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Robo-advisors vs. Traditional advisors: A comparative Study of Risk Management and Portfolio Performance

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ABSTRACT

This thesis investigates the comparative advantages of robo-advisors over traditional financial advisors in terms of cost efficiency, portfolio performance, and risk management. Results show that robo-advisory platforms deliver equivalent returns with significantly lower fees and reduced mid-term volatility. The findings support the value of automation as a scalable and disciplined approach to modern wealth management.

Keywords: Robo-advisors; Traditional financial advisors; Portfolio management; Cost efficiency; Algorithmic investing;

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Attestation

I Raphaël ZENOU-POEHR hereby declare that I am the sole author of this Master's thesis.

I hereby certify that it does not contain material which I have submitted for the qualification for any other degree.

I confirm that I am aware of and understand ESSCA's policy on plagiarism and I certify that all the sources that have been used to write this Master's thesis are explicitly referenced in conformity with the guidelines provided in the Master's thesis Handbook.

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Declaration on the Use of Artificial Intelligence

I, Raphaël ZENOU-POEHR, hereby declare that Artificial Intelligence (AI) tools were used exclusively to support the empirical implementation of this Master's thesis.

More specifically, AI was employed for the following technical purposes:

- **Python scripting assistance**: AI models were used to support the development of data processing scripts, including the automation of statistical computations, the formatting of batch outputs, and the generation of visualizations.
- **Data structuring and extraction**: Natural language processing models were leveraged to assist in the extraction of structured variables from U.S. SEC Form ADV Part 2 brochures. All forms were collected manually, and AI was applied solely for parsing and formatting the extracted content for subsequent human review.

No content generated by AI was included verbatim in the written sections of the thesis, and all analytical outputs were subject to human supervision and validation.

The exact prompts used during the data extraction phase are available in the cost_analysis/ directory of the project's GitHub repository, and are also included in ***Appendix 2 - ADV Parsing Prompt Specification***.

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1 Introduction

The transformational outcomes of technology on financial advisory services represent a major shift in the structure of modern investment management. This transformation is embodied by the emergence of robo-advisors, or Automated Financial Advisors (AFAs), defined as "digital platforms that offer automated, algorithm-driven financial planning and investment management services with minimal human intervention" (Brenner & Meyll, 2020). By leveraging advanced computational tools, these systems deliver personalized investment strategies at a fraction of the cost associated with traditional human advisors, providing a distinctive value proposition in an increasingly digitized financial marketplace.

The academic literature on robo-advisors is anchored in two major theoretical frameworks: Modern Portfolio Theory (MPT) and behavioural finance. MPT, developed by Markowitz (1952), establishes a normative model for portfolio construction that optimizes the trade-off between risk and return through diversification. Behavioural finance, inaugurated by Kahneman and Tversky (1979), identifies persistent cognitive biases—such as overconfidence, loss aversion, and herding—that impair rational investment behaviour and degrade long-term performance. These frameworks offer a powerful lens for assessing both the potential of AFAs and their empirical outcomes. Technologically, the integration of machine learning (ML) into robo-advisory platforms enhances their capabilities further. As shown by Rossi and Utkus (2021b), advanced ML techniques such as Boosted Regression Trees (BRT) allow iterative model improvement and refined portfolio personalization. Investor profiling and adaptive algorithms now enable what Reher & Sokolinski (2024) term a "double glide path", dynamically adjusting equity exposure based on age and wealth—a notable innovation over conventional target-date funds.

The relevance of this transformation is amplified by the recent explosion in the global fintech landscape. According to Statista (2024), the number of fintech companies more than doubled in just five years, reaching over 30,000 in early 2024. Within this expanding ecosystem, robo-advisory firms such as Betterment, Wealthfront, and Vanguard Digital Advisor have gained substantial traction, underpinned by growing Assets Under Management (AUM). This evolution responds not only to technological innovation but also to long-standing structural inefficiencies in traditional financial advising. Multiple studies have identified agency conflicts in conventional advisor-client relationships, with advisors often promoting high-cost, actively managed products despite empirical underperformance (Carhart, 1997; Linnainmaa et al., 2018). Robo-advisors, in contrast, offer a rules-based, fee-transparent model that may effectively mitigate such conflicts.

While the theoretical appeal of robo-advisory platforms is well-documented, the empirical validation of their actual performance, cost-efficiency, and behavioural impact remains incomplete. Much of the existing literature is descriptive or simulation-based, lacking comparative performance studies grounded in real-world financial data. In particular, the behavioural implications of automation—such as reduced overtrading or increased investment discipline—are widely hypothesized but rarely substantiated due to the opacity of platform-level data and the absence of investor-level behavioural metrics. This study thus identifies a dual gap: a lack of rigorous, comparative empirical analyses of cost and performance across advisor types, and an absence of accessible data for testing behavioural outcomes in robo-advisory usage.

Given these gaps, this thesis seeks to address the following central research question:

To what extent can robo-advisory platforms effectively reduce portfolio management costs and enhance investment performance, while simultaneously mitigating investors' behavioural biases relative to traditional financial advisors?

This research adopts a quantitative empirical approach. Phase 1 involves cost structure analysis based on regulatory filings and platform disclosures. Phase 2 evaluates risk-adjusted performance using annualized return, volatility, and Sharpe ratio metrics over one-, three-, and seven-year periods. All statistical computations are performed in Python (see Appendix 5) using open-source libraries such as pandas, NumPy, and scipy.

The contribution of this thesis is threefold. First, it provides empirical confirmation that robo-advisors deliver significant cost advantages. Second, it demonstrates that performance parity can be achieved without compromising risk-adjusted outcomes. Third, it identifies a critical data gap in assessing behavioural effects—an area that remains theoretically compelling but methodologically constrained. By offering a replicable framework for empirical analysis, the study supports both academic and practical advances in the evaluation of automated financial advice.

2 Literature Review

The financial advisory domain is on a crossroads that creates both change from the traditional methods of investment management and advances in technology capabilities. Such changes are driven by academic and market experiences that have run contrary to traditional models of advisement for a long time. Empirical evidence has shown how active management strategies tend to underperform passive benchmarks after treating all costs (Sharpe, 1991). More evidence was provided through detailed analysis where mutual fund underperformance is mainly generated by expenses, turnover, and transaction costs, with only a trivial portion of managers showing consistent skill (Carhart, 1991).

In response to these empirical challenges, the investment landscape witnessed the rise of passive management strategies, particularly through index funds that prioritize cost efficiency. However, this evolution coincided with advances in behavioural finance research during the late 20th century, introducing nuanced understanding of investment decision-making processes. Contemporary studies illuminate how cognitive biases influence both individual and institutional investors, affecting portfolio outcomes through systematic patterns of behaviour (Shanmuganathan, 2022).

The consistent presence of several behavioural biases, namely overconfidence, trend chasing, and loss aversion, have emerged as one of the major internal threats in portfolio management. A recent study suggested that, in practice, conventional advisors often fail to combat such biases effectively, at times even reinforcing them through their own decision-making processes (Linnainmaa et al., 2018). This barrier of tradition created room for technical innovation in automated financial advisers (AFAs).

The emergence of robo-advisory platforms marks a significant advancement in addressing these longstanding challenges. These systems leverage artificial intelligence and algorithmic trading mechanisms to deliver scalable, cost-efficient investment solutions while minimizing human bias. Leading platforms such as Wealthfront and Betterment exemplify this innovation through their automated approach to portfolio construction, diversification strategies, and systematic rebalancing protocols.

Recent empirical research supports the efficacy of these automated approaches. Studies demonstrate that robo-advisors achieve measurable success in mitigating behavioural biases while enhancing portfolio diversification (D'Acunto et al., 2019). Moreover, these platforms have expanded accessibility to sophisticated investment strategies for previously underserved demographic segments. However, some research suggests automated systems may face limitations during periods of heightened market volatility or when addressing complex, individualized financial planning needs (Berk and van Binsbergen, 2015).

The technological change continues to spark debates among scholars on performance perspectives. While a few researchers found considerable variations in robo-advisors' performance metrics (Puhle, 2019), others indicate that global platforms managed by algorithms could achieve far better results than current management techniques (Helms, 2021). However, this has to be weighed against certain potential downsides such as unintentional side effects, for instance, too much turnover in a portfolio might actually end up diminishing the returns on the investment (Horn, 2022).

Robo-advisory services do not just stop with the individual investment results; they can really rearrange how entire financial markets behave. This paradigm shows that fintech innovations, including robo-advisory services, lead to changing conditions in risk analyst behaviour of all these institutions which finally lead towards behavioural transformation of some kind in the intermediary pattern of the market (Deng, 2021). Such advances have been defined in terms of the Fourth Industrial Revolution, alleging to have the potential in transforming the field of investment management significantly due to the growing computation capacity for market scale (Tao, 2022).

This literature review seeks to critically examine the comparative advantages and limitations of AFAs across four key dimensions:

1. Behavioural bias mitigation: Evaluating the effectiveness of robo-advisors in addressing common cognitive biases compared to traditional advisors.
2. Portfolio performance: Analyzing risk-adjusted returns and cost-efficiency across investment strategies.
3. Diversification: Assessing the ability of different approaches to optimize asset allocation and minimize idiosyncratic risk.
4. Accessibility and democratization: Exploring the role of AFAs in broadening access to wealth management services.

2.1 Fundamentals Concepts

The theoretical foundation for analyzing modern financial advisory relationships stems from agency theory, first conceptualized in the context of organizational economics (Jensen and Meckling, 1976). This framework provides critical insights into the dynamics between principals (investors) and agents (financial advisors), particularly regarding the challenges of goal misalignment and information asymmetry. These dynamics carry significant implications for wealth management, where advisors make decisions that substantially impact their clients' financial well-being.

Conventional financial advisory models, while historically the most prominent, have structural weaknesses, from conflicts of interest to lack transparency. Recent studies suggest that these problems have worsened with the increasingly intricate financial markets, which often put a client at a disadvantage in terms of evaluating advisory quality (Reher and Sokolinski, 2024). This lack of information creates a blocking factor in the advisor-client equation that must be solved in modern enactments.

Agency theory says that agents can operate without sufficient oversight and may act in their own interests rather than those of the principals, giving rise to high agency costs. In financial advisory services, these costs take form in various guises, such as moral hazard or adverse selection. Research suggests that many financial advisers ration high-cost, actively managed funds, which have consistently underperformed passive alternatives, as due to the cognitive limitations they put in place (Linnainmaa et al., 2018). The trend coincides with earlier findings to show that mutual fund underperformance results mainly from high fees and turnover rather than lack of skill (Carhart, 1997).

