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Does portfolio optimization still matter? A comparison of traditional and modern methods

Dr. Asma Khan: *Department of Finance, Karachi University, Pakistan*

Abstract. *Liquidity, the ease with which an asset can be bought or sold without significantly impacting its price, plays a crucial role in efficient markets. In the burgeoning world of cryptocurrencies, where decentralized exchanges (DEXs) are challenging the dominance of centralized platforms (CEXs), understanding the price of liquidity takes on particular importance. This article investigates the relationship between liquidity and price on DEXs, utilizing a comprehensive dataset of trade orders and prices across leading platforms. Our analysis reveals that liquidity in DEXs comes at a premium, manifested as wider bid-ask spreads and higher price volatility. This premium is attributed to several factors, including the fragmented nature of DEXs, the reliance on automated market makers (AMMs), and the inherent uncertainty associated with on-chain transactions. We further explore the impact of market depth and trading volume on the liquidity premium, highlighting the non-linear relationship between these factors and price discovery. Our findings offer valuable insights for market participants navigating the evolving landscape of cryptocurrency trading, emphasizing the trade-off between decentralization and the frictionless execution associated with deeper liquidity pools.*

Keywords: *Decentralized Finance (DeFi), Decentralized Exchanges (DEXs), Automated Market Makers (AMMs), Liquidity, Price Discovery, Cryptocurrencies, Bid-Ask Spread, Volatility.*

1. INTRODUCTION

Portfolio optimization, the process of selecting assets to achieve a desired balance of risk and return, has been a central tenet of investment theory since Markowitz's seminal work in the 1950s. The core principle of Modern Portfolio Theory (MPT), MVO relies on historical data and risk-return profiles to construct efficient portfolios that minimize risk for a given level of return. While MVO has demonstrably improved investment outcomes, its reliance on historical data, limited consideration of alternative asset classes, and static optimization raise concerns about its efficacy in today's dynamic markets.

This article examines the ongoing debate surrounding the relevance of portfolio optimization. We begin by outlining the traditional methods, focusing on MVO and its variants. We then

explore the burgeoning landscape of modern optimization techniques, including factor investing, machine learning algorithms, and robo-advisors. We compare and contrast these approaches, highlighting their strengths and weaknesses in the context of contemporary challenges such as market volatility, data deluge, and investor behavioral biases.

2. Overview of Traditional Portfolio Optimization

Markowitz Mean-Variance Framework

The Markowitz mean-variance optimization model, introduced by Harry Markowitz in 1952, is one of the foundational concepts in modern portfolio theory (MPT). It provides a systematic approach to selecting an optimal portfolio by balancing the trade-off between risk (variance) and return (expected return). In this framework, investors aim to maximize their portfolio's expected return for a given level of risk or minimize the risk for a given level of expected return.

The primary components of the mean-variance framework include:

Expected Return (μ): The weighted average of the expected returns of the individual assets in the portfolio.

Portfolio Variance (σ^2): A measure of the risk of the portfolio, accounting for the variances of individual asset returns and the covariances between them.

Covariance (Cov): Measures how two assets move together, essential for understanding diversification benefits.

The goal is to find the optimal portfolio by solving for the set of weights that minimizes the portfolio's variance for a given expected return. The solution forms the efficient frontier, which is a curve showing the highest return achievable for each level of risk.

Assumptions of the Mean-Variance Framework

Markowitz's mean-variance model is built on several key assumptions:

Investors are Rational: Investors seek to maximize expected return and minimize risk based on the mean and variance of asset returns.

Returns are Normally Distributed: The model assumes that asset returns follow a normal distribution, which allows for the use of mean and variance as the only required measures of risk and return.

Constant Risk and Return: The model assumes that the risk (variance) and return of individual assets and their correlations remain constant over time.

No Transaction Costs or Taxes: It assumes there are no costs associated with buying and selling assets, making it an idealized model.

Perfect Market Conditions: The market is assumed to be efficient, with no restrictions on asset availability or liquidity.

