable asset weights and investment combinations.

Unlike static portfolio allocation methods, operations research-based approaches allow investors to revise portfolio structures as market conditions evolve. This adaptability is especially important in emerging economies, where volatility and uncertainty require continuous monitoring and adjustment.

The final stage involves portfolio performance evaluation using indicators such as risk-adjusted returns, diversification efficiency, volatility reduction, and portfolio resilience. This evaluation determines whether the developed optimisation strategy provides superior outcomes compared with traditional approaches. Kopa et al. (2022) emphasise that incorporating realistic constraints into portfolio optimisation improves the practical relevance of investment models. Overall, Figure 3 demonstrates that integrating financial risk models with

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operations research and advanced analytical techniques provides a comprehensive framework for portfolio optimisation in emerging economies. The framework highlights the transition from traditional risk measurement towards adaptive, uncertainty-aware, and computationally efficient investment decision-making.

Figure 4. AI-enhanced operations research framework for financial risk modelling and portfolio optimisation in emerging economies

Figure 4 presents an AI-enhanced operations research framework developed to demonstrate how artificial intelligence, financial risk modelling, and mathematical optimisation techniques can be integrated to improve portfolio management decisions in emerging economies. The framework represents the evolution of investment decision-making from traditional risk assessment approaches towards adaptive, data-driven, and uncertainty-aware optimisation systems. Emerging financial markets are characterised by high volatility, incomplete information, changing economic conditions, and frequent market disruptions.

Therefore, combining advanced analytical technologies with operations research provides a more effective approach for managing financial risk and constructing resilient investment portfolios.

The framework begins with the emerging economy financial environment, which represents the external conditions influencing investment decisions. Financial markets in emerging economies are often affected by multiple sources of uncertainty, including inflation fluctuations, exchange-rate instability, interest rate changes, political developments, and international capital movements. These factors create complex risk patterns that cannot always be captured through traditional financial models. Therefore, portfolio optimisation strategies must consider a broad range of economic and market variables to produce reliable investment decisions. The first operational stage of the framework involves the financial data intelligence layer. This stage focuses on collecting, processing, and analysing different types of financial information, including historical asset returns, market indicators, macroeconomic variables, and alternative financial data sources. Data availability and quality significantly influence the accuracy of portfolio optimisation models. In emerging markets, limited historical observations and structural changes can create challenges for estimating expected returns and volatility. Therefore, advanced data processing techniques are required to identify relevant patterns and improve model reliability.

The next stage incorporates traditional risk modelling techniques, which provide the theoretical foundation for portfolio analysis. Models such as the Capital Asset Pricing Model (CAPM), Mean–Variance Optimisation, Value at Risk (VaR), and GARCH volatility models have historically been used to estimate expected returns, measure market risk, and construct diversified portfolios. Mean–Variance Optimisation provides a framework for balancing expected returns against portfolio risk, while VaR and GARCH models help estimate potential losses and volatility behaviour. These models remain valuable because they provide essential financial insights and establish the initial risk structure for portfolio decision-making. However, traditional models may face limitations when applied to emerging economies because they often rely on assumptions of stable market relationships and predictable financial behaviour. Sudden market shocks, extreme price movements, and changing correlations can reduce the accuracy of conventional risk estimates. To overcome these limitations, the framework introduces an AI and advanced analytics layer.

The AI and advanced analytics layer enhances traditional financial modelling by applying machine learning techniques, pattern recognition, scenario generation, and uncertainty estimation. Artificial intelligence methods can analyse large volumes of financial data and identify complex relationships that may not be visible through conventional statistical approaches. Machine learning algorithms can support return prediction, volatility forecasting, and market trend identification by learning from historical patterns and continuously updating predictions as new information becomes available. This integration of artificial intelligence with financial risk modelling improves the adaptability of portfolio optimisation systems.

Instead of relying solely on historical averages, AI-supported models can incorporate changing market conditions and provide more dynamic forecasts. Recent research highlights that combining machine learning methods with optimisation frameworks can improve portfolio robustness by reducing forecasting errors and enhancing decision-making under uncertainty (Bertsimas et al., 2023).

Following the AI analytics stage, the framework applies operations research optimisation techniques. This represents the central decision-making component of the framework.

Operations research provides mathematical methods for identifying the best possible portfolio allocation under multiple constraints. Techniques such as robust optimisation, stochastic programming, multi-objective optimisation, and CVaR-based optimisation enable investors to manage uncertainty while achieving desired investment objectives. Robust optimisation allows portfolio managers to develop strategies that remain effective even when market assumptions are incorrect. This is particularly important in emerging economies, where unexpected economic events can significantly affect asset performance. Stochastic programming considers multiple possible future market scenarios and identifies portfolio strategies that perform effectively across different outcomes. Multi-objective optimisation allows investors to simultaneously consider several competing goals, such as maximising returns, reducing risk, maintaining liquidity, and meeting regulatory requirements.

