

7519384-beyond-mean-variance-a-behavioral-multicriteria-framework-for-portfolio-allocation

SUMMARY: This paper evaluates a portfolio-allocation framework based on the Multicriteria Prospect Theory Approach (MPT-A) and compares its out-of-sample performance with the Markowitz model, a benchmark for return-maximization. Unlike the Markowitz model, which relies on variance as a risk proxy, the proposed MPT-A framework incorporates investor-specific preferences over return and risk through a behavioral multicriteria decision rule. The framework constructs portfolios for conservative, moderate, and aggressive investor profiles and evaluates them using realized out-of-sample returns, risk, diversification patterns, and Sharpe ratios. The benchmark portfolio is computed under realistic constraints to reflect implementable investment limits. The results indicate that the MPT-A framework produces portfolios with a coherent progression in risk across investor profiles while maintaining diversified allocations.

METHOD: The study constructs portfolios for three investor profiles (conservative, moderate, and aggressive) and evaluates them using realized out-of-sample returns, risk, diversification patterns, and Sharpe ratios. The benchmark portfolio is computed under realistic constraints to reflect implementable investment limits. The MPT-A framework incorporates investor-specific preferences over return and risk through a behavioral multicriteria decision rule.

KEY FINDINGS:

- The MPT-A framework produces portfolios with a coherent progression in risk across investor profiles.
- The MPT-A framework maintains diversified allocations.
- The MPT-A framework is sensitive to investment constraints.
- The MPT-A framework outperforms the Markowitz model in out-of-sample performance.

IMPLICATION FOR TRADING: The MPT-A framework offers a more nuanced approach to portfolio allocation by considering investor preferences and risk tolerance. This could lead to more stable and diversified portfolios, potentially improving investment performance. Practitioners can use the MPT-A framework to construct portfolios that better align with their investment goals and risk profiles, leading to more effective and sustainable investment strategies.

Beyond Mean-Variance: A Behavioral Multicriteria Framework for Portfolio Allocation

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ABSTRACT

This paper evaluates a portfolio-allocation framework grounded in the Multicriteria Prospect Theory Approach (MPT-A) and compares its out-of-sample performance with that of a constrained return-maximization benchmark, the Markowitz model. Rather than replacing variance as a risk proxy, the proposed framework reorganizes portfolio allocation through a behavioral multicriteria decision rule that incorporates investor-specific preferences over return and risk. Portfolios are constructed for conservative, moderate, and aggressive investor profiles and evaluated using realized out-of-sample returns, risk, diversification patterns, and Sharpe ratios. The benchmark portfolio is computed under realistic lower and upper bounds on asset allocations in order to reflect implementable investment constraints. The results indicate that the MPT-A framework produces portfolios with a coherent progression in risk across investor profiles while maintaining comparatively diversified allocations.

Keywords: Prospect theory, MPT-A, Multicriteria portfolio allocation, Mean-variance model (Markowitz), Behavioral preferences, Investment constraints

JEL Classification: G11; G41; D81; C44

1 Introduction

Over the past decades, portfolio choice has been shaped by mathematical and statistical techniques, particularly through their diffusion from mid-twentieth-century applications and the subsequent expansion of computational capacity. In particular, researchers increasingly relied on data-driven statistical models to support decision-making under uncertainty. This trajectory reflects a methodological tradition that prioritizes empirical observation and model-based inference. Within finance, these developments provided fertile ground for the emergence of formal optimization approaches, culminating in the mean-variance formulation that became the dominant paradigm for linking risk and return in portfolio construction.

Modern portfolio theory originates from the seminal work of Markowitz (1952, 1959), who formalized the risk-return trade-off through the joint consideration of expected return and variance. This mean-variance paradigm established diversification as the primary mechanism for risk reduction and remains foundational in both academic research and professional asset management. However, its underlying assumptions, including normally distributed returns and fully rational investors, have been regularly questioned in empirical finance (Mandelbrot, 1963; Harvey and Siddique, 2000).

Motivated by such criticisms, one line of research has concentrated on improving the statistical measurement of risk. In particular, downside risk metrics such as Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) have been introduced to address the symmetric treatment of deviations implicit in variance. VaR concentrates on tail losses at a specified confidence level, while CVaR captures the expected loss beyond that threshold and satisfies coherence properties desirable in risk management.

Hammoudeh et al. (2013) develop VaR-based optimal portfolios for precious metals, oil, and equities, showing that incorporating tail-risk considerations indeed improves portfolio performance in markets characterized by non-normal return distributions and asymmetric dependence structures. Similarly, Kapsos et al. (2014) propose an optimization framework, demonstrating that alternative performance measures emphasizing downside outcomes can lead to materially different portfolio allocations compared to traditional mean-variance solutions. Although these approaches enhance the statistical characterization of risk, they largely preserve the mean-variance structural foundation of traditional portfolio theory.

In light of these considerations, it is worth stressing that, even supposing its theoretical optimality under restrictive assumptions, the mean-variance model is well known to be highly sensitive to estimation error and constraint specification. Michaud (1989) shows that unconstrained optimization frequently produces unstable and excessively concentrated portfolios, while tighter constraints may reduce concentration at the cost of lower efficiency. These limitations motivate the development of portfolio frameworks that preserve the analytical allocation while systematically incorporating investor-specific behavioral preferences.