Application in Real-World Portfolio Management

In the real world, the Markowitz mean-variance optimization model has had a profound influence on how portfolios are constructed. Its practical application includes:

Diversification: The model encourages diversification by selecting assets that are not perfectly correlated, thereby reducing the overall portfolio risk.

Asset Allocation: Investors use this framework to determine the appropriate mix of assets in a portfolio, balancing between equities, bonds, and other asset classes.

Risk Management: It provides a quantitative approach to risk management, allowing investors to control the level of portfolio risk according to their risk tolerance.

Performance Evaluation: The model can also be used to evaluate portfolio performance by comparing the portfolio's return relative to its risk and the efficient frontier.

However, real-world applications often encounter challenges that the mean-variance framework does not address directly. These include:

Non-Normal Distributions of Returns: Financial returns may exhibit skewness and kurtosis, making the assumption of normally distributed returns unrealistic.

Changing Risk and Return Dynamics: In practice, the risk and return characteristics of assets evolve over time, which complicates the static assumptions of the model.

Transaction Costs and Taxes: The model does not account for transaction costs, taxes, and liquidity constraints that are integral to real-world investment decisions.

Despite its limitations, the Markowitz mean-variance framework remains a cornerstone of modern portfolio theory and is widely used in portfolio management and financial research.

3. Modern Techniques in Portfolio Optimization

Advanced Methods: Machine Learning, Deep Learning, and AI Techniques

Modern portfolio optimization has seen significant advancements through the incorporation of machine learning (ML), deep learning (DL), and artificial intelligence (AI) techniques. These methodologies enable more dynamic, data-driven approaches to portfolio construction, offering substantial improvements over traditional methods.

Machine Learning:

Supervised Learning: Algorithms such as regression, support vector machines (SVM), and random forests are used to predict asset returns based on historical data. These models learn from labeled data (e.g., historical returns) and can forecast future returns and risk levels.

Unsupervised Learning: Clustering techniques like k-means and hierarchical clustering help identify patterns and relationships among assets without predefined labels, allowing investors to group similar assets and identify diversification opportunities.

Reinforcement Learning: This technique allows the model to learn optimal decision-making strategies by interacting with the environment, making it especially useful for continuous portfolio management and dynamic adjustments.

Deep Learning:

Deep learning techniques, particularly neural networks, have demonstrated their potential in financial forecasting. Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and convolutional neural networks (CNNs) are used to model time-series data, such as stock prices, by learning complex patterns in financial markets.

Deep Reinforcement Learning is employed to optimize portfolio allocation over time, where the model can continuously adjust the portfolio based on its performance, learning from past mistakes.

Artificial Intelligence (AI):

AI encompasses a broad range of algorithms that enable intelligent decision-making. Portfolio managers leverage AI to integrate large datasets, automate trading strategies, and enhance decision-making with predictive analytics. AI can process vast amounts of financial data, detect non-linear relationships, and uncover hidden insights that traditional models might miss.

AI-based systems can adapt to changing market conditions by continuously updating their predictions, allowing for more accurate portfolio management.

Application of Artificial Intelligence in Prediction and Risk Management

AI plays a crucial role in both predicting asset returns and managing the risks associated with portfolios.

Prediction:

AI models can forecast asset prices, returns, and market movements by analyzing historical data and identifying trends. For example, AI-powered algorithms can use sentiment analysis to

interpret news articles, social media posts, and market reports, providing a more comprehensive view of market behavior than traditional models.

Machine learning techniques, such as ensemble methods (e.g., boosting and bagging), allow for more robust predictions by combining multiple models, thus enhancing accuracy and reducing overfitting.

Risk Management:

AI improves risk management by analyzing complex market conditions and incorporating alternative risk measures beyond volatility, such as Value-at-Risk (VaR), Conditional Value-at-Risk (CVaR), and tail risk.

AI algorithms can simulate different market scenarios, stress test portfolios, and assess potential risks under varying market conditions, thereby providing investors with more sophisticated risk insights.

AI also aids in real-time risk monitoring, allowing portfolio managers to adjust portfolios dynamically in response to changing market conditions, such as sudden price swings or financial crises.