The financial implications of these agency-related inefficiencies are substantial. Research indicates that mutual funds charging expense ratios above 1.5% typically generate returns 2-3% lower than comparable passive funds over ten-year periods (Bogle, 2002). Such performance disparities underscore the urgent need for mechanisms to reduce or eliminate agency costs, creating an opportunity for technological solutions like robo-advisors.

Foundational research in financial economics demonstrates the systematic inefficiencies inherent in active management strategies (Sharpe, 1991). Subsequent studies have expanded this analysis, showing that exceptional returns generated by skilled managers are typically offset by underperformance elsewhere, resulting in zero aggregate alpha (Fama and French, 2010). Recent research confirms these findings, noting that even among top-performing managers, value creation diminishes significantly after accounting for fees (Berk and van Binsbergen, 2015).

The agency issues manifest in practical terms in various problematic behaviors among traditional advisors. Excessive trading activity, a lack of portfolio diversification, and high-fee investment vehicles are typical manifestations of such agency behaviour which all erode long-term client wealth (Helms et al., 2022). The presence of very ineffective monitoring mechanisms adds to this type of adverse behaviour since most clients do not have the capabilities to effectively evaluate advisory quality. Such malpractice makes retail investors the most vulnerable because they usually accept advisor recommendations without thoroughly examining the fees associated with them or their underlying motivations (Isaia and Oggero, 2022).

This is the solution that technology provides to all these agency-related issues. They use algorithms to implement rule-based investment protocols, are extremely open-minded, and restrict human cognitive biases, and finally, make sure that the best investment solution is provided (Reher and Sokolinski, 2024). This illustrates ways that processes can be automated but still provide for ongoing portfolio optimization and a high level of reduction in management fees. The leading AFAs charge as little as 0.25% annually, but that is at least 1% higher than traditional financial advisors on average. This algorithmic way therefore eliminates any misaligned incentives from the traditional advisory model. Younger investors preferring to see through the fuzzy world of investment are attracted to this kind of objectivity, as reports do claim (D'Acunto et al., 2019). Moving toward algorithmic advisory services comes with its specific complications, however.

While such systems indeed perform better on both counts in cost efficiency and systematic execution in their process handling, they may also prove inadequate because they are often scripted to handle diverse and complex individual financial situations. Research shows that most current algorithms lack the flexibility to respond to unique client needs or to changes in market conditions (Berk and van Binsbergen, 2015). This lack of flexibility raises more concerns about the future of pure robo-advisory services for high-net-worth individuals or those having more complicated investment needs.

The reliance on algorithmic decision-making introduces new forms of agency costs. The quality of a robo-advisor’s recommendations is intrinsically tied to the robustness of its underlying data and model assumptions. Shanmuganathan (2020) notes that poorly calibrated algorithms can perpetuate systemic biases or amplify market risks, thereby undermining the very efficiencies they are designed to achieve. Additionally, Reher and Sokolinski (2024) caution that algorithmic models often fail to account for the unique financial circumstances of underrepresented investor groups, further complicating their role in democratizing access to wealth management.

These concerns highlight the need for rigorous oversight and continuous refinement of algorithmic models to ensure their long-term efficacy. As Oehler and Horn (2024) suggest, the integration of adaptive learning algorithms capable of responding dynamically to market conditions could address some of these limitations. Furthermore, hybrid models that combine the scalability of robo-advisors with the personalized insights of human advisors may offer a balanced approach, aligning the strengths of both systems to address the diverse needs of modern investors. By strategically allocating client portfolios while incorporating behavioural insights, hybrid models promise to mitigate the rigidity of purely algorithmic strategies and the biases inherent in human-led advisories..

2.2 Behavioural Bias Mitigation

Intersecting behavioural finance with automated advisory services is arguably the most substantive development in attempting to overcome the cognitive biases that result in specific investment outcomes. Research carried out in behavioural economics found such biases to be entrenched determinants in the process of making inferior financial decisions (Kahneman and Tversky, 1979). Such integrated behavioural perspectives with respect to robo-advisory frameworks have brought about a transformation in orientation to investor psychology by financial services. New studies depict how algorithmic systems promote rationality in retail and institutional strategy as they apply to investing (D'Acunto et al., 2019).

One of the most far-reaching cognitive biases in financial decisions leading to overconfidence about the ability to predict the market. This usually leads to high trading and poor diversification of a portfolio. According to research, typical financial advisers show similar patterns of overconfidence due to their training, and often promote actively managed funds but their performance is less than that of the fee-adjusted returns (Linnainmaa et al., 2018).

Automated advisory platforms address this overconfidence through rule-based algorithmic systems that prioritize long-term investment objectives and systematic diversification. These platforms implement consistent rebalancing protocols that align portfolios with predetermined objectives, removing emotional influences from the investment process (D'Acunto et al., 2019). Evidence shows that leading platforms achieve enhanced risk-adjusted returns through systematic approaches such as tax-loss harvesting and algorithmic portfolio adjustments (Horn and Oehler, 2020).

Loss aversion represents another significant behavioural challenge, manifesting in investors' disproportionate focus on avoiding losses rather than securing gains. Research demonstrates this bias through the "disposition effect," where investors prematurely liquidate profitable positions while retaining underperforming assets. Studies estimate that this behaviour can reduce annual portfolio returns by up to 4% for individual investors (D'Acunto et al., 2019).

Robo-advisors combat loss aversion through automated rebalancing mechanisms that enforce systematic, counter-cyclical asset allocation. These systems redistribute capital between overperforming and underperforming asset classes, maintaining intended risk-return profiles regardless of market conditions. Evidence suggests that automated platforms successfully maintain disciplined allocation strategies during moderate market volatility, though challenges persist during extreme market conditions (Horn and Oehler, 2020).

Herding behaviour presents a third critical challenge in investment decision-making, occurring when investors mirror peer actions without independent analysis. This phenomenon often leads to asset concentration and price inflation, potentially creating systemic risks through amplified market volatility. Historical examples, including the dot-com bubble and the 2008 financial crisis, demonstrate the destructive potential of herding behaviour (D'Acunto et al., 2019).

2.3 Diversification

AFAs then proceeds to achieve wide diversification across asset classes, sectors, and geographical areas, in effect reducing exposure to idiosyncratic risks. However, research shows that such diversification strategies will not be effective for system-wide market shocks-such as happened during the COVID-19 pandemic, since fixed models could not adapt to unprecedented market conditions (Deng et al., 2021).

While automated systems demonstrate effectiveness in addressing behavioural biases during normal market conditions, their reliance on historical data presents challenges during unprecedented events. Studies indicate that algorithmic models may struggle to adapt to black swan events or significant geopolitical disruptions (Horn and Oehler, 2020). This limitation has prompted increased interest in hybrid advisory models that combine algorithmic efficiency with human judgment, particularly for managing complex financial scenarios during periods of market stress (Shanmuganathan, 2020).

The evolution of behavioural finance principles within robo-advisory frameworks represents a significant advancement in financial services. These platforms demonstrate measurable success in counteracting common behavioural biases while democratizing access to sophisticated investment strategies. However, their effectiveness during extreme market conditions remains an area for continued development. The emergence of hybrid models offers a promising solution by combining algorithmic precision with human expertise to address diverse client needs and market conditions (Reher and Sokolinski, 2024).

2.4 Portfolio Performance and Technology

The technological foundation of modern robo-advisory platforms represents a convergence of ML capabilities and advanced financial algorithms. These technological innovations enable automated complex decision-making processes, transforming portfolio management approaches previously reserved for institutional investors. Research demonstrates how these platforms effectively address traditional inefficiencies in advisory services through computational precision (D'Acunto and Rossi, 2019).

ML technologies serve as the cornerstone of modern robo-advisory systems, facilitating sophisticated data analysis for market behaviour prediction and investment optimization. These platforms employ supervised learning algorithms to forecast asset performance based on multiple factors, including historical trends and macroeconomic indicators. Studies indicate that these systems successfully identify complex correlations that often elude human analysis, enabling more precise asset allocation decisions (Puhle, 2019).

The enhancement in client segmentation capabilities by the application of unsupervised learning algorithms is the engine through which complex analysis of behavioural and demographic patterns occurs. Systems segment investors on multiple variables such as risk tolerance, investment horizons, and income stability. Evidence points out that this phenomenon of micro-segmentation enables precise portfolio customization, which, in most cases, has been cited as one of the main drawbacks of the conventional advisory models that typically apply a standardized approach (Helms et al., 2022).

The Modern Portfolio Theory underpins robo-advisory services in theory, which stresses optimal portfolio construction through diversification principles with its benefits. And all these suggest that indeed automated platforms continuously keep in line with the efficient frontier-presenting portfolios that give maximum expected returns on specified levels of risk (Markowitz, 1952). Robo-advisors, in contrast to human advisors, do not get caught in what behavioural finance calls a behavioural bias. They follow strict mathematical optimization protocols that guarantee uniform performance across client segments (Puhle, 2019).

Current AFAs differ and excel in that it applies adaptive algorithms in real time to change portfolios. These systems are able to continuously analyze the market activity, client behaviour patterns, and macroeconomic trends and recommend the optimal portfolio during a specified period. Research shows how automated rebalancing protocols do a great job of maintaining target risk-return profiles while avoiding emotional decision making (D'Acunto et al., 2019). These types of systematic mechanisms avoid being excessively overexposed to particular segments of the market yet still ensure a disciplined commitment to investment over the long term.

Advanced methodologies such as *BRT* represent the cutting edge of robo-advisory capabilities. These sophisticated algorithms capture non-linear relationships between multiple variables, enabling nuanced investment strategies. Studies show how *BRT* models effectively integrate factors such as income growth patterns, regional economic trends, and market cycles to generate highly personalized portfolio recommendations (Rossi and Utkus, 2021).

However, technological advancement brings inherent challenges. A primary concern centers on the reliance on historical data for algorithm training, potentially limiting adaptability to unprecedented market conditions. Research indicates that algorithms trained on pre-2010 data may struggle with emerging phenomena such as cryptocurrency markets or ESG investment considerations (Reher and Sokolinski, 2024). Moreover, automated platforms often face limitations in managing complex scenarios such as estate planning or cross-border tax optimization (Deng et al., 2021).

Algorithmic bias certainly ranks among the big challenges concerning data quality and representation. From the analysis, training datasets mostly reflect the affluent, technologically astute investors and tend to create poor recommendations for underrepresented groups. Evidence states that lower-income investor portfolios usually do not have much diversification, focusing more on domestic assets (Shanmuganathan, 2020).

Indeed, further advancements in *Industry 4.0* technologies are already set to bring transformations into financial advisory services augmented by improved automation and data analytic capabilities. Research has shown how these developments reduce costs of operations but improve access to sophisticated strategies in investments (Schwab and Gomber, 2017). Nonetheless, the successful launching into operations of these advancements requires a more determined appreciation of the technological limitations under which they could function and commitment to continuous improvement of the algorithms.