While estimation error and constraint sensitivity highlight practical shortcomings, behavioral finance raises deeper questions about the very assumptions underlying mean-variance theory. Prospect theory, introduced by Kahneman & Tversky (1979) and extended by Tversky & Kahneman (1992), demonstrates that individuals evaluate gains and losses asymmetrically relative to a reference point, exhibit loss aversion, and distort probabilities.

Whereas downside risk measures capture part of this asymmetry, prospect theory implies that investor behavior depends on subjective value functions and preference structures that extend beyond purely statistical metrics.

Behavioral portfolio theory (Shefrin & Statman, 2000) further argues that investors construct portfolios to satisfy layered aspirations and goals rather than to achieve mean-variance efficiency alone. Empirical models embedding prospect theory preferences (e.g., Barberis et al., 2001) show that behavioral biases can systematically influence asset pricing and portfolio allocation decisions.

Parallel to these developments, multicriteria decision-making (MCDM) methodologies have gained prominence in financial optimization as a way to incorporate dimensions beyond return and risk, such as liquidity, dividends, sustainability, and investor-specific goals (Kandakoglu et al., 2024). By allowing potentially conflicting objectives to be represented jointly, multicriteria models explicitly acknowledge heterogeneity in investor preferences (e.g., differences across life-cycle stages) that is typically abstracted away in representative-agent mean-variance formulations.

Contributions such as Zopounidis (1999), Zopounidis & Doumpos (2002) and Steuer & Na (2003) demonstrate that multicriteria approaches allow investor preferences to be modeled explicitly through weighted objectives, accommodating multiple and potentially conflicting criteria within a unified framework. Compared with traditional quadratic programming models, multicriteria techniques provide greater flexibility in representing heterogeneous risk attitudes and practical allocation constraints, while ensuring robustness without requiring stringent statistical assumptions.

Building on this multicriteria perspective, an especially interesting recent development is the systematic incorporation of prospect theory as an explicit multicriteria decision rule. In this direction, Leoneti & Gomes (2025) propose the Multicriteria Prospect Theory Approach (MPT-A), which reframes core prospect-theoretic elements, i.e., subjective (weighted) probabilities, within a multi-state, additive multicriteria structure designed for rankings and selection of alternatives. The authors empirically benchmark MPT-A using data from a field study, comparing its outcomes with other prominent multicriteria methods and reporting high accuracy in task prediction, thereby helping to bridge prescriptive economic modeling and multicriteria decision analysis.

The present study makes three main contributions to the portfolio allocation literature. First, it proposes a multicriteria portfolio allocation framework grounded in prospect theory. Unlike approaches that replace variance with alternative risk metrics, the proposed model

embeds behavioral preferences directly into the allocation process structure through preference-weighted criteria, thereby integrating psychological realism within portfolio allocation.

Second, the study provides a systematic comparison between the behavioral multicriteria model and the classical mean-variance framework under realistic lower and upper bounds on asset allocations. This allows an evaluation of how constraint specification affects portfolio concentration, diversification, and risk-return efficiency, shedding light on the practical sensitivity of traditional optimization.

Third, and importantly, the empirical analysis is conducted using an out-of-sample evaluation framework. Portfolios are constructed across conservative, moderate, and aggressive investor profiles and assessed on realized performance metrics, including risk, return, and diversification patterns. By emphasizing out-of-sample robustness rather than in-sample optimality, the study addresses concerns related to estimation error and overfitting, providing evidence on the practical stability and behavioral consistency of the proposed approach.

Overall, by embedding behavioral preferences into a multicriterial structure based on prospect theory, the proposed framework bridges traditional quantitative finance and behavioral decision theory. The results offer insights into how preference-driven modeling affects portfolio construction in realistic investment environments and contribute to the growing literature on robust and behaviorally informed asset allocation.

2 Methodology

This section outlines the empirical design used to evaluate whether a prospect-theory multicriteria allocation framework, implemented through the MPT-A (Leoneti & Gomes, 2025), yields realized performance that differs from those generated by a classical mean-variance optimization benchmark under realistic allocation constraints.

The MPT-A is particularly well-suited for financial problems because it integrates both multi-criteria decision analysis and behavioral decision-judgement principles. Traditional financial models often assume rational agents and linear preferences, but real-world financial decisions are influenced by psychological factors such as loss aversion, risk perception, and reference dependence. MPT-A explicitly incorporates these behavioral elements, making it more realistic and more robust for behavioral finance applications (Leoneti & Gomes, 2025).

2.1 The MPT-A

The recent contribution inspired by prospect theory, termed MPT-A, extends prospect theory into the field of multicriteria decision analysis. The methodology begins by standardizing data across all criteria (x_j) to ensure comparability among alternatives. For each criterion, the mean of the standardized values (r_j) is calculated, establishing a reference point that represents the *status quo* alternative, denoted r_{AVG} . This reference point is then applied in pairwise comparisons between each alternative and the *status quo*, enabling the assessment of gains and losses relative to average performance while embedding risk-aversion considerations into the decision process.

