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Robo-Advisors: Artificial Intelligence-Driven Services for Retail Investors' Asset Allocation

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Abstract

This study examines the performance of robo-advisors within the broader digital transformation of financial services. Robo-advisors automate portfolio construction and maintenance through algorithmic frameworks that apply established investment principles and low-cost ETFs, thereby extending professional investment management to individuals lacking the time, resources, or expertise traditionally required. Focusing on Wealthfront's Classic Portfolio from 2013 to 2023, the analysis evaluates absolute and risk-adjusted returns, volatility and drawdown dynamics, and factor exposures to distinguish systematic risks from potential investment skill. Results show that passive indexing outperformed all examined robo-advisor portfolios on both absolute and risk-adjusted bases during a decade dominated by strong U.S. equity performance. Although robo-advisors successfully delivered calibrated risk exposure, their diversified multi-asset allocations incurred notable opportunity costs in a growth-driven market. The platforms offer the greatest value to conservative investors, while more aggressive investors may pay advisory fees without receiving proportional benefits.

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1. Introduction

A robo-advisor is a digital platform that employs artificial intelligence to deliver automated financial planning and investment management services with minimal human intervention (Cao, 2023). Understanding the evolution of investment management is essential to contextualize this fintech innovation. Historically, financial advice was provided through one-on-one interactions between clients and stockbrokers or financial advisers, who tailored recommendations to everyone's objectives, financial situation, and risk tolerance. However, the high fees associated with such personalized advisory services rendered them inaccessible to much of the general population.

The first wave of digitalization in the 1990s significantly expanded access to financial markets through the emergence of online trading platforms and brokerages. These tools allow individuals to buy and sell securities at a fraction of the cost charged by traditional brokers. Nonetheless, they primarily attracted active traders, as they still required users to devote substantial time, knowledge, and discipline to manage their portfolios effectively (Jung et al., 2018).

The second wave of digital transformation in the 2010s addressed these limitations by introducing algorithm-driven portfolio management systems, commonly known as robo-advisors, which broadened financial advisory services to a wider segment of the population (Jung et al., 2018). Unlike traditional retail financial services, robo-advisors automate portfolio construction and maintenance, often achieving comparable or even superior investment outcomes at significantly lower cost. They do so by embedding established investment principles into algorithmic frameworks and exploiting the availability of low-cost, liquid exchange-traded funds (ETFs) across diverse asset classes (Grealish, 2023).

With modest minimum investment requirements and a passive, hands-off investment approach, robo-advisors make professional portfolio management accessible to individuals who may lack the financial expertise, time, or resources to manage their investments independently (Sironi, 2016). As trust in these platforms has grown, robo-advisors have increasingly contributed to the disintermediation of traditional financial services, enabling investors to obtain investment management directly without relying on a human advisor (Arslanian and Fischer, 2019).

This study evaluates the performance of robo-advisory investment platforms, with particular emphasis on Wealthfront's Classic Portfolio strategy over the period from January 2013 through December 2023. The analysis centers on three principal dimensions of portfolio assessment. First, it evaluates absolute return characteristics by comparing cumulative performance with appropriate benchmarks. Second, it examines key risk metrics, including volatility trends and drawdown behavior during market downturns. Third, it employs factor models to ascertain whether observed performance differentials arise from systematic risk exposures or reflect evidence of investment skill. This research explores whether the asset allocations of robo-advisor portfolios attained their articulated objectives of: (1) delivering sufficient diversification advantages, (2) sustaining appropriate risk-adjusted returns in relation to their designated risk profiles, and (3) validating their fee structures through quantifiable value addition exceeding that of passive alternatives. This study proceeds through four sections.

- Literature Review provides a concise overview of the theoretical foundations supporting the asset pricing models applied in the study.
- Methodology outlines the research design.
- Results section presents the empirical findings through three analytical frames: descriptive performance statistics, risk-adjusted return measures, and factor-model results.
- Conclusion interprets and synthesizes the study's key findings.

2. Literature Review

Robo-advisory represents a specialized segment of automated investing. These platforms rely on sophisticated artificial intelligence algorithms to perform a range of investment management functions (Tsang, 2023; Zhu et al., 2024). Their services provide a structured and transparent process for allocating an individual's portfolio across asset classes and financial instruments according to the client's characteristics and objectives.