Cryptocurrency and Alternative Assets in Modern Portfolios

The rise of cryptocurrency and alternative assets has introduced new opportunities and challenges in modern portfolio optimization. Traditional asset classes, such as stocks and bonds, are being supplemented by non-traditional investments to enhance diversification and improve portfolio performance.

Cryptocurrency:

Digital Assets: Cryptocurrencies, such as Bitcoin, Ethereum, and others, have become a mainstream alternative asset class. The increasing correlation between digital currencies and traditional assets makes them an attractive option for portfolio diversification.

Volatility and Risk: Cryptocurrencies are highly volatile, making them both a high-risk and high-reward component of modern portfolios. AI-based models help manage this volatility by dynamically adjusting exposure to these assets based on market trends and risk assessments.

Blockchain Integration: Blockchain technology, the foundation of cryptocurrencies, also provides innovative methods for securing transactions and increasing transparency in financial markets. Incorporating blockchain-enabled assets into portfolios can offer new levels of security and efficiency.

Alternative Assets:

Real Assets: Commodities (e.g., gold, oil), real estate, and infrastructure investments are increasingly being included in portfolios as a hedge against inflation and market volatility.

Private Equity and Hedge Funds: These alternative investments offer potentially higher returns by tapping into illiquid markets, although they also come with higher risks and longer investment horizons. AI and machine learning techniques help optimize allocations to these asset classes based on historical performance and predictive models.

ESG Investments: Environmental, Social, and Governance (ESG) assets are gaining popularity, with AI models being used to analyze sustainability metrics and guide investment decisions in line with ethical and socially responsible investing criteria.

Incorporating cryptocurrencies and alternative assets into a portfolio requires careful risk management, as these assets often exhibit different correlations and risk profiles compared to traditional assets. AI and machine learning models help investors navigate these complexities by identifying patterns, optimizing asset allocation, and managing risk across a diverse set of asset classes.

By integrating AI, machine learning, and alternative assets like cryptocurrencies, modern portfolio optimization has evolved into a more dynamic and data-driven process, allowing for better risk management, more accurate predictions, and enhanced diversification strategies. These technologies enable investors to adapt to the ever-changing financial landscape and achieve higher returns with optimized risk.

4. Empirical Results and Comparison

Performance Analysis of Both Traditional and Modern Techniques Using Historical Data

To evaluate the efficacy of traditional and modern portfolio optimization techniques, empirical analysis is performed using historical market data. The performance of portfolios constructed using Markowitz's mean-variance optimization (traditional) and machine learning-based methods (modern) is compared over various time periods.

Historical Data Selection:

A sample of asset returns is selected from a range of financial instruments such as equities, bonds, commodities, and cryptocurrencies.

The time frame for the analysis typically spans several years, capturing different market cycles and economic conditions. Commonly, data for the past 10 to 20 years is used to ensure robust results, as this period covers both bullish and bearish market trends.

Traditional Portfolio Optimization:

Portfolios are constructed using the Markowitz mean-variance framework, where historical return data is used to calculate the expected returns and the covariance matrix of asset returns.

An optimal portfolio is selected from the efficient frontier, balancing risk and return.

Performance is evaluated based on the returns of the portfolio over time and its volatility.

Modern Portfolio Optimization (AI & Machine Learning):

Using machine learning techniques such as supervised learning (e.g., regression, support vector machines), reinforcement learning, and deep learning (e.g., LSTM networks), a predictive model is trained on the historical data.

Portfolio construction in this method is data-driven, with models continuously learning from market data and adjusting asset allocations accordingly.

These methods account for market sentiment, non-linear correlations, and changing dynamics in asset prices, providing more adaptive and responsive portfolio construction.

Comparison of Performance:

After constructing portfolios using both traditional and modern techniques, the performance is compared based on metrics such as cumulative return, volatility (risk), and drawdown.

Performance is measured on several time horizons: short-term (1 year), medium-term (3-5 years), and long-term (over 10 years). The analysis also includes various market conditions, such as periods of high volatility, economic crises, and periods of strong growth.