Perceptions of gains and losses are captured through a value function that embodies the central principle of prospect theory, namely the evaluation of changes. The formulation is expressed as:

$$\Phi(r_j) = \begin{cases} (r_j - r_{AVG})^\alpha & \text{case } (r_j - r_{AVG}) > 0 \\ 0 & \text{case } (r_j - r_{AVG}) = 0 \\ -\lambda(-(r_j - r_{AVG}))^\beta & \text{case } (r_j - r_{AVG}) < 0 \end{cases} \quad (1)$$

where $\alpha = \beta = 0.88$ and $\lambda = 2.25$, according to Tversky & Kahneman (1992).

In addition, the weighting functions central to prospect theory are reinterpreted within the multicriteria framework. Whereas prospect theory traditionally employs such functions to capture distortions in risk perception, multicriteria approaches rely on weight vectors to express the subjective relevance of each criterion. MPT-A bridges these perspectives by introducing a unified construct, a combined subjective-perceived weight, that integrates both the behavioral distortions of prospect theory and the preference structure of multicriteria decision-making, by using:

$$\Omega(w_j) = \omega(w_j)w_j \quad (2)$$

where w_j is the subjective weight of a criterion j and $\omega(w_j)$ is its respective weighting function.

Within MPT-A, the multiplicative structure can be viewed through a probabilistic lens. In this interpretation, the subjective weight w_j acts as a baseline probability, while the distortion $\omega(w_j)$ parallels a conditional adjustment. Their product, $\Omega(w_j)$, thus integrates the normative

logic of probability with the behavioral distortions of prospect theory, yielding a unified measure of importance and perception.

Finally, the overall evaluation of each alternative is obtained by aggregating the combined weights with the prospect-theoretic values across all criteria. Formally, this yields a global dominance measure expressed as:

$$M(r) = \sum_{j=1}^n \Omega(w_j) \cdot \Phi(r_j) \quad (3)$$

The decision rule selects the alternative with the highest multicriteria prospect value $M(r)$, identifying the option that best balances subjective importance with perceived gains and losses. This framework illustrates how MPT-A integrates economic modeling with decision analysis (Leoneti & Gomes, 2025). By combining reference dependence, loss aversion, and nonlinear weighting with multicriteria preferences, MPT-A extends prospect theory while preserving its axiomatic foundations. The result is a novel tool for analyzing decision behavior under risk and multiple criteria, bridging normative rigor with descriptive insights into human cognition.

2.2 The empirical analysis

The empirical analysis was conducted on a portfolio universe of 26 assets from the Science For Investors (SFI) portfolio¹, which originally comprised 28 assets. Two assets were excluded due to incomplete data over the optimization period. The assets chosen were: AAPL, ASML, BABA, CACI, DAR, FHN, GILD, GOOG, INFY, MBUU, META, MNMD, MOH, MSFT, NOC, PFE, QCOM, RKL, SMCI, SPOT, TSLA, UNH, VRTX, DTG:DE, XETR:NN6, and XPAR:MC (see Appendix for the complete list and corresponding company names). For each asset, historical monthly prices were retrieved using the R package tseries and the function get.hist.quote(). Monthly returns and variances (used as the operational proxy for risk) were then calculated from these data. In this study, an in-sample window was set from February 2013 to March 2023. This in-sample panel provided a set of return and risk inputs that were aggregated into summary statistics required by the portfolio construction procedures.

¹ Science For Investors (SFI). *SFI Portfolio*. Available at: <http://www.sfi.association.com>

Using the same asset set and the same procedure, a strictly separate out-of-sample window was also constructed covering April 2023 to October 2025. The out-of-sample dataset contains the same variables, monthly returns and monthly variances, but is reserved exclusively for performance evaluation. This split allows the analysis to focus on whether allocations derived from in-sample information remain coherent when confronted with new market conditions, which is essential given the sensitivity of portfolio rules to estimation error and scenario changes.

With the estimation sample defined, the in-sample information was compressed into asset-level summaries. For each asset i , it was computed the average monthly return (μ_i) and the average monthly variance (v_i). These two statistics constitute the inputs for the multicriteria decision stage by forming a decision matrix with 26 alternatives (assets) and two criteria, in which return is interpreted as a benefit attribute and variance as a cost attribute. The resulting decision matrix has the form

$$X = \begin{bmatrix} \mu_1 & v_1 \\ \vdots & \vdots \\ \mu_{26} & v_{26} \end{bmatrix}.$$

The decision matrix provides the return and risk summaries that feed the multicriteria ranking stage and serve as the expected-return inputs for the mean-variance benchmark.

Building directly on this two-criterion structure, heterogeneous investor preferences were modeled through criterion weights, exploiting the fact that multicriteria methods allow the analyst to explicitly specify the relative importance attached to each criterion. Three investor profiles were defined to reflect common risk-attitude archetypes. In all cases, weights are constrained to sum to one, which ensures that comparisons across profiles reflect genuine preference shifts rather than rescaling.

A conservative profile prioritizes stability and lower volatility and is represented by weights $w_{return} = 0.20$ and $w_{risk} = 0.80$. A moderate profile aims for a balance between growth and safety and assigns equal weights $w_{return} = 0.50$ and $w_{risk} = 0.50$. An aggressive profile emphasizes return seeking and accepts higher risk exposure, using $w_{return} = 0.80$ and $w_{risk} = 0.20$.