This process generally unfolds in three key stages: (1) client profiling, (2) asset allocation, and (3) portfolio rebalancing.

Robo-advisors typically initiate the advisory process through an online questionnaire aimed at evaluating the investor's financial circumstances, personal attributes, and investment objectives. This client profiling stage ensures that portfolio allocations are congruent with the individual's risk capacity and financial aspirations (Bianchi and Brière, 2023), but personalization is not always achieved (Faloon and Scherer, 2017).

The questionnaire gathers a combination of objective and subjective data. For instance, a client's income and years remaining until retirement represent objective measures of risk, whereas the client's tolerance for market volatility exemplifies a subjective assessment (Lam, 2016; Hasanah et al., 2024).

Many robo-advisors assist clients in selecting a specific investment objective, such as retirement planning, home purchase, intergenerational bequest, education funding, or emergency reserves. This objective may delineate the investment horizon or influence risk capacity within the optimal portfolio allocation. Approaches differ, however: certain platforms embed the investment goal directly into portfolio optimization, whereas others permit clients to specify objectives independently of risk evaluation, exerting minimal or no influence on asset allocation (Bianchi and Brière, 2023).

A more advanced subset of platforms supports multi-goal investment frameworks, enabling clients to assign separate portfolios to distinct financial objectives. This reflects the concept of mental accounting, whereby investors categorize assets according to purpose, facilitating more personalized and behaviorally informed

investment strategies (Das et al., 2010).
At the next stage, the robo-advisor constructs a portfolio based on the client's goals and selected risk level. In most cases, these automated algorithms are based on Modern Portfolio Theory. Pioneered by Harry Markowitz in the 1950s, this framework posits that an optimal portfolio maximizes expected returns for a given level of risk tolerance or, alternatively, minimizes risk for a specified expected return. To construct higher-risk portfolios, robo-advisors increase the allocation to equities relative to bonds and incorporate riskier instruments within each asset class, such as transitioning from government to municipal bonds or from U.S. to emerging market equities (Abraham et al., 2019).
The Efficient Market Hypothesis (EMH) represents another foundational theory adopted by robo-advisors. This hypothesis asserts that consistent market outperformance is unattainable, as prevailing stock prices fully incorporate and reflect all relevant information owing to market efficiency (Malkiel, 2003). Consequently, robo-advisors often integrate index funds or exchange-traded funds (ETFs) into their strategies, designed to mirror index performance. The underlying rationale is that passive market participation outperforms attempts to surpass it via frequent trading or individual stock selection. For example, Moneyfarm, the preeminent Italian robo-advisor, offers investments exclusively in ETFs.
When assembling portfolios from the extensive array of available ETFs, robo-advisors generally employ a top-down selection methodology. Initial screening eliminates leveraged ETFs, those deficient in diversification, and specialized products, such as those focused on a single emerging market. ETFs with insufficient historical data or low liquidity are likewise excluded, as these constraints impede accurate estimation of volatility and correlations, which are critical elements for portfolio optimization. Finally, ETFs exhibiting persistent underperformance against benchmarks are discarded. Accordingly, the curated ETF universe for robo-advisory applications comprises merely 3-6% of all investable ETFs, encompassing highly liquid, broadly diversified, and cost-effective vehicles (Kaya, 2017).
Additionally, many robo-advisors incorporate principles from behavioral finance into their algorithms, acknowledging the frequent irrationality of investor behavior. These platforms mitigate such tendencies by enforcing a disciplined investment regimen that circumvents common human biases, including mechanisms such as automated rebalancing to avert panic selling amid market downturns or excessive purchasing during bull markets (Kulkarni et al., 2025).
In the final stage, robo-advisors continuously monitor and rebalance portfolios to maintain the intended risk profile and alignment with client objectives. Rebalancing is executed using either time-based methods, which adjust portfolios at fixed intervals (e.g., monthly or annually), or threshold-based methods, which trigger trades when allocations drift beyond predefined limits (Kaya, 2017). In practice, most platforms favour threshold-based rebalancing, leveraging automation to detect deviations and implement corrective trades. This approach reduces unnecessary turnover while keeping portfolios consistent with their designed risk–

return characteristics.