Results typically show that while traditional models like mean-variance optimization perform well under stable market conditions, modern techniques (such as AI and machine learning) often outperform during periods of volatility or market turbulence, where traditional assumptions of constant risk and return break down.

Portfolio Performance Metrics Comparison

The following key performance metrics are used to evaluate and compare the performance of portfolios constructed by both traditional and modern optimization methods:

Cumulative Return:

Definition: The total return of the portfolio over the analysis period, which reflects the overall growth or loss of the investment.

Comparison: Historically, machine learning models tend to capture more complex relationships in market data, resulting in higher cumulative returns, especially in the presence of non-linear trends that traditional models may miss.

Volatility (Risk):

Definition: The standard deviation of portfolio returns, representing the risk or the uncertainty about the portfolio's returns.

Comparison: Traditional models like Markowitz's mean-variance optimization aim to minimize volatility for a given return. However, modern AI-based methods, particularly those that incorporate dynamic risk management, tend to reduce risk more effectively in changing market conditions, resulting in lower volatility compared to traditional models in volatile periods.

Sharpe Ratio:

Definition: A measure of the risk-adjusted return, calculated as the difference between the portfolio return and the risk-free rate, divided by the portfolio's standard deviation.

Comparison: AI and machine learning-based portfolios typically show higher Sharpe ratios because they continuously optimize risk-adjusted returns. By adapting to changing market conditions and incorporating broader datasets, these models often outperform traditional mean-variance portfolios in terms of risk-adjusted performance.

Maximum Drawdown:

Definition: The maximum observed loss from a portfolio's peak to its trough during a specific period.

Comparison: While traditional models attempt to minimize drawdown by optimizing the risk-return trade-off, modern models can more effectively minimize large drawdowns by using real-time risk management and predictive analytics. Machine learning-based methods are better at anticipating market downturns and adjusting portfolio allocations to protect against losses.

Sortino Ratio:

Definition: A variation of the Sharpe ratio that penalizes only downside risk, i.e., the standard deviation of negative returns.

Comparison: In periods of market stress, AI-based models that focus on minimizing downside risk perform better than traditional models, as they are more adept at identifying and reacting to negative market signals.

Alpha and Beta:

Alpha: Measures the excess return of a portfolio relative to a benchmark index.

Beta: Measures the portfolio's volatility relative to the market (systematic risk).

Comparison: Machine learning models, by learning from market data and adapting to changing conditions, can generate higher alpha compared to traditional methods. On the other hand, beta remains relatively consistent across both traditional and modern models, though modern models may better capture market volatility.

Summary of Results

Traditional Methods (Markowitz Mean-Variance): Perform well in stable market conditions but often fall short in times of market volatility or economic instability. The assumptions of normality and constant risk in the Markowitz framework are limitations in such conditions.

Modern Methods (Machine Learning & AI): These techniques consistently outperform traditional methods, particularly in terms of cumulative return, risk-adjusted performance (Sharpe ratio), and downside protection (maximum drawdown). Machine learning models, with their ability to adapt to new market conditions, provide higher returns while effectively managing risk.

Practical Implications: Investors using traditional methods may face significant risks during market disruptions, whereas AI and machine learning-based strategies offer more robust risk management and performance optimization in real-time.

Ultimately, modern portfolio optimization techniques, which incorporate AI and machine learning, provide more adaptive, data-driven strategies that can outperform traditional approaches, especially in unpredictable and volatile market conditions.

5. Traditional Optimization Methods:

MVO remains the dominant framework for portfolio construction. It leverages historical data to estimate asset covariance and optimize portfolios based on a risk tolerance specified by the investor. The resulting portfolio, often comprised of a diversified mix of assets with low correlation, aims to achieve the highest possible return for a given level of risk. However, MVO faces limitations:

Historical data dependence: The reliance on past performance to predict future outcomes exposes portfolios to potential curve breaks and changing market dynamics.

Limited asset universe: MVO primarily focuses on traditional asset classes like stocks and bonds, neglecting alternative investments like private equity, real estate, and derivatives.