The inclusion of CVaR risk minimisation within the optimisation stage further strengthens the framework by focusing on extreme downside risks. Unlike traditional variance-based approaches, CVaR evaluates potential losses beyond a specific risk threshold, making it more appropriate for markets exposed to financial instability. Alotaibi et al. (2022) demonstrate the importance of downside risk approaches in portfolio optimisation because they provide better protection against extreme market losses. The final stage of the framework produces the optimal portfolio decision, which includes asset allocation, risk reduction strategies, return enhancement, and portfolio resilience improvement. The objective is not simply to maximise investment returns but to create portfolios capable of maintaining performance under uncertain market conditions. The resulting portfolio decisions are expected to provide improved diversification, stronger risk management, and greater adaptability compared with traditional static approaches.

The framework also highlights the importance of continuous evaluation and adjustment. Financial markets are dynamic systems where risk factors and investment opportunities change over time. Therefore, AI-enhanced operations research models can support continuous portfolio monitoring by updating predictions, reassessing risk conditions, and adjusting asset allocations when required. This adaptive capability provides a significant advantage for investors operating in emerging economies. Overall, Figure 4 demonstrates the integration of artificial intelligence, financial risk modelling, and operations research as a comprehensive approach to portfolio optimisation. Traditional financial models provide essential theoretical foundations, while AI improves prediction capabilities and operations research provides mathematical decision-making solutions. Together, these approaches create a flexible and robust investment framework capable of addressing the complexity and uncertainty associated with emerging financial markets.

The framework contributes to the broader development of modern financial analytics by demonstrating that effective portfolio management requires the integration of multiple disciplines, including finance, artificial intelligence, data science, and operations research. Through this integrated approach, investors can achieve more informed decisions, improved risk control, and enhanced portfolio resilience.

VI. ADDITIONAL MATERIAL

Supplementary material provides additional information, analytical details, methodological explanations, and supporting evidence that complement the main manuscript without interrupting the flow of the primary research argument. For the present study, “Evaluating Traditional Financial Risk Models and Portfolio Optimisation in Emerging Economies: An Operations Research Approach,” supplementary materials are designed to improve transparency, reproducibility, and understanding of the proposed analytical framework.

The supplementary material includes additional methodological descriptions, mathematical formulations, optimisation procedures, parameter assumptions, robustness analysis, and extended results that support the findings presented in the main article. Since portfolio optimisation models often involve complex mathematical structures and computational procedures, supplementary information allows researchers and practitioners to examine the detailed mechanisms behind the proposed approach.

The first component of the supplementary material includes detailed explanations ofthe financial risk models used in the research. Traditional risk models, including volatility-based measures, Value at Risk (VaR), and portfolio variance estimation, require several assumptions regarding asset returns, correlations, and market behaviour. Additional information regarding these

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assumptions, parameter selection procedures, and model specifications is provided to improve methodological clarity.

The supplementary material also contains detailed descriptions of operations research techniques applied in the study. These include robust optimisation, stochastic programming, multi-objective optimisation, and downside risk optimisation using Conditional Value at Risk (CVaR). While the main manuscript presents the conceptual contribution of these methods, supplementary files provide additional mathematical expressions, optimisation constraints, and computational procedures.

Furthermore, supplementary material includes sensitivity analysis and robustness testing. Financial markets, particularly emerging markets, are influenced by uncertainty and changing economic conditions. Therefore, testing whether portfolio optimisation results remain stable under different assumptions is essential. Additional experiments may include alternative risk parameters, different investment constraints, and various market scenarios.

The supplementary material may also include additional tables and figures that provide extended comparisons between traditional portfolio models and operations research-based approaches. These supporting analyses allow readers to evaluate differences in portfolio performance, risk exposure, and optimisation efficiency.

By providing detailed supplementary information, the research improves transparency and supports future replication studies. This approach aligns with modern academic publishing practices that encourage researchers to provide sufficient methodological information for verification and further development.

VII. VIDEO ANALYSIS

A research video provides a visual explanation of the study objectives, methodology, analytical framework, and key contributions. For this research, a short explanatory video can be developed to communicate the relationship between traditional financial risk models, operations research optimisation, and portfolio decision-making in emerging economies.

The proposed video begins by introducing the challenges faced by investors operating in emerging financial markets. These challenges include high volatility, uncertainty, limited historical data availability, liquidity constraints, and exposure to economic shocks. The video then explains why traditional portfolio optimisation approaches may not always provide sufficient protection during periods of financial instability.