2.5 Accessibility and democratization

Automated advisory services must be integrated into the financial ecosystem without also failing to consider scrutiny by different regulators and future market outlooks. *Industry 4.0* technologies entirely reshape the traditional financial paradigms through the confluence of artificial intelligence, blockchain infrastructure, and advanced analytics. They have shown by research how they can improve efficiency and broaden access to financial services (Schwab and Gomber, 2017).

An example of financially democratizing fintech is robo-advisory platforms, which use algorithm-based frameworks to widen access to high-caliber wealth management services. They have proven that automated platforms bring down, if not eliminate, the barriers set up by traditional investment services, particularly for mid-and lower-income investors (Reher and Sokolinski, 2024). Leading platforms demonstrate equal access through simplified fee structures and reduced minimum investments, thus effectively widening participation in the market (Isaia and Oggero, 2022).

The enhancement of personalization capabilities through AI-driven analytics represents a significant advancement in automated advisory services. Research shows how real-time data processing enables precise strategy customization based on individual financial objectives and risk preferences. These capabilities particularly resonate with younger demographic segments who prioritize technological integration and service flexibility (D'Hondt et al., 2020). Evidence indicates that features such as automated rebalancing and tax optimization significantly enhance both portfolio performance and user engagement (Reher and Sokolinski, 2024).

However, the proliferation of algorithmic systems introduces important structural considerations regarding inclusivity and fairness. Studies reveal that automated platforms sometimes struggle with representation bias, as their training datasets often disproportionately reflect affluent, technologically sophisticated investor behaviour patterns. Research demonstrates how this bias can result in conservative portfolio recommendations for underrepresented demographics, potentially limiting long-term wealth accumulation opportunities (Shanmuganathan, 2020).

Regulatory frameworks play an increasingly critical role in ensuring algorithmic fairness and transparency. The European Union's Artificial Intelligence Act exemplifies emerging regulatory approaches, establishing requirements for high-risk AI applications in financial services. These regulations mandate comprehensive documentation of algorithmic processes and regular bias assessment protocols (Deng et al., 2021). Such regulatory initiatives demonstrate growing recognition of oversight importance in maintaining market integrity and investor protection.

Blockchain technology emerges as a complementary innovation within the Industry 4.0 framework, enabling secure, decentralized financial transactions. Research indicates that blockchain infrastructure enhances payment system efficiency while reducing intermediation costs (Gomber et al., 2017). Studies particularly highlight blockchain's potential in expanding financial service accessibility through branchless banking models, effectively serving previously underserved market segments (Puhle, 2019).

The evolution of hybrid advisory models represents a promising development in addressing automated system limitations. These models effectively combine algorithmic precision with human expertise, particularly valuable for complex financial planning scenarios. Evidence demonstrates their effectiveness during market volatility periods, where human advisors provide critical emotional support and strategic guidance (Helms et al., 2022). However, research also indicates that hybrid models face implementation challenges, particularly regarding cost structures and seamless integration of human and automated components.

Looking forward, the success of automated advisory services depends on their ability to address several critical challenges. These include developing more inclusive algorithms, enhancing adaptability to unprecedented market conditions, and maintaining cost efficiency while expanding service sophistication. Research suggests that continued technological advancement, coupled with thoughtful regulatory oversight, will shape the next evolution of financial advisory services (Reher and Sokolinski, 2024).

The transformation of financial advisory services through Industry 4.0 technologies represents both significant opportunities and important challenges for market participants. As these platforms continue to evolve, their success will increasingly depend on balancing technological innovation with regulatory compliance, while ensuring equitable access to financial services across diverse demographic segments

3 Hypotheses

Based on the theoretical frameworks discussed above - particularly agency theory, behavioural finance, and technological innovation in financial services - we propose three hypotheses that will guide our empirical investigation. These hypotheses address key aspects of robo-advisory services and their impact on portfolio management, focusing on cost efficiency, performance, and behavioural aspects.

Our first hypothesis examines the cost-reduction potential of automated financial advisory services, building on the agency theory literature that highlights the cost implications of traditional advisory models. The second hypothesis explores the effectiveness of hybrid models in portfolio management, acknowledging both the advantages and limitations of pure algorithmic approaches identified in the literature. Finally, our third hypothesis addresses the behavioural dimension of automated investment services, examining their potential to mitigate cognitive biases that traditionally impact investment decisions.

H1: *The use of robo-advisors reduces portfolio management costs.*

H2: *Automated advisors provide better returns than traditional ones*

H3: *Investment automation reduces investors' behavioural biases.*

These hypotheses will be tested using a comprehensive methodology that combines quantitative analysis of portfolio performance data with behavioural assessment metrics, as detailed in the following sectio

4 Empirical Analysis

4.1 Introduction

4.1.1 Research Design

This study adopts a quantitative methodological approach to examine the comparative effectiveness of robo-advisory platforms, traditional financial advisors, and hybrid advisory models regarding cost efficiency, portfolio performance, and behavioural bias mitigation. The empirical framework is systematically structured to empirically test the hypothesis.

This research employs rigorous statistical methods and comprehensive financial analyses based exclusively on publicly accessible data, ensuring transparency, replicability, and academic rigor.

4.1.2 Data Collection and Sample Selection

The empirical analysis relies on publicly available online databases, ensuring methodological transparency and reproducibility. Primary data sources include:

- **Yahoo Finance:** Historical performance metrics for mutual funds and index funds (daily returns, volatility metrics).
- **Morningstar.com:** Publicly available mutual fund data, including expense ratios, portfolio category and portfolio composition.
- **U.S. Securities and Exchange Commission (SEC):** Publicly disclosed regulatory filings (Form ADV) detailing advisory fees and related cost structures.
- **Bloomberg:** For indices data.

The study covers a comprehensive period from **January 2017 to December 2024** capturing a broad spectrum of market conditions, including significant recent crises. The dataset comprises portfolios divided across three advisory groups: robo-advisors, traditional advisors, and hybrid advisory models.

The sample criteria are as follows:

- Investment size: USD 500,000

- Minimum operational period: 24 months
- Standardized asset allocation baseline: Moderate Risk (60% equities, 40% fixed income)
- Geographic focus: United States (USD denominated)

4.1.3 Analytical Framework

The analytical framework comprises four distinct but interrelated analytical phases:

4.1.3.1 Phase 1: Cost Structure Analysis (H1)

The first phase of the empirical investigation examines whether automated advisory platforms offer a more cost-efficient investment structure than traditional human-led advisors. This analysis addresses Hypothesis H1, which posits that robo-advisors and hybrid models significantly reduce portfolio management costs relative to traditional advisory firms.

The comparison is based on three core variables:

- **Expense Ratio** the highest disclosed management fee for a standardized $500,000 portfolio allocated 50% to equities and 50% to bonds.
- **Tax Efficiency Score** a composite metric (0–10) constructed from five binary indicators reflecting explicit tax optimization practices (e.g., tax-loss harvesting, asset location strategies).
- **Log-transformed Assets Under Management (log AUM)** used as a proxy for institutional scale and as a control for structural disparities across advisory models.

Data were extracted from SEC Form ADV Part 2 brochures for 36 advisory entities (18 automated, 18 traditional), parsed through a custom Python pipeline, and validated via manual cross-verification. The final dataset was curated to ensure consistency and replicability.

To evaluate group-level differences, the analysis employs the Mann–Whitney U test, a non-parametric method suited to small, independent samples with non-normal distributions. All computations and visualizations were executed in Python, within a documented and reproducible research environment.

The variable “transaction costs” was excluded from the inferential analysis due to inconsistent or incomplete disclosure across the sample.

4.1.3.2 Phase 2: Risk-Adjusted Performance Analysis (H2)

The second phase of the empirical investigation addresses Hypothesis H2, which assesses whether portfolios managed by automated advisory platforms deliver superior performance when adjusted for risk, compared to portfolios managed by traditional human advisors. This analysis is conducted over three investment horizons—1 year, 3 years, and 7 years—ending on December 31, 2024.

The evaluation is based on three key metrics:

- **Annualized Return** (geometric mean of monthly returns)
- **Annualized Volatility** (standard deviation of monthly returns, scaled by $\sqrt{12}$)
- **Sharpe Ratio** calculated using a composite benchmark composed of 60% MSCI World Index and 40% Bloomberg Aggregate Bond Index as a proxy for the risk-free rate.

The dataset includes 13 traditional portfolios and 13 automated portfolios, selected from the “Global Moderate Allocation” category to ensure consistency in investment strategy and risk profile. Traditional portfolio data were retrieved from Yahoo Finance, while the performance of automated portfolios was compiled from validated third-party sources.

To test for statistically significant differences between groups, the analysis relies on Welch’s t-test, a parametric method robust to unequal variances.

4.1.4 <u>Technical Implementation</u>

All empirical analyses were conducted in Python within a modular, version-controlled, fully reproducible computational environment. The analytical pipeline involves the following open-source libraries:

- **Data Collection & Processing**: pandas, NumPy, and yfinance were used to retrieve historical fund prices, compute monthly returns, and transform time series into standardized formats suitable for multi-horizon analysis.
- **Statistical Inference**: The scipy.stats module facilitated the use of Welch's t-tests to compare means with heteroscedasticity, as well as Mann–Whitney U tests for

distributional comparisons under non-parametric conditions. Permutation-based inference was enabled through custom routines coded by the authors using NumPy and random.

- **Visualization**: All plots including boxplots, bar charts, and distributional comparisons were plotted simply with matplotlib and seaborn, adhering to academic styling restrictions: grayscale schemes, high-resolution export resolution (300 DPI), and embedded Times New Roman fonts only.
- **To ensure Reproducibility & Version Control**: All scripts and outputs were deposited following a structured project hierarchy. The entire codebase, along with routines for loading and analyzing data and plotting, is also public on GitHub for reproducibility and peer review:
  - **https://github.com/raphphrz/afas_masterthesis_essca**

The project deliberately focused on interpretability and transparency, and did not require the use of advanced econometric libraries such as statsmodels, arch, pypfopt, or QuantStats, given the scope of metrics retained and the sample structure.

4.1.5 Robustness Checks and Methodological Limitations

The robustness of the results was primarily addressed using multiple statistical testing frameworks. For each performance dimension—return, volatility, and Sharpe ratio—group comparisons were conducted using both parametric (Welch's t-test) and non-parametric (permutation testing) methodologies. This dual approach mitigates the risk of inference distortion due to non-normality or variance heterogeneity, particularly given the moderate sample size and observed dispersion in volatility and Sharpe ratios.