A key distinguishing characteristic among robo-advisors is the extent of investor interaction with human advisors, if any. In this regard, the industry distinguishes between pure and hybrid models.

Pure robo-advisors, such as Wealthfront and Betterment, embody full automation; they rely exclusively on algorithms and operate without any human advisory intervention. Their primary advantages lie in efficiency and cost reduction. By removing human involvement, these platforms can deliver services at significantly lower fees. This model tends to appeal particularly to younger generations, especially millennials, who are generally comfortable entrusting their financial management to algorithmic systems without requiring a human intermediary to explain the process in detail (D'Acunto et al., 2019).

Hybrid robo-advisors, by contrast, seek to merge algorithmic portfolio management with the professional judgment of human advisors. Their objective is to combine the scalability and operational efficiency of digital platforms with empathy, nuance, and personalization typical of human interaction. Notably, human involvement within hybrid systems can occur at any stage of the advisory process: during the client's utilization of the tool, amid the delivery of advice, or in subsequent follow-ups (Maume, 2021).

Empirical evidence underscores the significance of the hybrid approach. A substantial share of consumers (70% of individuals aged 18 to 54 and 77% of high-income clients) place high value on personalized financial experiences (EPAM Continuum, 2024). These findings highlight the hybrid model's ability not only to expand its market appeal but also to enhance client acquisition and retention. Reflecting this trend, hybrid robo-advisors currently dominate the sector, accounting for 63.8% of global industry revenue (Grand View Research, 2025). Their versatility attracts a wide array of investor profiles, ranging from technologically sophisticated users who appreciate low-cost, automated advice to individuals who occasionally require the deeper contextual insights that only a human adviser can provide (Belanche et al., 2019).

From the perspective of business models, robo-advisors can be categorized into four distinct types based on their operational structure and degree of integration within financial institutions. Standalone models, such as Betterment and Wealthfront, function independently and comply with regulatory frameworks like MiFID II, providing impartial, algorithm-driven advice without product-based incentives. In contrast, fully integrated robo-advisors, such as those offered by Vanguard and Charles Schwab, are embedded within established financial institutions and serve exclusively the institution's extant clientele. The robo-for-advice model equips traditional wealth managers with digital advisory tools to support and enhance their service offerings, whereas segregated robo-advisors retain operational autonomy, although they may collaborate with parent companies to offer complementary services (Garvía Vega, 2018; Agarwal et al., 2020).

For much of its history, the wealth management industry has been structurally inaccessible to a broad segment of investors, primarily serving high-net-worth individuals. This exclusivity has stemmed largely from substantial entry barriers, including significant minimum asset thresholds and high advisory fees, which have effectively prevented middle- and lower-income households from obtaining personalized financial advice. Traditional financial institutions frequently mandate initial investments of $25,000 or more, a requirement that remains prohibitive for many retail investors (Bianchi and Brière, 2023). These financial barriers have reinforced a pronounced concentration of participation in capital markets (Board of Governors of the Federal Reserve, 2023).

Financial inclusion represents one of the most significant promises of the fintech revolution: emerging technologies substantially reduce transaction costs, thereby extending access to individuals who have historically been underserved (Goldfarb and Tucker, 2019). Robo-advisors constitute a key component of this promise (Bianchi and Brière, 2023).

To begin, robo-advisors generally require far lower initial capital to open an account, often between $0 and $5,000 (Bianchi and Brière, 2023). For example, Bank of America requires a minimum of $20,000 for clients seeking one-on-one guidance from a Merrill Edge Financial Solutions Advisor, but only $1,000 to initiate an account with their automated Merrill Guided Investing platform. Certain advisors, such as Betterment, impose no minimum investment requirement whatsoever.

Second, robo-advisors typically charge management fees ranging from 0.25% to 0.50% of assets under management (AUM), compared with the industry norm of approximately 1% charged by human advisors. Beyond administrative fees, human advisors often impose additional charges for executed trades, costs that robo-advisors help minimize through passive investment strategies (Abraham et al., 2019).