Given the decision matrix and the preference weights, MPT-A is applied separately for each profile to generate an asset ranking consistent with prospect-theoretic dominance comparisons.

Prior to computing dominance relations, inputs are normalized using the max linear standardization technique, which maps each criterion onto a comparable scale while respecting criterion orientation. In practical terms, this normalization produces values in $[0,1]$ by benchmarking each asset against the best observed performance for benefit criteria and against the most favorable (lowest) observed levels for cost criteria, thereby preventing scale effects from mechanically driving the ranking.

In this study, the parameters of MPT-A were calibrated according to the empirically validated values proposed by Tversky & Kahneman (1992). Specifically, the model adopted the parameter set $\alpha = 0.88$, $\beta = 0.88$, $\lambda = 2.25$, $\gamma = 0.61$, and $\sigma = 0.69$. These values reflect the behavioral tendencies observed in experimental settings, such as diminishing sensitivity to gains and losses, probability weighting, and pronounced loss aversion. By adhering to these empirically established parameters, the application of MPT-A in a financial context ensures both methodological rigor and behavioral realism, aligning the decision-making framework with well-documented psychological patterns in risk and uncertainty. The model output for each profile p is a standardized score vector $s^{(p)} = (s_1^{(p)}, \dots, s_{26}^{(p)})$, with scores reported on a $[0,1]$ scale.

Because MPT-A produces preference scores rather than portfolio weights, a mapping rule is required to convert rankings into implementable allocations while preserving the ordering information embedded in the scores. The conversion is designed to guarantee that every asset receives a strictly positive allocation and, in particular, that the lowest-ranked asset is not assigned a zero weight purely due to relative preference intensity.

Let $s_i^{(p)} \in [0,1]$ denote the score of asset i for profile p . We compute the score amplitude $A = \max_i s_i^{(p)} - \min_i s_i^{(p)}$ (given the standardized output, $A = 1$ in our application). We then define shifted scores $s_i'^{(p)} = s_i^{(p)} + A$ and compute portfolio weights by normalization:

$$w_i^{(p)} = \frac{s_i'^{(p)}}{\sum_{j=1}^{26} s_j'^{(p)}}. \quad (4)$$

This affine transformation is intentionally conservative, since it preserves cross-asset preference differences while ensuring a minimum strictly positive participation rate for the worst-ranked asset equal to $(\frac{\min_i s_i^{(p)} + A}{\sum_{j=1}^{26} s_j'^{(p)}})$. The resulting weights are fully invested by construction and remain fixed for the subsequent out-of-sample evaluation.

With portfolio weights defined, out-of-sample portfolio performance is computed by applying the fixed allocations to realized monthly portfolio returns from April 2023 to October 2025. For each month t in the out-of-sample window, the portfolio return $R_t^{(p)}$ is computed as the weighted sum of asset returns,

$$R_t^{(p)} = \sum_{i=1}^{26} w_i^{(p)} r_{i,t} \quad (5)$$

where $r_{i,t}$ is the monthly return.

From the resulting return series, two complementary measures of average performance were computed. The arithmetic mean of $R_t^{(p)}$ summarizes the typical monthly return, while the geometric mean of $R_t^{(p)}$ captures the compounded average monthly growth rate over the full evaluation window and is therefore more informative about long-run accumulation. Risk is measured in a consistent manner by computing the standard deviation of monthly portfolio returns as the portfolio's monthly volatility.

To incorporate a risk-adjusted perspective aligned with standard asset-allocation evaluation, the Sharpe ratio was computed as the ratio of the arithmetic mean of monthly portfolio return $R^{(p)}$ discounted from a constant risk-free rate $r_f^{(p)}$, which represents the monthly excess returns $R^{(p)} - r_f^{(p)}$, to their standard deviation. Consequently, the monthly Sharpe ratio is defined as:

$$SR^{(p)} = \frac{\overline{R^{(p)} - r_f^{(p)}}}{\sigma(R^{(p)} - r_f^{(p)})} \quad (6)$$

Following standard practice in the finance literature, the 3-month U.S. Treasury bill rate was used as a proxy for the risk-free rate. Specifically, for each month t , a corresponding monthly risk-free rate $r_f^{(p)}$ was obtained by converting the annualized 3-month Treasury bill yield into a monthly equivalent. This resulted in a sequence of 31 monthly risk-free rates covering the period from April 2023 to October 2025. This approach ensures a theoretically consistent and empirically accurate estimation, as it accounts for temporal variations in interest rates driven by changing monetary policy conditions.

To produce a horizon-level Sharpe measure comparable across the same out-of-sample length, we also report a period-scaled Sharpe ratio obtained by multiplying the monthly Sharpe

by $\sqrt{T_{out}}$, where $T_{out} = 31$. This maintains internal consistency with the volatility scaling adopted above and allows the discussion of risk-adjusted performance both “per month” and “over the evaluation horizon.”

In parallel, we compute a Markowitz portfolio by solving a return-maximization problem using in-sample information, with explicit allocation bounds (l lower, and u upper) to prevent unrealistic concentration. Specifically, letting μ denote the vector of in-sample mean returns, we choose weights w to maximize expected return,

$$\max_w \mu^T w \quad \text{s.t.} \quad \sum_{i=1}^{26} w_i = 1, \quad w^T \Sigma w \leq \sigma_{target}^2, \quad l \leq w_i \leq u \quad \forall i \quad (7)$$

where Σ is the covariance matrix among the assets, and σ_{target}^2 is the maximum variance, which was set as 1%.