However, several limitations must be acknowledged. First, the analysis relies on a finite number of portfolios (n = 44 / 26), which—while balanced between automated and traditional groups—may limit statistical power for marginal differences. Second, the automated portfolios are based on harmonized third-party performance data, whereas traditional fund metrics were reconstructed from raw price series, potentially introducing methodological asymmetries despite efforts to standardize computation pipelines. Third, certain advanced risk metrics (e.g., Sortino ratio, Value-at-Risk, Jensen's alpha) were excluded due to incomplete disclosure on the automated side.

Finally, while the selection of funds was based on objective Morningstar categorization criteria ("Global Moderate Allocation"), residual selection bias cannot be entirely ruled out. All methodological constraints were transparently documented, and code-based replicability has been ensured to support critical validation and future extension.

4.2 Phase 1: Cost Structure Analysis

This initial phase of the empirical investigation aims to assess the cost efficiency of robo-advisors compared to traditional and hybrid financial advisory models. The objective is to evaluate whether the use of automated portfolio management tools effectively reduces the overall investment costs borne by clients, as formalized in hypothesis **H1**.

4.2.1 Data Source and Collection Procedure

Data were systematically collected from SEC Form ADV Part 2 brochures, which registered investment advisers are required to file with the U.S. Securities and Exchange Commission. These documents provide standardized disclosures on fee structures, advisory services, discretionary and non-discretionary AUM, and other firm-level characteristics relevant for empirical analysis. A total of 44 ADV documents were compiled and processed, with an equal distribution across three predefined advisory categories: robo-advisors, hybrid advisory models, and traditional human-led advisory firms.

To ensure replicability and analytical rigor, each Form ADV was extracted in PDF format and processed using a Python-based automated parsing engine. This pipeline leverages OpenAI's GPT-4.1-mini model, which was strictly instructed to extract only explicitly stated variables without inference or assumption[1]. If any key metric—such as management fee, transaction costs, or AUM—was not explicitly reported in the document, the corresponding database field was left blank.

All extracted values were subjected to a systematic human review. This step aimed to correct any residual misclassifications or misreading by the language model, ensure consistency in units (e.g., percentages versus basis points), and validate context-specific footnotes or exceptions (e.g., fee reductions based on account size or service tier). Following this review, manual adjustments were applied directly to the structured SQLite database as needed.

[1] View code: https://github.com/raphphrz/afas_masterthesis_essca/blob/main/costs_analysis/main.py

Furthermore, each advisory entity was reassessed and, if necessary, reclassified into one of the three model categories (Robo-advisor, Hybrid, Traditional) based on comprehensive reading of the ADV narrative sections and service descriptions. In particular, platforms initially tagged as "Hybrid" were scrutinized to determine whether human advisory services were offered in a discretionary or consultative manner, and whether they were accessible to all clients or limited to premium tiers. This classification process is documented in the annotated dataset made available on GitHub[2].

4.2.2 Cost Variables and Standardization

For each advisory entity, we extract the following quantitative variables:

- **Expense Ratio**: the highest applicable management fee (in %) for a $500,000 investment under a 50/50 equity/bond portfolio allocation. If a fee range was provided, the upper bound applicable to that investment level was retained. Importantly, the analysis excludes any underlying fund expenses, such as the management fees embedded within ETFs or mutual funds used by the advisor. Only the direct advisory fee charged by the portfolio manager or platform is considered, in accordance with the scope of this study.
- **Transaction Costs**: any additional fees associated with trading activity, custody, fund transfers, or brokerage commissions, expressed as a percentage.
- **Assets Under Management (AUM)**: total discretionary AUM reported by the firm, serving as a proxy for client base size and market position.
- **Document Date**: the effective reporting date of the Form ADV, used to align disclosures with prevailing market conditions at the time of filing.

All extracted variables were stored in a structured, normalized SQLite database. Each row of data includes a free-text field summarizing the extraction context, source location, and any relevant

[2] Link to final dataset:
https://github.com/raphphrz/afas_masterthesis_essca/blob/main/costs_analysis/Portfolio_Analysis_final.xlsx

limitations (e.g., partial disclosure or outdated reporting). This annotation field also supports traceability in cases where data had to be corrected or interpolated by human validation.

4.2.3 Tax Efficiency Score

To complement the direct cost analysis, a standardized tax efficiency score was computed for each advisory platform. This variable, ranging from 0 to 10, reflects the extent to which an advisor offers structured, tax-optimized investment services. The score was based on five independent binary indicators, each weighted equally at 2 points:

- **Tax-loss harvesting** services explicitly mentioned
- **Tax-optimized asset location** strategies offered
- **Use of ETFs or index funds** as underlying instruments
- **Explicitly reported turnover rate below 50%**
- **Client-specific tax strategy disclosures**, including separate taxable and retirement account treatment

Platforms that met all five criteria received a score of 10. If none of these features were present or disclosed, the score was 0. This approach ensures uniformity across heterogeneous disclosures and provides a robust proxy for tax optimization efforts.

A presentation of the dataset, including all human-reviewed adjustments and classification decisions, is provided in

4.2.4 Grouping Rationale and Comparative Strategy

Given the moderate size of the final analytical sample (n = 44) and the observed distribution imbalance across advisory models—particularly the limited number of hybrid advisors (n = 6)—the initial three-group structure was adapted to ensure the robustness of statistical testing. In alignment with the core research objective of assessing the impact of automation on investment costs, hybrid advisors were grouped with robo-advisors under a single classification: automated advisory models.

This decision is theoretically supported by the fact that hybrid platforms, although incorporating human advisory components, systematically rely on algorithmic portfolio construction and rebalancing engines. They thus share the foundational feature of automation that differentiates them from fully discretionary, human-led traditional advisors.

Following a manual data-cleaning process, several portfolios were excluded due to critical omissions such as missing AUM, undefined document dates, or inconsistencies in data extraction. The **final sample** (see *Table 7 - Final Advisors Data Set - Cost Structure)* retained for quantitative analysis includes:

- **Automated Advisory Models (n = 18)**
  Including platforms that rely primarily on algorithmic asset allocation and automatic portfolio rebalancing, with or without optional access to human advisors.
- **Traditional Advisory Models (n = 18)**
  Including portfolios constructed and monitored by human financial advisors using discretionary methods.

This binary classification forms the basis for the comparative analysis of cost-related outcomes across models.

4.2.5 Variable Selection and Statistical Testing

Three core variables were retained for hypothesis testing:

- **Expense Ratio**
- **Tax Efficiency Score**
- **Log-transformed AUM**

Note: *The variable transaction_costs was excluded from the statistical analysis due to inconsistent and often missing reporting across Form ADV filings.*

4.2.5.1 Mann–Whitney U test

To test for statistical differences between the Automated and Traditional groups, we employed the Mann–Whitney U test, a non-parametric test appropriate for small samples and non-normal distributions.

Let:

n_1 and n_2 be the sample sizes for each group,

R_1 be the sum of ranks for group 1,

Then the U statistic is defined as:

$$U_1 = n_1 n_2 + \frac{n_1(n_1 + 1)}{2} - R_1$$

To assess statistical significance, the test statistic is converted into a z-score under a normal approximation:

$$Z = \frac{U - \mu_U}{\sigma_U}, \mu_U = \frac{n_1 n_2}{2}, \sigma_U = \sqrt{\frac{n_1 n_2 (n_1 + n_2 + 1)}{12}}$$

A two-sided p-value was computed for each variable using this transformation. A significance threshold of 5% (α = 0.05) was applied.

4.2.6 <u>Implementation in Python</u>

All cost analysis computations were conducted in Python and structured as a modular, transparent, and reproducible pipeline. The complete codebase is hosted on GitHub at: https://github.com/raphphrz/afas_masterthesis_essca/tree/main/costs_analysis

4.2.6.1 Project Structure and Modules

The cost analysis was implemented in the `costs_analysis/` directory, organized to separate data preprocessing, statistical computation, and output generation. The following files form the analytical backbone:

- **import_reprocess.py:** Parses and integrates manually cleaned ADV Part 2 data into a structured SQLite database (`portfolio_data.db`).
- **analysis.py:** Computes descriptive statistics, performs the Mann–Whitney U test, and generates plots.
- **export.py:** Exports test results and descriptive statistics to Excel.

4.2.6.2 Selected Code Snippets

4.2.6.2.1 Advisor Classification and AUM Transformation (analysis.py)

```
# Classify advisors as Automated or Traditional
AUTOMATED = ["Robo-advisor", "Hybrid"]
df["advisor_group"] = df["advisor_type"].apply(lambda x: "Automated" if x in AUTOMATED else "Traditional")

# Log-transform AUM to reduce skewness
import numpy as np
df["Log AUM"] = np.log1p(df["assets_under_management"])
```

This transformation ensures the asset size distribution is less sensitive to large outliers, facilitating more robust statistical comparisons.

4.2.6.2.2 Mann–Whitney U Test (analysis.py)

```
import pandas as pd
import numpy as np
from scipy.stats import mannwhitneyu

# Prepare the advisor groups
df["advisor_group"] = df["advisor_type"].apply(lambda x: "Automated" if x in ["Robo-advisor", "Hybrid"] else "Traditional")
df["log_aum"] = np.log1p(df["assets_under_management"])

# Mann-Whitney U test
def run_mannwhitney(var):
    group1 = df[df["advisor_group"] == "Automated"][var].dropna()
    group2 = df[df["advisor_group"] == "Traditional"][var].dropna()
    return mannwhitneyu(group1, group2, alternative='two-sided')

# Apply test to selected variables
results = {}
for var in ["expense_ratio", "tax_efficiency", "log_aum"]:
    stat, pval = run_mannwhitney(var)
    results[var] = {"U-statistic": stat, "p-value": pval}

results_df = pd.DataFrame(results)
```

The non-parametric Mann–Whitney U test is used due to the presence of heteroskedasticity and non-normality in several variables, particularly Expense Ratio.

4.2.6.2.3 Visualization with Boxplots (analysis.py)

```
import seaborn as sns
import matplotlib.pyplot as plt
import os

sns.set(style="whitegrid")
plt.rcParams.update({"font.family": "Times New Roman"})
colors = ["white", "black"]

for var in ["Expense Ratio", "Tax Efficiency", "Log AUM"]:
    plt.figure(figsize=(8, 5))
    sns.boxplot(x="advisor_group", y=var, data=df, palette=colors)
    plt.title(f"{var} by Advisor Group")
    plt.tight_layout()
    plt.savefig(f"results/plots/{var.replace(' ', '_').lower()}_boxplot.png", dpi=300)
    plt.close()
```

Each variable is visualized using boxplots formatted in grayscale with clear distinction between groups.