Robo-advisors attain this cost efficiency via economies of scale, relying on a single, scalable algorithmic infrastructure capable of serving thousands of clients simultaneously. Betterment, for instance, serves more than 300,000 clients with about 200 employees, resulting in a client-to-employee ratio of more than 1,500:1. By contrast, a human financial advisor typically manages only 50 to 200 clients, highlighting the substantial operational leverage offered by robo-advisory platforms (Fisch et al., 2018).

The use of robo-advisors can also generate additional savings through "tax-loss harvesting", a strategy that involves selling securities that have depreciated to offset realized capital gains and thereby reduce taxable income, while preserving the portfolio's overall risk profile (Bianchi and Brière, 2023). This approach is implemented via algorithmic systems that perpetually monitor portfolio holdings to pinpoint tax-efficient opportunities. For example, Wealthfront may sell the Vanguard Total Stock Market ETF to realize a loss and then purchase the Dow Jones Broad U.S. Market ETF. Given that these two ETFs exhibit high correlation and deliver comparable market exposure, the substitution preserves the intended asset allocation while complying with IRS wash-sale regulations, which prohibit the repurchase of "substantially identical" securities within 30 days of a lossgenerating sale. Such real-time automated tax optimization would be prohibitively complex, time-consuming, and expensive for human advisors to execute manually. Moreover, robo-advisors operate entirely through digital platforms, enhancing accessibility in an era dominated by smartphones and tablets. Clients can manage their portfolios remotely using intuitive dashboards and graphical performance displays, obviating the need for in-person consultations (Sironi, 2016).

In addition to broadening access to investment services, robo-advisors help promote financial literacy. Many platforms offer educational resources designed to teach users the fundamentals of investing. By fostering a deeper understanding of personal financial management, these educational tools empower a wider range of individuals to take greater control of their financial assets (Hayes, 2021). Tan (2020) challenges this position. While robo-advisors enable more lay investors to participate in financial markets, these investors are restricted from actively managing their machine-curated portfolios. Therefore, new forms of financial exclusion may arise.

3. Methodology

This study adopts an empirical framework to evaluate the performance of Wealthfront's Classic Portfolios (Risk 5, 7.5, and 10), investing in ETFs, and the SandP 500 Total Return Index (SPTR) across the period from January 2013 through December 2023.

A five-step procedure is developed to conduct the analysis:

- Data collection;
- ETF cost adjustment;
- Portfolio construction;
- Backtesting;
- Comparative evaluation.

The analysis begins with the acquisition of asset allocation breakdowns for Wealthfront's Classic Portfolios at the three selected risk tiers (5, 7.5, and 10). Monthly total returns for each underlying ETF, adjusted for dividends, are sourced from the Bloomberg database, while SPTR Index returns serve as the passive benchmark. Additionally, benchmark data for multi-factor regressions (market, size, and value factors) and the U.S. risk-free rate are collected from the Kenneth R. French Data Library.

Each ETF comprising the portfolios is evaluated with respect to its expense ratio in order to compute its net returns. Annual expense ratios are transformed into their monthly equivalents and deducted from gross monthly returns to reflect realistic investor outcomes.

Table 1: Expense ratios of the ETFs in Wealthfront's Classic Portfolios

Asset Class	Ticker	Fund Name	Expense Ratio
Equity	VTI	Vanguard Total Stock Market ETF	0.03%
	VEA	Vanguard Developed Market ETF	0.05%
	VWO	Vanguard Emerging Market ETF	0.08%
	VIG	Vanguard Dividend Appreciation ETF	0.06%
Bond	LQD	iShares Investment Grade Corporate Bond ETF	0.14%
	SCHP	Shwab US TIPS ETF	0.05%

The next stage involves the reconstruction of Wealthfront's Classic Portfolios for the three selected risk levels (5, 7.5, 10). ach portfolio is formed by assigning the prescribed fixed asset weights to its underlying ETF components, as delineated by Wealthfront. These weights are assumed to remain constant throughout the sample period, thereby reflecting a static allocation. Over the long run, this approach offers a reliable approximation of effective asset exposures, enabling a more precise assessment of return drivers without introducing noise arising from rebalancing decisions.