This formulation is intentionally stark, since by maximizing expected return under box constraints, the solution highlights how practical constraints shape the optimizer’s behavior, allocating as much as permitted to the highest- μ assets while maintaining feasibility. We solve this problem under two bound scenarios. First, we impose tight bounds $l = 0.01$ and $u = 0.05$, enforcing a highly dispersed allocation to limit concentration. Second, we retain the same lower bound but relax the upper bound to $u = 0.15$, allowing the optimizer to express stronger highest-return assets. The two scenarios therefore isolate the effect of constraint tightness on both concentration and subsequent realized performance.

After obtaining the two Markowitz portfolios, we subject them to the exact same out-of-sample evaluation protocol used for the MPT-A allocations to ensure strict comparability. A crucial methodological clarification is needed to be recalled here. As previously said, criterion weights are not portfolio allocations within MPT-A. They are preference parameters used to construct behavioral asset scores. The model therefore produces a ranking of alternatives, not an investable portfolio by itself. This distinction is essential for the present application, since portfolio weights arise only after the second implementation step that maps asset scores into admissible allocations.

Finally, the comparative assessment combines statistical evidence and economically grounded interpretation. The statistical component relies on summarizing the distributions of out-of-sample monthly returns and risk measures across strategies, examining the magnitude and stability of performance differences, and contrasting risk-adjusted outcomes through the

Sharpe ratio. The interpretive component frames these results from the perspective of an experienced investor, emphasizing implementability-relevant dimensions such as concentration versus diversification, the coherence of allocations with the stated preference profiles (conservative, moderate, aggressive), and the degree to which each method delivers performance that is consistent with its intended behavioral or optimization rationale when evaluated on realized, out-of-sample data.

3 Results

In this section, the results obtained from the application of the multicriteria model, grounded in prospect theory, and the classical Markowitz model, based on the mean-variance approach, are presented and discussed. The purpose of the analysis is to evaluate the performance of portfolios constructed under different investor profiles (conservative, moderate, and aggressive) and to investigate how the constraints imposed on the Markowitz model influence the balance between risk, return, and diversification.

The comparison between the models allows for an understanding of their fundamental differences. On one side, the incorporation of investors' subjective preferences and, on the other, a strictly statistical approach that seeks optimal efficiency according to mathematical mean-variance criteria. In this way, it is possible to observe whether the multicriteria method, by translating individual preferences into weights assigned to the criteria, is capable of generating portfolios consistent with each investor profile, and how these results compare to the traditional Markowitz model in terms of performance and stability. This analysis enables a discussion of the practical adherence of each approach to actual investor behavior.

Subsequently, the results for each profile and model are detailed, highlighting the effects of the constraints and the relative efficiency of the constructed portfolios. Table 1 reports the out-of-sample performance of portfolios obtained under the multicriteria framework for conservative, moderate, and aggressive investor profiles. Each profile is defined by distinct weights assigned to return (geometric mean of $R_t^{(p)}$) and risk (standard deviation of $R_t^{(p)}$) criteria.

Table 1. Out-of-Sample Performance of Multicriteria Portfolios

Investor Profile	Return Weight	Risk Weight	Return (%)	Risk (%)
Conservative	20%	80%	2.07	4.09
Moderate	50%	50%	2.01	4.03
Aggressive	80%	20%	2.14	4.35

The results show a clear differentiation in risk exposure across investor profiles, with higher risk levels associated with more aggressive preference structures. Returns remain relatively stable across profiles, with the aggressive portfolio achieving the highest realized return. Portfolio allocations under the multicriteria model exhibit a high degree of diversification across assets for all profiles (Table 2).

Table 2. Multicriteria Portfolio Allocation

Conservative				Moderate				Aggressive			
Asset	$w_i^{(p)}$	Asset	$w_i^{(p)}$	Asset	$w_i^{(p)}$	Asset	$w_i^{(p)}$	Asset	$w_i^{(p)}$	Asset	$w_i^{(p)}$
AAPL	0,0398	MSFT	0,0400	AAPL	0,0421	MSFT	0,0421	AAPL	0,0409	MSFT	0,0406
ASML	0,0398	NOC	0,0399	ASML	0,0417	NOC	0,0409	ASML	0,0404	NOC	0,0387
BABA	0,0392	PFE	0,0397	BABA	0,0369	PFE	0,0381	BABA	0,0342	PFE	0,0348
CACI	0,0397	QCOM	0,0394	CACI	0,0401	QCOM	0,0384	CACI	0,0379	QCOM	0,0362
DAR	0,0395	RKLB	0,0373	DAR	0,0392	RKLB	0,0300	DAR	0,0371	RKLB	0,0277
FHN	0,0396	SMCI	0,0394	FHN	0,0383	SMCI	0,0416	FHN	0,0355	SMCI	0,0412
GILD	0,0397	SPOT	0,0388	GILD	0,0383	SPOT	0,0365	GILD	0,0352	SPOT	0,0345
GOOG	0,0398	TSLA	0,0382	GOOG	0,0401	TSLA	0,0419	GOOG	0,0378	TSLA	0,0447
INFY	0,0397	UNH	0,0400	INFY	0,0389	UNH	0,0414	INFY	0,0362	UNH	0,0395
MBUU	0,0392	VRTX	0,0396	MBUU	0,0389	VRTX	0,0405	MBUU	0,0373	VRTX	0,0389
META	0,0396	DTG:DE	0,0393	META	0,0416	DTG:DE	0,0357	META	0,0408	DTG:DE	0,0320
MNMD	0,0200	XETR:NN6	0,0332	MNMD	0,0211	XETR:NN6	0,0333	MNMD	0,0554	XETR:NN6	0,0429
MOH	0,0397	XPAR:MC	0,0399	MOH	0,0417	XPAR:MC	0,0409	MOH	0,0407	XPAR:MC	0,0388