4.2.6.3 Automated Output Generation

All statistical outputs, including descriptive statistics, test results, and figures, are stored in the `results/` directory. The script `export.py` consolidates all outputs into a single timestamped Excel file for traceability:

```
with pd.ExcelWriter(EXPORT_FILE, engine="xlsxwriter") as writer:
    df.to_excel(writer, sheet_name="Raw Data", index=False)
    summary.to_excel(writer, sheet_name="Summary Stats")
    results_df.to_excel(writer, sheet_name="MannWhitneyU")
```

This modular and automated setup ensures full reproducibility of all cost analysis steps, from raw database querying to final statistical interpretation.

4.2.7 Findings

This section presents the findings from the empirical analysis aimed at evaluating **Hypothesis H1**, which posits that *the use of robo-advisors reduces portfolio management costs*. The refined dataset comprises 36 observations, evenly split between **automated** and **traditional** advisory models (n = 18 each).

Table 1 - Descriptive Statistics by Advisor Group

Group	**Expense Ratio**				**Tax Efficiency**				**Log AUM**			
	x̄	σ	M	n	x̄	σ	M	n	x̄	σ	M	n
Automated	**0.37**	0.26	0.35	18	7.33	1.19	8.00	18	22.64	2.94	22.74	18
Traditional	**1.29**	0.83	1.13	18	6.67	0.97	6.00	18	25.08	3.42	26.64	18

Table 2 - Mann–Whitney U Test Results

Variable	U-statistic	p-value
Expense Ratio	53	**0.0006 < 0.05**
Transaction Costs	*162.5*	*1.0000 > 0.05*
Tax Efficiency	210	0.0859 > 0.05
Log AUM	89	**0.0218 < 0.05**

4.2.7.1 Expense Ratio

Among the clearest results in the analysis is the substantial and statistically significant difference in management fees. Traditional advisors exhibited a mean expense ratio of **1.29%** (σ = 0.83), while automated platforms reported a considerably lower average of **0.37%** (σ = 0.26). Median values further reinforce this difference, at **1.13%** for traditional models versus **0.35%** for automated ones.

The Mann–Whitney U test returned a **U statistic of 53** with a **p-value of 0.00058**, indicating a highly significant difference at the 1% level. This result is visually corroborated by Figure 1, which shows a tighter, more compressed distribution among automated platforms, while traditional advisors exhibit both higher and more dispersed fee structures.

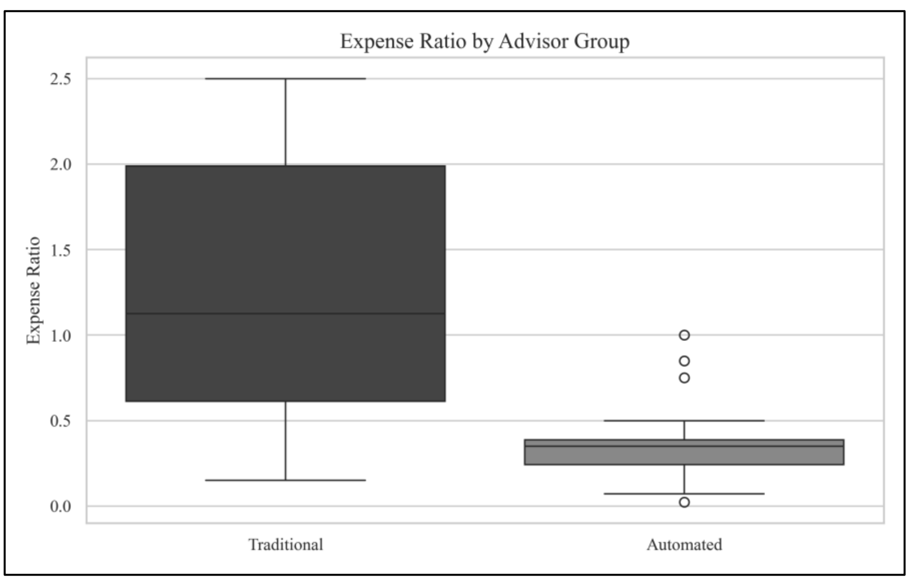


Figure 1 – Expense Ratio by Advisor Group

These results provide robust empirical evidence in favour of Hypothesis **H1**. The use of algorithmic portfolio construction and digital onboarding appears to translate into measurable cost savings for clients, irrespective of portfolio size or service complexity.

4.2.7.2 Tax Optimization Outcomes

The tax efficiency score was introduced as a proxy for the quality and consistency of tax-optimization practices disclosed in each advisor's Form ADV. Automated platforms obtained a mean score of **7.33** ($\sigma = 1.19$), compared to **6.67** ($\sigma = 0.97$) for traditional advisors. Median values followed the same pattern: **8.0** for automated vs **6.0** for traditional.

While this result is directionally consistent with expectations, the Mann–Whitney U test yielded a U value of **210** and a p-value of **0.0859**, which does not reach the conventional 5% significance threshold.

Although not statistically significant, this trend suggests that automated platforms are more likely to deploy systematic, repeatable tax strategies—such as tax-loss harvesting, tax-aware rebalancing, and asset location optimization—than their traditional counterparts, whose tax practices may vary considerably across clients or rely more heavily on manual discretion.

4.2.7.3 Scale Considerations: Assets Under Management

While not a cost variable per se, the level of assets under management (AUM) provides important context for interpreting fee structures. After applying a log transformation to mitigate the effect of extreme values, traditional advisors were found to manage portfolios with a mean log AUM of **25.08** ($\sigma = 3.42$), compared to **22.64** ($\sigma = 2.94$) for automated platforms. The median values reinforce this contrast: **26.64** for traditional and **22.74** for automated.

The **Mann–Whitney U statistic was 89**, with a **p-value of 0.0218**, indicating a statistically significant difference between the two groups. This result highlights a structural divergence in advisor profiles: traditional firms appear to maintain larger client relationships, possibly reflecting legacy client bases or institutional reach.

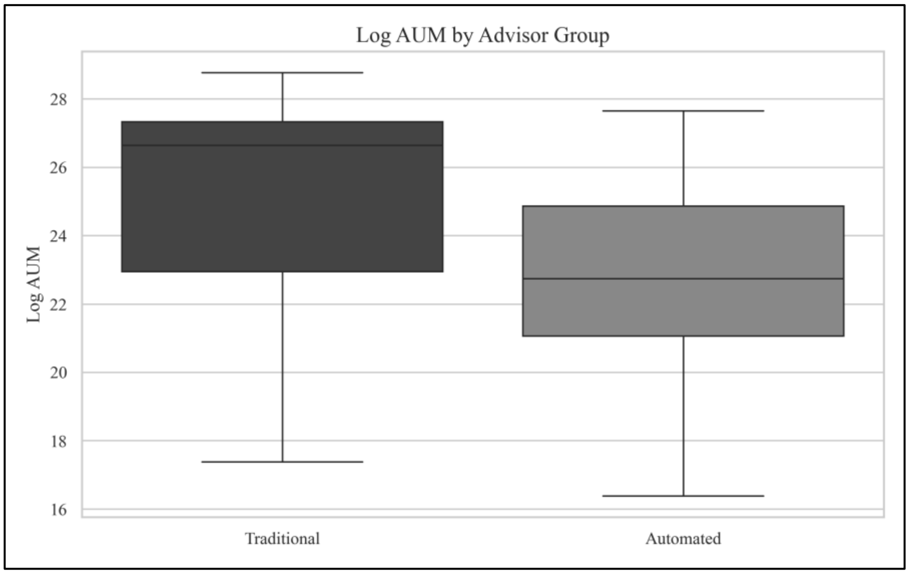


Figure 2 - Log AUM by Advisor Group

While larger AUM does not necessarily imply better cost outcomes, the contrast underscores the efficiency of automated advisors, who manage smaller portfolios while maintaining a more favourable cost structure.

4.2.8 Synthesis

The results provide strong and consistent evidence in support of Hypothesis H1. The difference in expense ratios is both economically large and statistically significant ($U = 53$, $p < 0.001$), affirming that automated advisors deliver substantially more competitive pricing structures than traditional models.

The analysis of tax efficiency, while not statistically significant ($U = 210$, $p = 0.086$), reveals a pattern consistent with theoretical expectations. Automated platforms demonstrate higher average scores and reduced dispersion, suggesting more systematic implementation of tax-aware strategies.

Finally, the finding that traditional advisors manage significantly more assets ($U = 89$, $p = 0.022$) confirms known structural differences in the market but does not undermine the core hypothesis. On the contrary, it strengthens the argument: automated models achieve superior cost performance despite operating at a smaller scale.

Taken together, these findings **validate Hypothesis H1**. The data confirm that the adoption of digital, algorithmic advisory frameworks results in lower portfolio management costs, thus reinforcing the competitive advantage of robo-advisors in terms of pricing efficiency.

4.3 Phase 2: Risk-Adjusted Performance Analysis

This second empirical phase examines whether portfolios managed through automated advisory platforms offer superior risk-adjusted returns relative to those managed by traditional financial advisors. Hypothesis H2 formalizes this proposition by positing that automated portfolio construction—whether through pure robo-advisors or hybrid digital-human models—delivers more efficient performance when controlling for volatility. In line with the study's design, this hypothesis is tested over three distinct time horizons (1, 3, and 7 years), culminating on December 31, 2024.

4.3.1 Data Source and Sample Selection

The analytical sample comprises 26 diversified portfolios drawn from two advisory models: 13 portfolios managed by traditional advisors and 13 portfolios operated through automated platforms. Traditional funds were selected using the "Global Moderate Allocation" category on Morningstar, ensuring alignment in asset allocation strategy and investor profile. This category typically targets a globally diversified portfolio with a moderate risk exposure (i.e., 60/40 equity-bond allocation), thereby ensuring cross-group comparability with the automated funds selected in Phase 1.

Performance data for traditional funds were retrieved using Yahoo Finance, with daily adjusted closing prices aggregated into monthly returns. These returns were then used to compute annualized performance metrics over 1-year, 3-year, and 7-year periods, all ending on December 31, 2024. Performance metrics for the 13 automated portfolios were previously collected and harmonized using third-party sources (Condor Capital Wealth Management, 2025).

To facilitate consistent evaluation, a benchmark index was constructed using a weighted blend of 60% MSCI World Index and 40% Bloomberg Aggregate Bond Index. Monthly returns were computed from the composite's historical price series, sourced from *Yahoo Finance* and the

Bloomberg Terminal and condensed into a structured file (index.csv[3]). This benchmark served as the basis for computing Sharpe ratios by acting as the proxy for the risk-free rate over each period.