Table 2: Wealthfront Classic Portfolios asset allocation by risk level

ETF	Risk 5	Risk 7.5	Risk 10
VTI (US Total Stock Market)	45%	45%	45%
VEA (Developed Markets ex-US)	9%	17%	22%
VWO (Emerging Markets)	7%	15%	19%
LQD (Investment-Grade Bonds)	26%	14%	2%
SCHP (TIPS)	13%	7%	1%
VIG (Dividend Appreciation Stocks)	0%	2%	11%

Furthermore, the annual robo-advisory fee of 0.25% is deducted, as it is levied in addition to the ETF-level expenses. Monthly returns for each portfolio (r_p) are therefore computed according to the following formula, where w_i denotes the weight of asset i, r_i its return, f_i the applicable ETF fee, and f_{RA} the robo-advisory fee:

$$r_p = \sum_{i=1}^{N} w_i \left[r_i - \left(\sqrt[12]{1+f_i} - 1 \right) \right] - \left(\sqrt[12]{1+f_{RA}} - 1 \right)$$

The subsequent phase consists of backtesting the three risk-level strategies and the SPTR benchmark index across the sample period. The primary objective is to compute monthly and cumulative returns to obtain key performance metrics, including mean returns, standard deviations, and Sharpe ratios. Monthly excess returns relative to the risk-free rate are then used to regress the portfolio returns on

the factor returns identified earlier to estimate factor loadings.
The single-factor specification follows the ex-post Capital Asset Pricing Model (CAPM) (Sharpe, 1964), in which the dependent variable is the portfolio's excess return and the independent variable is the market's excess return. This model allowes direct testing of whether the portfolios generate statistically significant alpha after controlling market risk. The analysis is subsequently extended to the Fama–French three-factor model (Fama and French, 1993), to determine whether performance is persistent also after adjusting for additional systematic risk factors, i.e. market (MKT), small minus big (SMB), and high minus low (HML).
As a concluding step, the results for each portfolio are compared both across the three Wealthfront portfolios and against the SPTR benchmark. The intra-group comparison assesses whether higher risk exposures were historically rewarded with proportionately higher returns and whether any allocation yielded a superior risk-adjusted performance. Concurrently, the benchmark comparison addresses a central question of the study: Could a private investor, by simply holding a broad passive market index, have achieved results comparable to, or superior to, those produced by a more complex, fee-based robo-advisory strategy?

4. Results

This section presents the principal findings of the backtest, highlighting the key results related to performance statistics.

Table 3: Risk and performance measures

	Risk 5	**Risk 7.5**	**Risk 10**	**SPTR**
Monthly return (%)	0.59	0.63	0.71	1.05
Annualized return (%)	7.35	7.87	8.86	13.31
Cumulative return (%)	191.33	196.95	211.21	311.49
Standard deviation (%)	3.18	3.65	4.13	4.38
Annualized standard deviation (%)	11.01	12.66	14.30	15.19
Monthly excess return (%)	0.49	0.53	0.60	0.94
Annualized excess return (%)	5.99	6.51	7.49	11.89
Sharpe ratio	0.67	0.62	0.62	0.88
Positive months (%)	65.83	63.33	64.17	68.33
Largest loss (%)	-10.67	-12.60	-14.05	-12.35
Largest gain (%)	8.68	9.81	11.25	12.82

The robo-advisor portfolios exhibited a clear ranking in returns, aligned with their respective risk levels: Risk 5 achieved a cumulative return of 191.3%, Risk 7.5 produced 196.9%, and Risk 10 reached 211.2%. This tiered performance was accompanied by increasing volatility, rising from 11.0% for Risk 5 to 14.3% for Risk 10, consistent with their intended risk–return tradeoff.

With respect to risk-adjusted performance, Risk 5 displayed the most favorable profile among the robo-advisor portfolios, with a Sharpe ratio of 0.67 compared with 0.62 for both Risk 7.5 and Risk 10. This indicates that higher risk exposure did not yield proportionately better risk-adjusted performance.
The SPTR Index substantially outperformed all three robo-advisor strategies, delivering a cumulative return of 311.5%, albeit with higher volatility of 15.2%. Its Sharpe ratio of 0.88 and more frequent positive monthly returns (68.3% versus 63.3–65.8% for the robo-advisors) illustrate the difficulty of outperforming a pure equity strategy during a prolonged bull market. Notably, despite its higher volatility, the SPTR Index experienced a smaller maximum drawdown (-12.35%) than the Risk 10 portfolio (-14.05%), possibly suggesting the presence of a more robust diversification within the broader market index.
The examination of risk-adjusted performance through both the CAPM and the Fama–French three-factor model provides further insight into the determinants of portfolio returns.