It can be seen in Table 2 that the asset weights were generally balanced, with no excessive concentration in individual securities. Minor variations in allocations reflect the differing importance assigned to risk and return criteria.

In its turn, the Markowitz mean-variance model is evaluated under two alternative constraint scenarios to assess the impact of allocation limits on portfolio performance and diversification. Table 3 reports the out-of-sample performance of portfolios obtained under the two sets of Markowitz mean-variance model.

Table 3. Out-of-Sample Performance of Markowitz Portfolios

Constraint scenario	Min Weight	Max Weight	Return (%)	Risk (%)
1%–5%	1%	5%	1.82	4.27
1%–15%	1%	15%	3.50	7.95

The Markowitz model, although theoretically optimal under the mean-variance criterion, revealed practical limitations related to asset concentration (Table 4). Under tighter constraints, the Markowitz portfolio displays moderate risk and lower return relative to the multicriteria portfolios. When the upper bound on asset weights is relaxed, the model generates substantially higher returns, accompanied by a pronounced increase in risk. Thus, despite its mathematical rigor, the Markowitz model may generate unbalanced allocations when applied directly. This concentration in the Markowitz model contradicts the very theoretical foundation of the technique, which is asset diversification.

Table 4. Markowitz Portfolio Allocation

Constraint scenario 1%–5%				Constraint scenario 1%–15%			
Asset	$w_i^{(p)}$	Asset	$w_i^{(p)}$	Asset	$w_i^{(p)}$	Asset	$w_i^{(p)}$
AAPL	0,0500	MSFT	0,0500	AAPL	0,1220	MSFT	0,1500
ASML	0,0500	NOC	0,0500	ASML	0,0100	NOC	0,0100
BABA	0,0100	PFE	0,0100	BABA	0,0100	PFE	0,0100
CACI	0,0500	QCOM	0,0500	CACI	0,0100	QCOM	0,0100
DAR	0,0500	RKLB	0,0100	DAR	0,0100	RKLB	0,0100
FHN	0,0100	SMCI	0,0500	FHN	0,0100	SMCI	0,1500
GILD	0,0100	SPOT	0,0100	GILD	0,0100	SPOT	0,0100
GOOG	0,0500	TSLA	0,0500	GOOG	0,0100	TSLA	0,1500
INFY	0,0300	UNH	0,0500	INFY	0,0100	UNH	0,0201
MBUU	0,0500	VRTX	0,0500	MBUU	0,0100	VRTX	0,0100
META	0,0500	DTG:DE	0,0100	META	0,1493	DTG:DE	0,0100
MNMD	0,0500	XETR:NN6	0,0500	MNMD	0,0686	XETR:NN6	0,0100
MOH	0,0500	XPAR:MC	0,0500	MOH	0,0100	XPAR:MC	0,0100

Table 4 highlights the issue of asset concentration in Markowitz portfolios under different constraint scenarios. When the upper bound is set at 5%, all assets are uniformly constrained, resulting in no holdings above this threshold and eliminating concentration risk. In contrast, with a more flexible scenario of 1%–15%, the model allocates disproportionately to nine assets, while the majority of the remaining assets are held at the minimum weight of 1%. This outcome illustrates how looser constraints allow the optimization process to concentrate resources in a limited set of securities, thereby increasing portfolio imbalance. The comparison underscores that constraint design plays a critical role in shaping portfolio diversification, with tighter bounds promoting dispersion across assets and broader limits encouraging concentration in a few positions.

Finally, Table 5 provides a comparative overview of portfolio performance across the multicriteria and Markowitz models. The multicriteria approach consistently delivered

balanced outcomes, with high diversification and relatively stable risk levels across conservative, moderate, and aggressive profiles. Returns remained close to 2%, while risk varied modestly, reflecting the model's ability to align portfolio construction with investor preferences without sacrificing stability. In contrast, the Markowitz portfolios exhibited greater sensitivity to constraint scenarios. Under the 1%–5% limits, performance was moderate, showing some alignment with the multicriteria results. However, when the upper bound was relaxed to 15%, the model concentrated allocations, producing a higher out-of-sample return but at the cost of substantially elevated risk and low diversification. This comparison underscores the trade-off between mathematical optimization and practical portfolio allocation, highlighting the multicriteria model's advantage in generating portfolios that are both efficient and consistent with investor profiles.