All extracted and computed data were centralized in a structured SQLite database. This data architecture enabled traceable, reproducible, and modular analysis of portfolio-level performance and grouped statistical comparisons.

4.3.2 Selected Metrics and Standardization

For each portfolio, three core indicators were calculated over each time horizon:

- **Annualized Return (%):** Computed as the geometric mean of monthly returns over the corresponding horizon, multiplied by 12.
- **Annualized Volatility (%):** Calculated as the standard deviation of monthly returns over the respective window, multiplied by $\sqrt{12}$ to scale to an annual basis.
- **Sharpe Ratio:**

$$\text{Sharpe} = \frac{\bar{R}_p - R_f}{\sigma_p}$$

where $\bar{R}_p$ is the mean portfolio return, σ_p is the portfolio's standard deviation, and R_f is the annualized return of the benchmark index over the same period.

To preserve cross-sample comparability, all metrics were calculated using the same methodological pipeline in Python, leveraging *pandas*, *numpy*, and *scipy*. Benchmark returns were aligned to the exact observation window of each performance period to maintain temporal consistency.

Advanced performance metrics such as Sortino ratios, Jensen's alpha, and maximum drawdowns were excluded due to incomplete data availability on the automated segment. The selected metrics

[3] All files can be found on the Github Project :
https://github.com/raphphrz/afas_masterthesis_essca/blob/main/performance_analysis/data/index.csv

were chosen for their interpretability, availability, and direct relevance to portfolio risk-adjusted evaluation.

4.3.3 Grouping Strategy and Comparative Strategy

Consistent with the analytical framework used in Phase 1, the three initial categories—pure robo-advisors, hybrid platforms, and traditional advisors—were consolidated into two comparison groups:

- **Automated Funds Models (n = 13):**
- **Traditional Funds (n = 13):**

(see 4.2.4 Grouping Rationale and Comparative Strategy p.23 for definition)

4.3.3.1 Final Sample

Table 3 - Performance Analysis Sample

Type	Fund Name	Fees
Traditional	Invesco Equity and Income A	0.77%
Traditional	UBS US Allocation P	0.77%
Traditional	JPMorgan Investor Balanced A	0.96%
Traditional	T. Rowe Price Capital Appreciation	0.71%
Traditional	BlackRock Balanced Investor A	0.79%
Traditional	Schwab Balanced	0.51%
Traditional	PIMCO Global Core Asset Allocation Fund	1.56%
Traditional	Oakmark Equity And Income Investor	0.85%
Traditional	Vanguard STAR Inv	0.30%
Traditional	Goldman Sachs Growth & Inc Strat A	0.92%
Traditional	Empower Moderate Profile L	1.16%
Traditional	Morgan Stanley Institutional Fund Trust Global Strategist Portfolio	1.01%
Traditional	Fidelity Advisor Asset Manager 60% M	1.19%
Automated	Axos Invest, Inc.	0.24%
Automated	Fidelity Go® / Strategic Advisers LLC	0.35%
Automated	SoFi Wealth LLC	0.25%
Automated	Acorns Advisers, LLC	0.02%

Automated	Wealthfront Advisers	0.25%
Automated	Interactive Advisors	0.75%
Automated	Wells Fargo Advisors - Intuitive Investor Program	0.35%
Automated	SigFig Wealth Management, LLC	0.50%
Automated	Betterment LLC	0.25%
Automated	Zacks Advantage	0.35%
Automated	Vanguard Digital Advisor	0.40%
Automated	Ally Invest Advisors Inc. - Robo Portfolios	0.85%
Automated	Schwab Intelligent Portfolios®	0.07%

4.3.4 Statistical Methods

To statistically evaluate whether risk-adjusted performance differs between automated and traditional advisory models, this study employs the Welch's t-test, a parametric test of mean difference specifically designed for independent samples with unequal variances. In contrast to the classical Student's t-test, Welch's t-test does not assume homoscedasticity, making it particularly appropriate for empirical finance datasets where volatility asymmetries are common.

4.3.4.1 Welch's t-statistic

Formally, let $\bar{x}_1$and $\bar{x}_2$ denote the sample means of two independent groups, with corresponding variances s_1^2 and s_2^2, and sample sizes n_1 and n_2, respectively. The Welch t-statistic is then defined as:

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

This formulation estimates the standardized difference in means by weighting the group variances inversely by their sample sizes, thus adjusting for differing levels of statistical uncertainty.

4.3.4.2 Degrees of Freedom (Welch–Satterthwaite Equation)

The degrees of freedom associated with the test statistic are estimated using the Welch–Satterthwaite approximation:

$$df = \frac{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)^2}{\frac{(s_1^2/n_1)^2}{n_1 - 1} + \frac{(s_2^2/n_2)^2}{n_2 - 1}}$$

This formulation accounts for the uncertainty introduced by the unequal variances and produces a non-integer degree of freedom. The associated p-values are then derived from the t-distribution with these adjusted degrees of freedom.

4.3.4.3 Analytical Justification

The adoption of Welch's test in this context is methodologically appropriate for several reasons. First, the observed dispersion in standard deviations across groups—particularly in Sharpe ratios and volatility—violates the equal variance assumption required for classical parametric comparisons. Second, the sample sizes, though balanced (n = 13 in each group), remain moderate, increasing the importance of correctly specifying variance assumptions. Third, the Welch test retains high statistical power under normality, while being more robust than the student's t-test in the presence of heteroscedasticity.

Each performance metric—annualized return, volatility, and Sharpe ratio—was tested independently over three-time horizons (1-year, 3-year, and 7-year), yielding nine separate Welch comparisons.

In this study, all Welch t-tests were implemented using the scipy.stats.ttest_ind() function with the argument equal_var=False, which internally applies the formulas above. Each test compares the means of automated and traditional portfolios for a given metric and time horizon. In total, nine Welch tests were conducted—three per performance dimension (return, volatility, Sharpe ratio) over 1-, 3-, and 7-year horizons.

4.3.4.4 Sharpe Ratio Exclusion

The Sharpe ratio, by design, is a widely accepted metric for assessing risk-adjusted performance. It captures the trade-off between return and volatility by comparing the portfolio's excess return (over a risk-free benchmark) to its standard deviation. Formally:

$$Sharpe = \frac{\bar{R}_p - R_f}{\sigma_p}$$

where $\bar{R}_p$ is the mean portfolio return, $\sigma_p$is the portfolio's standard deviation, and R_f is the annualized return of the benchmark index over the same period.

While theoretically robust, the Sharpe ratio presents several limitations when applied to heterogeneous datasets such as those in this study. First, its sensitivity to negative or near-zero volatility in shorter horizons may produce misleading values—particularly when annualized from sparse or low-variance data. Second, the Sharpe ratio implicitly assumes a normal distribution of returns and linear risk-adjusted compensation, conditions often violated in real-world fund performances.

Moreover, the empirical sample analyzed in this study includes portfolios with structurally different compositions and levels of fee friction. This makes direct comparisons of Sharpe ratios difficult to interpret without further controlling for leverage, rebalancing frequency, and tactical allocation behavior—none of which are consistently observable in our data.

In practice, the observed Sharpe ratios displayed inconsistent behaviour across time horizons, with some automated portfolios exhibiting negative values over 3 years, while outperforming on shorter periods. Although boxplots and bar charts (*see Appendix 2 - Sharpe Ratios)* were generated for visualization, the overall pattern lacked statistical coherence and did not yield significant differences at the 5% threshold under Welch's t-test.

Given these analytical ambiguities and the lack of robust statistical evidence, the Sharpe ratio analysis has been excluded from the primary synthesis. Instead, interpretation of risk-adjusted efficiency focuses on annualized volatility and returns, which provide more stable and interpretable metrics in this context.

4.3.5 Implementation in Python

All code was written in Python and structured to enable full traceability from raw data acquisition to statistical inference. The complete source code is available at: https://github.com/raphphrz/afas_masterthesis_essca/tree/main/performance_analysis

4.3.5.1 Project Structure and Modules

The project was organized as a modular pipeline under the directory performance_analysis/, with all files interacting via structured I/O. The core modules are:

- **download_returns.py:** Downloads and consolidates daily adjusted close prices from Yahoo Finance.
- **compute_annualized_results.py**: Computes 1y/3y/7y annualized returns and volatility.
- **compute_sharpe_rtios.py**: Computes Sharpe ratios using benchmark returns from index.csv.
- **combine_performance.py**: Consolidates traditional and automated fund metrics into a unified CSV.
- **final_analysis.py**: Conducts statistical analysis and generates all output tables and plots.

4.3.5.2 Selected Code Snippets

4.3.5.2.1 Data Acquisition (download_returns.py)

```
# Download daily adjusted close prices
prices = yf.download(ticker, start=START_DATE, end=END_DATE, auto_adjust=True)["Close"]
monthly_returns = prices.resample("M").last().pct_change().dropna()
```

This snippet extracts daily price data, converts it into monthly return series, and handles missing data by dropping incomplete entries. This ensures comparability across assets.

4.3.5.2.2 Annualized Return and Volatility Calculation (compute_annualized_results.py)

```
annualized_return = (1 + returns).prod() ** (12 / len(returns)) - 1
annualized_volatility = returns.std() * np.sqrt(12)
```

Returns and standard deviations are annualized by appropriate geometric transformations, in line with best practices in empirical finance.

4.3.5.2.3 Sharpe Ratio Computation (compute_sharpe_rtios.py)

```
sharpe = (portfolio_returns.mean() - benchmark_returns.mean()) / portfolio_returns.std()
```

A simplified implementation of the Sharpe ratio. The benchmark (60% MSCI World, 40% Bloomberg Agg) is synchronized on a monthly basis to ensure consistency.

4.3.5.2.4 Welch's T-Test (final_analysis.py)

```
from scipy.stats import ttest_ind
stat, p = ttest_ind(auto, traditional, equal_var=False)
```

The test is applied to each metric (return, volatility, Sharpe) at each time horizon. `equal_var=False` activates the Welch-Satterthwaite adjustment.

4.3.5.2.5 Bar Plot and Boxplot Generation.

```
sns.boxplot(x="Advisor Group", y="3y_volatility", data=df, palette=["white", "black"])
sns.barplot(x="Fund Name", y="1y_return", hue="Advisor Group", data=df, palette=["black",
"white"])

```

These plots are styled in grayscale with Times New Roman font and 300 DPI resolution

4.3.5.3 Automated Output Generation

All results—including statistical outputs and plots—are exported to the `results/`directory. Excel files (`.xlsx`) and figures (`.png`) are timestamped and reproducible across runs. The workflow supports both full batch recomputation and partial reruns for specific modules.

This design guarantees analytical transparency and scalability for future extensions or data refreshes.