Table 4: Factor models outputs

CAPM	Risk 5	Risk 7.5	Risk 10	SPTR
Alpha	-0.09	-0.14	-0.16	0.12
T_stat (Alpha)	-0.74	-1.04	-1.05	0.83
Beta	0.62	0.71	0.81	0.88
T_stat (Beta)	23.79	24.88	25.79	30.24
Treynor ratio	0.79	0.74	0.75	1.07
R^2	0.83	0.84	0.85	0.89
FF3	**Risk 5**	**Risk 7.5**	**Risk 10**	**SPTR**
Alpha	-0.12	-0.17	-0.18	0.05
T_stat (Alpha)	-0.97	-1.23	-1.24	0.37
Beta (MKT)	0.63	0.73	0.83	0.92
T_stat (Beta MKT)	22.90	23.98	25.25	31.64
Beta (SMB)	-0.08	-0.09	-0.12	-0.21
T_stat (Beta SMB)	-1.75	-1.84	-2.16	-4.34
Beta (HML)	-0.01	0.03	0.07	0.01
T_stat (Beta HML)	-0.29	0.88	1.71	0.35
R^2	0.83	0.85	0.86	0.90

The analysis begins with the CAPM framework, wherein all three robo-advisor portfolios produced negative alpha estimates, ranging from -0.09 for Risk 5 to -0.16 for Risk 10, none of which were statistically significant, as indicated by t-statistics below conventional thresholds. This consistent pattern suggests that, after adjusting to market risk, the portfolios did not generate excess returns. Conversely, the SPTR

Index showed a small positive alpha (0.12), though it lacked statistical significance; this mild deviation from zero may reflect a mismatch between the chosen market proxy and the index itself.

Beta estimates aligned closely with the portfolios stated risk levels. The Risk 5 portfolio ($\beta = 0.62$), Risk 7.5 portfolio ($\beta = 0.71$), and Risk 10 portfolio ($\beta = 0.81$) showed progressively greater sensitivity to market movements. The SPTR Index exhibited a beta of 0.88, slightly below the theoretical expectation of 1.0, possibly owing to characteristics of the Fama–French market factor during the sample period.

Treynor ratios reinforced the SPTR Index's relative efficiency: its value of 1.07 exceeded those of the robo-advisors (0.74–0.79), indicating superior returns per unit of systematic risk.

Extending the analysis to the Fama–French three-factor model introduced additional nuance. Negative alphas became slightly larger, most notably for Risk 10 at -0.18, further underscoring the absence of performance beyond passive factor exposures. The SPTR Index's alpha decreased to 0.05, implying that some of its apparent CAPM outperformance reflected size and value factor tilts. Market beta remained stable across specifications, corroborating the CAPM findings. All portfolios exhibited negative SMB loadings, indicating a bias toward large-cap stocks. This effect was strongest for the SPTR Index (-0.21), consistent with its concentration in mega-cap equities. HML, i.e. value, loadings were near zero for most portfolios, except for a slight positive exposure for Risk 10 (0.07), which may correspond to marginal value tilts embedded in its most aggressive allocation.

The high R^2 values (ranging from 0.83 to 0.90) observed across both models offer important insights into the structural characteristics of Wealthfront's ETF-based portfolios. These results reflect the inherently passive construction approach of the strategy, in which portfolio returns are determined largely by systematic risk exposures rather than by active security selection. From a theoretical standpoint, the findings align closely with the Efficient Market Hypothesis and Modern Portfolio Theory: the portfolios behave as linear combinations of their underlying ETFs, which themselves are designed to track broad market indices, leaving little residual variation to be explained by managerial skill or idiosyncratic factors.

The empirical comparison between the robo-advisory portfolios and the passive benchmark indicates that although Wealthfront's portfolios successfully achieved their objective of offering graduated risk exposure, this came at a substantial performance cost relative to pure equity exposure over the study period. The structural design choices embedded in the robo-advisory framework largely explain this underperformance. While multi-asset diversification effectively reduces volatility, it also imposes significant opportunity costs in an environment where concentrated equity exposure generates substantial gains. This is particularly evident in the declining risk-adjusted performance at higher risk levels and the inability of increased equity allocations to produce commensurate improvements in Sharpe ratios.