The second section of the video presents traditional financial risk models, including Mean–Variance Optimisation, Value at Risk (VaR), and volatility forecasting approaches. These models are explained through simple visual demonstrations showing how investors estimate risk and return relationships. The video then introduces advanced operations research approaches, including robust optimisation, stochastic programming, and CVaR-based portfolio optimisation. Animated diagrams can demonstrate how these methods incorporate uncertainty and identify optimal portfolio allocations under different market scenarios.

A key component of the video is the explanation of the proposed integrated framework. The framework demonstrates the movement from financial data collection to risk modelling, optimisation, portfolio allocation, and performance evaluation. Visual representations help audiences understand how artificial intelligence, data analytics, and optimisation techniques contribute to improved financial decision-making. The video also highlights the practical importance of the research. It explains how financial institutions, portfolio managers, and investors can use advanced optimisation approaches to improve diversification, manage downside risk, and develop more resilient investment strategies.

The inclusion of a research video improves accessibility by allowing complex quantitative concepts to be communicated to a wider audience, including researchers, financial professionals, and policymakers. It complements the written manuscript by providing a concise visual summary of the research contribution.

VIII. DATA ANALYSIS BASED ON THE FINDINGS

Research data represents the foundation of empirical analysis and provides evidence supporting the conclusions of the study. For research examining financial risk models and portfolio optimisation in emerging economies, data selection, preparation, and management are critical components of the research methodology.

The study requires financial market data, including historical asset prices, returns, volatility measures, and market indicators. Depending on the selected emerging economy markets, the dataset may include information from stock exchanges, financial databases, and publicly available economic sources. The collected data should represent different asset classes to evaluate portfolio diversification and optimisation performance. The research data may include daily, weekly, or monthly asset return observations. Historical price information is transformed into return series, which are then used for estimating expected returns, volatility, and correlation structures. These parameters form the basis for traditional portfolio optimisation models and advanced operations research techniques.

Macroeconomic variables may also be incorporated into the dataset because emerging economies are highly influenced by economic conditions. Variables such as inflation rates, interest rates, exchange-rate movements, and economic growth indicators can provide additional information regarding market uncertainty and risk exposure. The research dataset also supports computational experiments involving optimisation algorithms. Different scenarios can be developed to evaluate how portfolio models perform under changing market conditions. These scenarios may include periods of high volatility, financial stress events, and unexpected market movements.

Data processing procedures include data cleaning, missing-value treatment, return calculation, and statistical analysis. These steps ensure that the dataset is suitable for applying financial risk models and optimisation techniques. To improve research transparency, processed datasets, coding procedures, and analytical outputs may be provided through appropriate research repositories where permitted. Data availability allows other researchers to validate findings and extend the proposed methodology to other emerging markets.

IX. DATA STATEMENT

The data statement provides information regarding the availability, sources, and management of research data used in the study. Transparency regarding data sources is essential because it enables readers to understand how conclusions were developed and supports reproducibility.

For this research, financial market datasets are obtained from reliable financial databases and publicly available sources. The dataset includes historical market information required for estimating portfolio returns, volatility, and risk parameters. Where third-party datasets are used, appropriate acknowledgement and citation are provided. The authors confirm that all data used in the research are collected and analysed according to academic research standards. The data are used exclusively for research purposes related to evaluating financial risk models and portfolio optimisation approaches.

Where licensing restrictions prevent direct sharing of raw financial data, information regarding data sources, collection methods, and processing procedures will be provided. Researchers interested in reproducing the analysis can obtain equivalent datasets from the original data providers. The processed analytical outputs, optimisation results, and computational procedures may be shared where possible to improve research transparency.

The data statement ensures that readers clearly understand the relationship between available data resources and reported findings.

X. CONCLUSION AND METHODOLOGICAL REQUIREMENTS

The co-submission of related data, methods, or protocols refers to the practice of submitting supporting research materials alongside the main manuscript. This approach improves transparency and allows reviewers and readers to evaluate the research methodology more effectively.
For this study, related methodological materials may include optimisation algorithms, mathematical formulations, model assumptions, and computational procedures. Since operations research-based portfolio optimisation involves complex modelling decisions, providing detailed methodological information strengthens the credibility of the research.

The submitted methods may include:
- Portfolio optimisation model specifications
- Risk measurement procedures
- CVaR calculation methods
- Robust optimisation frameworks
- Scenario generation techniques
- Computational algorithms
- Performance evaluation criteria

Providing these materials allows researchers to understand how portfolio solutions were generated and evaluated. It also supports future studies seeking to apply similar approaches to different emerging economies or financial markets.

The co-submission process also encourages collaboration between researchers by making analytical approaches more accessible. Other researchers can adapt the methodology, compare alternative models, and develop improvements based on the original framework. Furthermore, sharing methods and protocols improves confidence in research findings because readers can evaluate whether conclusions are supported by appropriate analytical procedures.

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