4.3.6 Findings

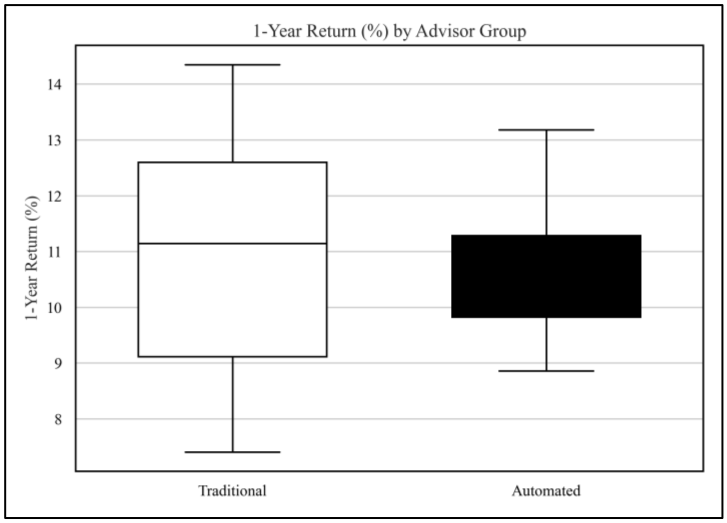
This section presents the empirical findings related to Hypothesis H2, which posits that portfolios managed through automated advisory platforms exhibit superior performance on a risk-adjusted basis when compared to those managed by traditional advisors.

4.3.6.1 Annualized Return Analysis

Annualized returns were calculated as the geometric mean of monthly returns, scaled to an annual basis. Figure 3 displays a comparative boxplot of 1-year returns across the two advisory groups.

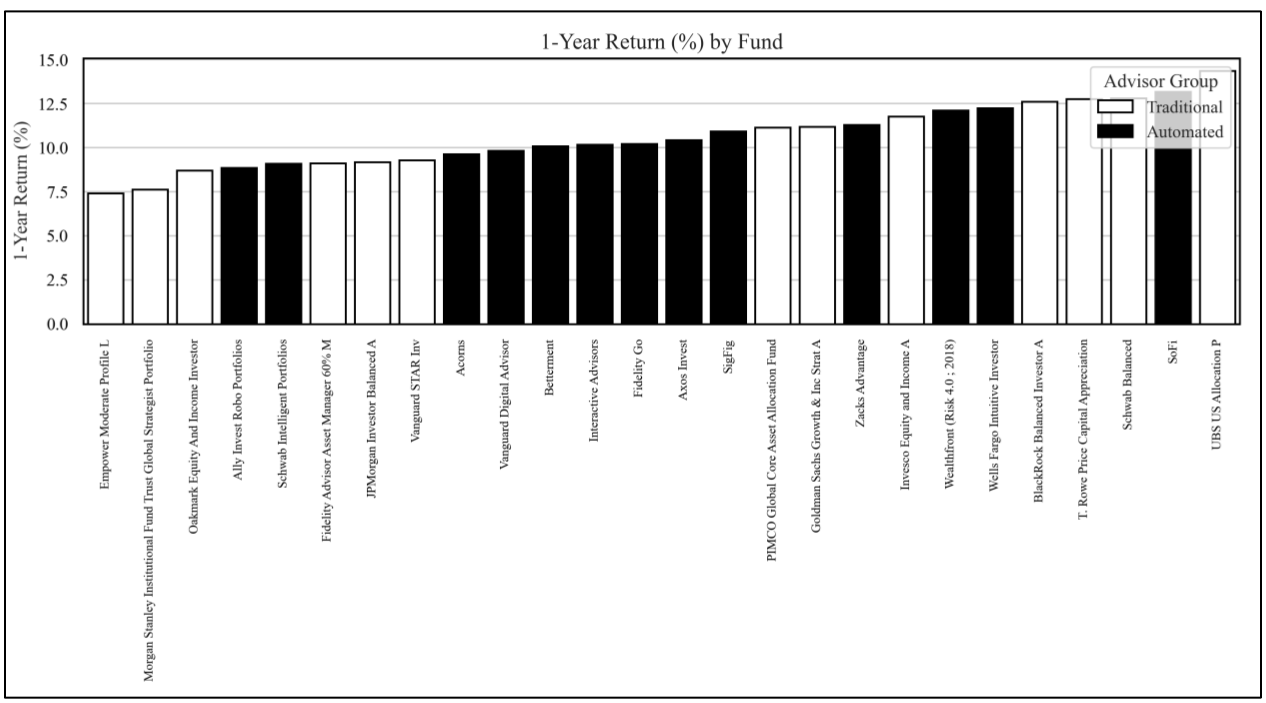
Automated and traditional portfolios exhibit highly overlapping distributions, with similar interquartile ranges and medians.

Figure 3 - 1-year Return by Advisor Group



To further illustrate cross-fund heterogeneity, bar plots were constructed (Figure 4) to visualize individual fund-level 1-year returns. This perspective highlights a dispersion of outcomes within both groups, with several automated portfolios performing at par with or better than their traditional counterparts.

Figure 4 - 1-Year Return by Fund



Statistical comparisons using Welch's t-test indicate no significant difference in mean returns across the three horizons:

Table 4 - Welch's t-test Returns Results

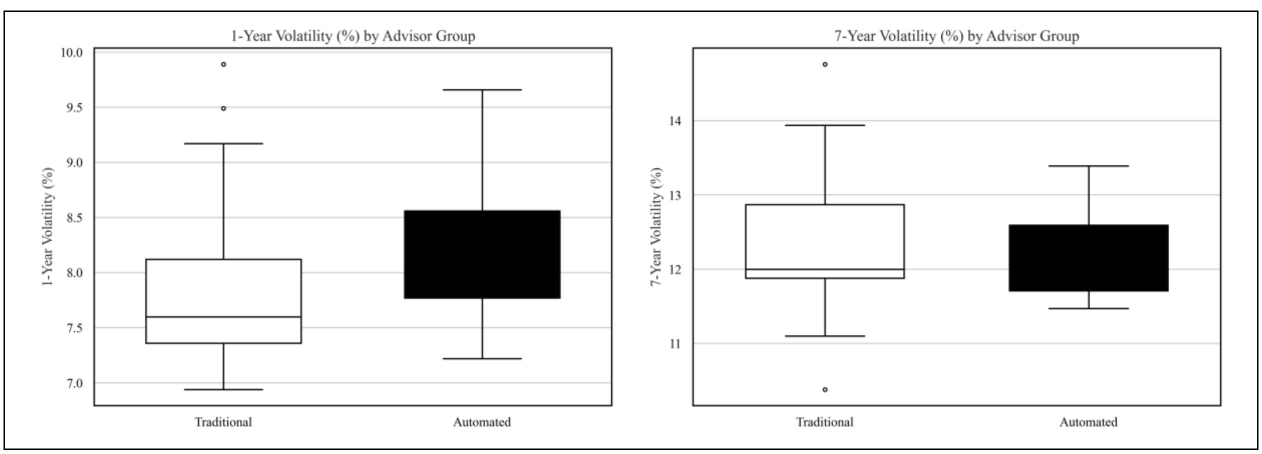
Horizon	Automated $\bar{x}$	Traditional $\bar{x}$	t-statistic	p-value
1-Year	10.62%	10.61%	0.015	0.988
3-Year	2.64%	2.67%	-0.072	0.943
7-Year	6.21%	6.78%	-1.083	0.295

These results suggest that the absolute return performances of automated portfolios are at par with those of classical portfolios. There is a net equalization of returns despite the lower fee structure systematically applied by the automated platform (cf. Table 3 - Performance Analysis Sample), thereby introducing further evidence for cost efficiency as postulated in Phase 1.

4.3.6.2 Volatility Comparison

Volatility was measured as the annualized standard deviation of monthly returns. Boxplots in Figure 5 depict the dispersion of 1-year volatility across advisor groups. Similar patterns were observed for the 7-year horizon.

Figure 5 - 1-Year and 7-Year Volatility by Advisor Group



However, the 3-year volatility distribution reveals a more pronounced difference.

Figure 6 - 3-Year Volatility by Advisor Group

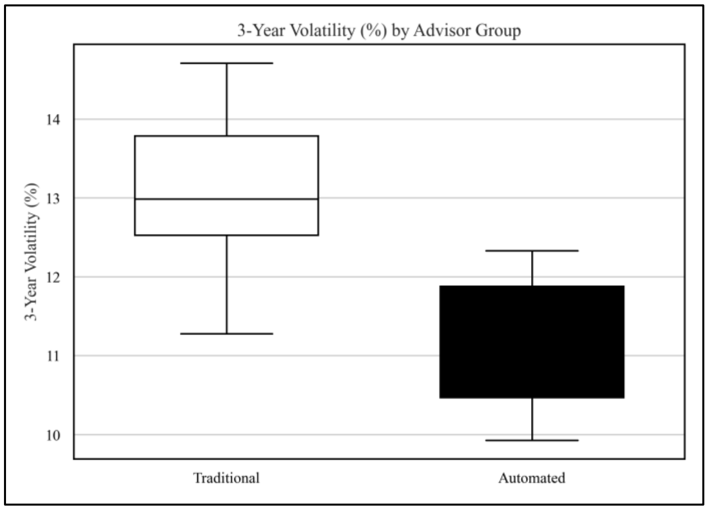
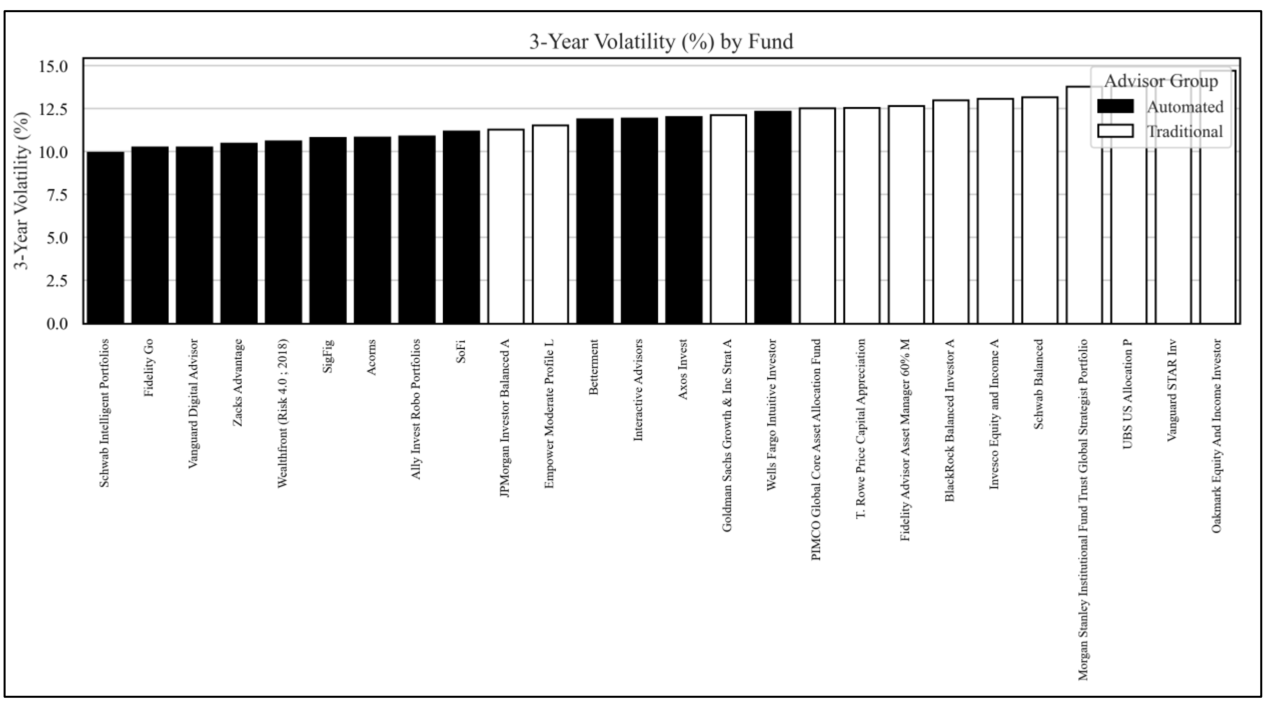