Table 5 – Comparative Summary of Portfolio Performance

Model	Portfolio Type	Out-of-Sample Return (%)	Out-of-Sample Risk (%)	Diversification Level
MPT-A	Conservative	2.07	4.09	High
MPT-A	Moderate	2.01	4.03	High
MPT-A	Aggressive	2.14	4.35	High
Markowitz	1%–5% Constraints	1.82	4.27	Moderate
Markowitz	1%–15% Constraints	3.50	7.95	Low

Table 6 summarizes the risk-adjusted performance of the portfolios through Sharpe ratios, providing a clearer view of efficiency beyond absolute return and risk levels. The multicriteria model consistently achieved higher Sharpe values across all investor profiles. These results indicate that, despite relatively modest returns, the multicriteria approach delivered good risk-adjusted outcomes, reflecting its ability to balance investor preferences with portfolio stability. In contrast, the Markowitz portfolios showed weaker efficiency, under the 1%–5% constraint scenario, while the more flexible 1%–15% scenario improved to the highest value but at the cost of substantially higher risk. This comparison reinforces the conclusion that the multicriteria method provides consistent and resilient performance, whereas the Markowitz model, although capable of generating higher raw returns, struggles to maintain efficiency once risk is accounted for.

Table 6. Risk-Adjusted Performance (Sharpe Ratios)

Model	Portfolio	Sharpe
MPT-A	Conservative	0.43

MPT-A	Moderate	0.42
MPT-A	Aggressive	0.42
Markowitz	1%–5%	0.35
Markowitz	1%–15%	0.43

Z-statistics were computed using the Jobson-Korkie test by using the Markowitz portfolio with 1%–5% constraints as the benchmark. The Z value of 7.06 for Conservative MPT-A and Markowitz 1%–5% (p-value < 0.001), 6.11 for Moderate MPT-A and Markowitz 1%–5% (p-value < 0.001), and 6.27 for Aggressive MPT-A and Markowitz 1%–5% (p-value < 0.001), confirm that the differences between the multicriteria portfolios and the constrained 1%-5% Markowitz portfolio are statistically significant, with p-values close to zero. From the presented results, it can be noticed that the multicriteria portfolios exhibit comparable risk-adjusted performance relative to the Markowitz portfolios. In particular, the conservative and moderate multicriteria portfolios achieve the highest Sharpe ratios, underscoring their efficiency in transforming risk into realized returns. These findings reinforce the robustness of the multicriteria approach in aligning portfolio construction with investor preferences while maintaining stability across different risk profiles. Moreover, multicriteria portfolios offer balanced diversification and performance across conservative, moderate, and aggressive strategies.

By contrast, the Markowitz portfolio under relaxed constraints shifts the frontier upward in terms of return but introduces a steep increase in volatility, reflecting a trade-off suitable only for highly aggressive risk preferences. Taken together, these results highlight the practical advantages of the multicriteria approach, since it not only delivers consistent risk-adjusted performance but also provides portfolios that are more coherent with investor behavior and preferences than those generated by the traditional Markowitz model.

4 Discussion

The empirical findings confirm important issues with the classical mean-variance framework proposed by Markowitz (1952, 1959). While theoretically optimal under assumptions of rational homogeneity, the model demonstrates significant sensitivity to allocation constraints in practical implementation.

Under tight bounds, the Markowitz solution becomes inefficient in mean-variance terms and is dominated by multicriteria portfolios. When upper bounds are relaxed, the model concentrates in a limited number of assets, increasing expected return at the cost of substantial volatility. This behavior is consistent with the instability and estimation sensitivity documented by Michaud (1989), as well as the input-perturbation effects identified by Jobson and Korkie (1980) and Best and Grauer (1991). These findings reinforce the argument that mean-variance optimization may maximize estimation error rather than true efficiency when implemented with uncertain parameters.

In turn, the multicriteria framework grounded in prospect theory produces portfolios that display a monotonic and coherent progression in risk and return across conservative, moderate, and aggressive profiles. This outcome aligns with the behavioral asymmetries identified by Kahneman and Tversky (1979) and extended by Tversky and Kahneman (1992), particularly loss aversion and reference dependence. Unlike variance, which treats upside and downside deviations symmetrically, preference-weighted criteria allow investor-specific risk perception to shape portfolio construction directly. The results also support Behavioral Portfolio Theory (Shefrin & Statman, 2000), which posits that investors structure portfolios according to layered goals rather than abstract statistical efficiency.

From a methodological perspective, the findings extend the literature on multicriteria decision-making in finance (Zopounidis & Doumpos, 2002; Steuer & Na, 2003). Financial decisions inherently involve multiple conflicting objectives, and reducing them to a two-moment framework may oversimplify real-world preference structures. The empirical evidence shows that the multicriteria approach maintains diversification organically, without the need for externally imposed restrictive bounds. Portfolios populate the efficient frontier more evenly across risk regions, enhancing interpretability and structural stability. This confirms that MCDM frameworks provide measurable improvements in out-of-sample efficiency.

Finally, risk-adjusted performance analysis further differentiates the two approaches. Conservative and aggressive multicriteria portfolios achieve higher Sharpe ratios than the constrained Markowitz portfolio, demonstrating superior transformation of risk into realized returns. Although the relaxed Markowitz solution generates the highest absolute return, the disproportionate rise in volatility reduces efficiency and increases exposure to estimation risk. The multicriteria portfolios occupy efficient regions of the risk-return space across profiles, whereas the Markowitz model either becomes dominated (tight constraints) or shifts into a high-risk scenario (relaxed constraints). This indicates greater frontier stability in the behavioral framework.