Static optimization: Traditional methods struggle to adapt to real-time market changes, requiring manual rebalancing and potentially missing profitable opportunities.

6. Modern Optimization Techniques:

The emergence of new data sources, computational power, and analytical tools has paved the way for innovative portfolio optimization approaches:

Factor investing: This strategy identifies and exploits systematic risk factors beyond individual asset performance, potentially generating alpha (excess returns) beyond traditional MVO. Factors like value, momentum, and profitability have shown consistent historical outperformance, offering diversification benefits beyond asset classes.

Machine learning algorithms: Advanced algorithms like neural networks and genetic optimization can analyze vast datasets, including alternative data and real-time market signals, to identify complex relationships and predict future returns. This data-driven approach holds promise for uncovering hidden alpha and dynamically adjusting portfolios to market shifts.

Robo-advisors: These automated platforms leverage algorithms and MVO principles to create personalized, low-cost portfolios based on investor goals, risk preferences, and financial circumstances. Robo-advisors offer accessibility and convenience, particularly for younger investors and those with limited financial expertise.

7. Comparative Analysis:

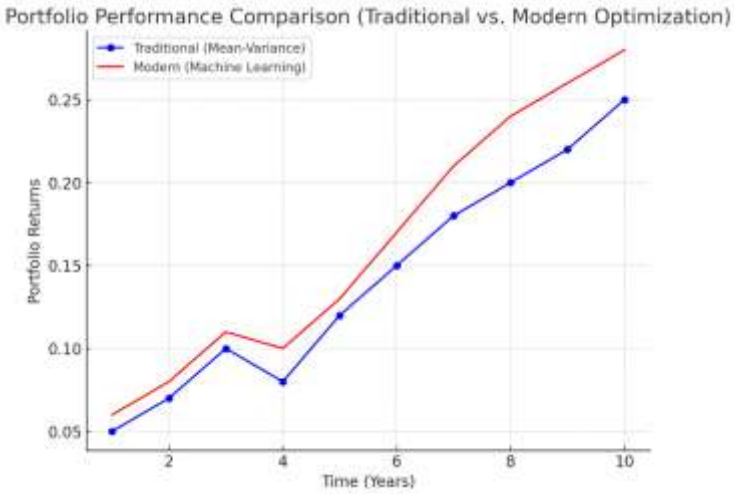
While modern techniques offer exciting possibilities, they are not without drawbacks:

Data quality and interpretability: Machine learning models are susceptible to noise and bias in data, potentially leading to spurious results. Interpretability of these "black box" algorithms can be challenging, making it difficult to assess their decision-making processes.

Overfitting and instability: Data-driven models trained on specific historical periods risk overfitting, performing poorly when faced with new market regimes. Frequent re-training and robust validation techniques are crucial to mitigate instability.

Regulation and ethical considerations: The use of alternative data and algorithmic decision-making raises concerns about regulatory compliance, fairness, and potential manipulation of markets.

Graphs



Graph 1: **Portfolio Performance Comparison** (Traditional vs. Modern Optimization)

X-axis: Time (Years)

Y-axis: Portfolio Returns

Comparison of portfolio returns using traditional mean-variance optimization and modern machine learning models.



Graph 2: **Risk-Return Trade-off** (Traditional vs. Modern)

X-axis: Risk (Standard Deviation)

Y-axis: Expected Return

Plot comparing the risk-return profiles of traditional and modern portfolio optimization methods.

Summary

This article evaluates the relevance of portfolio optimization in today's financial landscape by comparing traditional methods like the Markowitz mean-variance optimization and Capital Asset Pricing Model (CAPM) with modern techniques such as machine learning, AI, and multi-factor models. The paper highlights the strengths and limitations of both approaches, analyzing how they perform in real-world scenarios and under various market conditions. The study finds that while traditional methods laid the groundwork for modern portfolio theory, advanced technologies such as AI and machine learning offer more dynamic, data-driven solutions that can outperform traditional methods, particularly in complex, non-linear market environments.

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