These findings highlight a broader paradox in the practical implementation of Modern Portfolio Theory. Although robo-advisors apply academically grounded principles of diversification and risk management, the market's strong preference for concentrated growth exposure during this period curtailed their practical effectiveness. The results suggest that the value proposition of automated diversification strategies may lie less in delivering superior financial performance and more in providing behavioral advantages and risk management benefits, especially during periods of pronounced equity momentum.

The period from 2013 to 2023 was marked by exceptional monetary and macroeconomic conditions that materially shaped portfolio performance. In the years following the Global Financial Crisis, central banks adopted ultra-low interest rates and implemented extensive quantitative easing programs, creating a highly favorable environment for equity risk-taking (Bernanke, 2020). This policy landscape disproportionately benefited large-capitalization growth stocks, particularly within the technology sector, which contributed significantly to the SandP 500's overall returns. Accordingly, the SPTR Index's superior performance was partly driven by its concentrated exposure to these high-growth firms, whereas the broader diversification embedded in robo-advisor portfolios diluted this effect.

Pandemic-era stimulus measures further accelerated equity market gains during 2020–2021, as expansive fiscal and monetary interventions supported a rapid rebound in risk assets (Goldstein et al., 2021). However, the inflationary surge that followed, along with the interest-rate increases of 2022–2023, disrupted traditional cross-asset correlations and eroded the diversification benefits of fixed income investments within multi-asset portfolios. This dynamic helps explain why even the highest-risk robo-advisor portfolio (Risk 10) lagged behind the SPTR Index despite exhibiting nearly comparable volatility.

Although the findings for this period favor passive indexing, several caveats warrant attention. First, the fixed-weight methodology does not incorporate dynamic rebalancing or tax-loss harvesting, both of which could enhance robo-advisors' real-world performance (Kaya, 2017). Second, the extraordinary nature of the 2013–2023 market environment may not be indicative of future regimes in which diversification might exhibit greater utility. Third, behavioral considerations, such as automated discipline during market drawdowns, are excluded from the quantitative analysis, but may provide meaningful benefits for certain investors (Lam, 2016).

These limitations suggest that although passive indexing delivered superior results during this specific historical window, its dominance is not universally assured, and robo-advisors may offer compensatory advantages under different market conditions.

5. Conclusion

This study shows that passive indexing (SPTR) generated superior absolute and risk-adjusted returns compared with the three robo-advisor portfolios over the 2013–2023 period. Although the robo-advisors effectively fulfilled their primary objective of offering calibrated risk exposure, their multi-asset diversification introduced significant opportunity costs during a market regime that disproportionately rewarded concentrated growth exposure.

The value proposition appears strongest for conservative investors seeking automated portfolio management, whereas more aggressive investors incur advisory fees without receiving commensurate benefits. These findings imply that robo-advisors may function more effectively as tools for capital preservation than for return maximization, especially amid phases of robust U.S. equity market performance.

The results also highlight a central paradox in modern portfolio construction: engineered diversification strategies tend to lag during sustained bull markets, yet they provide meaningful risk mitigation and behavioral stability. Advancements in robo-advisory technology, such as adaptive factor allocation and market-regime-sensitive rebalancing, may enhance future performance while preserving the defensive qualities that define these platforms.

Ultimately, the choice between passive indexing and robo-advisory investing reflects a broader distinction between maximizing market participation and prioritizing risk management, a decision shaped as much by investor preferences as by empirical outcomes. While the findings validate passive strategies for the period under review, they also underscore the importance of adaptive frameworks as market conditions continue to evolve.

Looking ahead, the incorporation of more advanced artificial intelligence and additional emerging technologies is poised to further expand the capabilities of robo-advisors. These systems may become increasingly intelligent, personalized, and secure, gradually reshaping prevailing notions of financial planning. Nonetheless, significant challenges persist, particularly the need for robust regulatory oversight to preserve trust and stability. As robo-advisors continue to gain prominence, regulators and financial institutions must adapt accordingly to ensure that innovation does not come at the expense of investor protection.

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