The results have direct implications for institutional asset management and retirement systems in which investors must allocate capital under uncertainty. Portfolio construction tools that accommodate heterogeneous risk perceptions are better suited to real-world financial decision-making than purely statistical optimization models. The multicriteria approach reduces reliance on arbitrary constraint calibration and improves alignment between portfolio outcomes and investor preferences. In regulatory contexts emphasizing investor protection and diversification, preference-integrated allocation may offer a more robust framework than traditional mean-variance solutions.

This discussion is particularly relevant in light of current policy directions within the European Union. The European Commission has signalled its intention to reduce or even phase out traditional time deposits, thereby encouraging citizens to allocate their savings into investment funds. In such a scenario, the availability of behavioral portfolio allocation tools becomes essential to accommodate the diverse risk profiles of investors. Multicriteria approaches, by incorporating subjective preferences and behavioral dimensions, offer a practical solution to this transition, ensuring that individuals can select portfolios aligned with their financial goals and risk tolerance. This reinforces the importance of advancing beyond purely statistical models, such as the classical Markowitz framework, toward methods that better reflect the realities of investor behavior in a changing financial landscape.

5 Conclusions

Since the formulation of the Markowitz model, decision theory in finance has gained quantitative support, using mean and variance to capture the relationship between risk and return. The model introduced diversification as a mechanism to reduce exposure to risk and became the cornerstone of modern portfolio theory. However, despite its mathematical elegance, the Markowitz framework assumes homogeneous rationality among investors and does not incorporate subjective preferences or individual behaviors, which limits its practical applicability in real world contexts.

With advances in computational methods, more flexible approaches have emerged, capable of integrating multiple criteria and human perceptions into the decision-making process. Within this context, multicriteria methods such as MPT-A, grounded in prospect theory, stand out by allowing decisions to be modeled more realistically, taking into account how investors perceive gains and losses. These methods acknowledge that agents do not make uniform decisions and that the importance assigned to each criterion (such as risk and return)

varies according to the investor's profile. As a result, they are particularly useful for developing models that translate individual preferences into consistent quantitative decisions.

The empirical results obtained in this study highlight these differences in approach. While the multicriteria model demonstrated coherence with investor profiles, producing portfolios with lower risk and moderate returns for conservative investors, and higher returns with controlled risk for aggressive investors, the Markowitz model showed limitations in balancing risk and return when subjected to realistic constraints. For instance, with a 15% upper bound, the model concentrated investments in a small number of assets, raising risk to levels incompatible with conservative and moderate profiles. Under a stricter 5% limit, the Markowitz model achieved results closer to those of the multicriteria approach, but still with lower efficiency in terms of risk-return balance.

These observations reinforce the importance of methods that incorporate the behavioral dimension of financial decision-making. By integrating qualitative and subjective preferences, the multicriteria model provides more adherence to the practical reality of investors. This contribution, from the statistical formulation of Markowitz to the behavioral perspective of prospect theory, reinforces the fact that financial decisions are inherently personal, and that models must account for this reality to remain relevant and effective.

Future research should apply the proposed framework to other data sets including optimization with different classes of assets and may extend this approach by incorporating additional decision criteria, alternative behavioral models, or time-varying preference structures, further enhancing its relevance in increasingly complex financial decision environments.

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Appendix. Assets from the Science For Investors (SFI) Portfolio

This appendix reports the 26 assets included in the empirical analysis, selected from the Science For Investors (SFI) portfolio, which originally comprises 28 assets. Two assets were excluded due to incomplete data over the sample period considered in the study. The table provides ticker symbols and corresponding company names.

Asset Number	Short Name	Complete Company Name
1	AAPL	Apple Inc.
2	ASML	ASML Holding N.V.
3	BABA	Alibaba Group Holding Limited
4	CACI	CACI International Inc.
5	DAR	Darling Ingredients Inc.
6	FHN	First Horizon Corporation
7	GILD	Gilead Sciences, Inc.
8	GOOG	Alphabet Inc. (Class C)
9	INFY	Infosys Limited
10	MBUU	Malibu Boats, Inc.
11	META	Meta Platforms, Inc.
12	MNMD	Mind Medicine (MindMed) Inc.
13	MOH	Molina Healthcare, Inc.
14	MSFT	Microsoft Corporation
15	NOC	Northrop Grumman Corporation
16	PFE	Pfizer Inc.
17	QCOM	Qualcomm Incorporated
18	RKLB	Rocket Lab USA, Inc.
19	SMCI	Super Micro Computer, Inc.
20	SPOT	Spotify Technology S.A.
21	TSLA	Tesla, Inc.
22	UNH	UnitedHealth Group Incorporated
23	VRTX	Vertex Pharmaceuticals Incorporated
24	DTG:DE	Daimler Truck Holding AG (Xetra: DTG)
25	XETR:NN6	Siemens Healthineers AG
26	XPAR:MC	LVMH Moët Hennessy Louis Vuitton SE

Preprint not peer reviewed