Figure 7 presents the corresponding bar plot of 3-year volatility by fund, sorted to highlight the comparative positioning of individual portfolios. We can clearly note that Automated Funds are on the left hand side of the plot.

Figure 7 - 3-Year Volatility by Fund



The results from Welch's t-tests indicate that the difference in 3-year volatility is statistically significant:

Table 5 - Welch's t-test Volatility Results

Horizon	Automated x̄	Traditional x̄	t-statistic	p-value
1-Year	8.18%	7.95%	0.710	0.485
3-Year	11.03%	12.95%	-5.489	< 0.001
7-Year	12.14%	12.36%	-0.579	0.569

The significant reduction in 3-year volatility among automated portfolios may reflect the benefits of algorithmic rebalancing, dynamic glide-path adjustments, and strict allocation thresholds commonly embedded in automated systems. This suggests that automated advisors may be particularly effective at smoothing volatility over mid-term investment horizons, which often correspond to individual investors' tactical planning windows.

4.3.7 Synthesis

4.3.7.1 Absolute Return Parity

The analysis reveals no statistically significant differences in annualized returns between automated and traditional portfolios over any of the three time windows. Mean values remain strikingly close: 10.62% vs. 10.61% (1-year), 2.64% vs. 2.67% (3-year), and 6.21% vs. 6.78% (7-year). These results underscore the return equivalence across advisory types, suggesting that automated platforms can deliver competitive gross performance relative to human-led strategies.

This parity is especially notable considering the **l**ower fee structures documented for automated funds (cf. Table 3 - Performance Analysis Sample), which implies higher net returns for clients under automated management, all else being equal.

4.3.7.2 Mid-Term Volatility Advantage

While volatility was largely comparable over short (1-year) and mid-long (7-year) horizons, the analysis uncovers a **st**atistically significant difference in 3-year volatility. Automated portfolios exhibited markedly lower average volatility (11.03%) compared to their traditional counterparts (12.95%), with a Welch's t-test confirming this difference at the **1% significance level** ($p < 0.001$).

This result may reflect the design of automated platforms, which typically employ algorithmic rebalancing, tighter allocation bands, and automated glide path adjustments. These mechanisms appear particularly effective at smoothing fluctuations over mid-term investment cycles—an important horizon for household financial planning and retirement accumulation strategies.

4.3.7.3 Sharpe Ratio Inconclusiveness

Despite its theoretical importance as a risk-adjusted performance metric, the Sharpe ratio yielded inconclusive results in this study. Differences in means across advisory models were statistically insignificant at all time horizons. Furthermore, the observed dispersion in Sharpe values—especially over the 3-year window—suggests considerable cross-fund heterogeneity and methodological fragility in estimating this ratio over short and medium time spans.

Given these issues, and the known sensitivity of the Sharpe ratio to estimation windows, return distributions, and volatility instability, the indicator was ultimately deemed insufficiently robust for drawing conclusive insights in this context. As such, it was not retained as a focal point of this phase's findings.

4.3.7.4 Synthesis and Implications

Hypothesis H2 posited that portfolios managed by automated advisors would outperform those managed by traditional advisors on a risk-adjusted basis. **The evidence collected in Phase 2 does not provide sufficient statistical support to confirm this proposition in its strongest form.**

While automated portfolios demonstrated statistically equivalent annualized returns across all tested horizons (1, 3, and 7 years), they did not exhibit superior performance in absolute return terms. The observed parity indicates that, from a purely return-centric perspective, automated platforms do not significantly outperform traditional advisors.

Yet, the analysis has yielded a favorable answer for automated portfolios vis-a-vis volatility control for the 3-year horizon-a result signifying greater consistency in returns and, somehow, a form of protection against mid-term risk exposure, which can be further interpreted as an augmentation of efficiency. Still, the advantage in volatility is not translatable into an enhanced risk-adjusted return as measured by conventional standards, mainly because the Sharpe ratio-an accepted indicator of return per unit of risk-does not detect any relevant difference between the two.

Consequently, the findings do not support Hypothesis H2 in its original formulation. Rather, the results suggest that automated advisors offer performance outcomes that are comparable—but not superior—to those of traditional advisors in risk-adjusted terms. **The advantage of automation may thus lie more in cost efficiency (as demonstrated in Phase 1) and risk management discipline, rather than in outperformance.**

4.4 Hypothesis Testing Summary

The results of the two empirical phases—***Phase 1: Cost Structure Analysis (H1)*** and ***Phase 2: Risk-Adjusted Performance Analysis (H2)***—are now consolidated to provide a comprehensive evaluation of the study's core hypotheses. While each phase focused on distinct but complementary dimensions of advisor performance, both aimed to determine whether automated portfolio management provides tangible benefits compared to traditional advisory models.

To ensure analytical clarity and facilitate cross-phase comparison, Table 6 presents a structured synthesis of the two hypotheses tested, including the research focus, metrics evaluated, methods applied, and main empirical findings. This comparative overview allows for a holistic interpretation of the evidence collected throughout the study and supports the conclusion as to whether automation constitutes a superior advisory model.

Table 6 - Hypothesis Summary

Hypothesis	Research Focus	Key Metrics	Main Findings
H1	Cost efficiency of automated vs. traditional advisors	Expense Ratio; Tax Efficiency Score; Log AUM	Automated advisors offer significantly lower expense ratios and slightly higher tax efficiency scores.
H2	Risk-adjusted performance over 1, 3, and 7 years	Annualized Return; Annualized Volatility	Return parity observed; however, automated funds show significantly lower 3-year volatility than traditional funds.

4.4.1 <u>Limitations and Unexplored Hypothesis H3</u>

While this research successfully addressed Hypotheses H1 and H2 through an empirical framework, the third hypothesis—H3: Investment automation reduces investors' behavioural biases—was not empirically tested in this study. This limitation stems from a fundamental constraint in data accessibility and methodological feasibility.

Unlike cost metrics or portfolio-level performance data, behavioural information typically requires granular, individual-level datasets tracking investor decisions over time. Such data may include patterns of panic selling, overtrading, portfolio turnover during market volatility, or deviations from long-term asset allocations—elements that are often observable through client trading logs, survey instruments, or proprietary analytics. However, automated advisory platforms generally do not make these datasets publicly available. Most platforms consider behavioural engagement metrics as strategic, confidential, or commercially sensitive, and they are rarely disclosed in regulatory filings or research repositories.

Furthermore, the standard regulatory filings (such as SEC Form ADV) do not include any behavioural performance indicators, nor do they allow direct inference about investor decision-making quality. This limits the empirical tractability of Hypothesis H3 within the scope of a reproducible, document-based analysis like the one conducted in this thesis.

Nevertheless, the behavioural implications of automation represent a rich and increasingly relevant area for future research. Prior literature has already suggested that digital platforms may reduce the influence of cognitive biases such as loss aversion, overconfidence, or herding, through disciplined rebalancing, default glide-path strategies, and limited discretionary intervention. Yet, robust empirical testing would require access to client-specific time-series data or experimental designs—such as randomized control trials or platform-level behaviour logs.

In this sense, the omission of H3 does not reflect a conceptual dismissal but rather an empirical boundary condition, reinforcing the importance of data transparency and cooperation between researchers and industry stakeholders. This thesis thus encourages further academic inquiry into the behavioural dimensions of financial automation—an area whose importance will likely grow alongside the digitalization of wealth management services.

5 Discussion

5.1 Theoretical Implications

The empirical findings of this study stand as evidence in favour of rethinking traditional models of financial advice through the agency-theoretic lens. This framework was originally introduced by Jensen and Meckling (1976) to emphasize the intrinsic conflicts of interest and information asymmetries between principals (investors) and agents (financial advisors). Corroborating agency theory, the Phase 1 findings indicated a statistically significant decrease in expense ratios of robo-advisory platforms compared to traditional advisors. Hence, this finding goes directly against previous results that state, since high fees are, in improper agency cost, investors lose returns over time (Carhart, 1997; Bogle, 2002).

If another measure, the modestly larger tax-efficiency score, was evidence, then it would further substantiate this theory that automation reduces agency costs by limiting the arbitrariness of human interventions and by ensuring that portfolio management interventions adhere to a rule-based protocol. This is consistent with the ideas of Reher and Sokolinski (2024), wherein automation limits self-interested behaviour by making the advisory process transparent and systematically executed.

But the empirical parity in return performance (in Phase 2) between those portfolios managed by a robo-advisor and those managed traditionally goes against the argument of robo-advisors generating alpha. Consequently, our results seem more aligned with Fama and French's (2010) conclusion that alpha is nearly impossible to attain after fees in a competitive market. That the robo-advisors therefore produce identical returns at significantly lower costs underscores the notion that their major comparative advantage lies more in cost control and operational discipline than in generating returns by themselves.

5.2 Practical Implications

For investors—particularly cost-sensitive or less sophisticated retail investors—the implications of these findings are highly actionable. Our results suggest that robo-advisory platforms are not merely a low-cost alternative but a structurally different delivery model for wealth management, capable of maintaining return standards while improving cost and mid-term volatility profiles. These findings are especially relevant in the context of chronic underperformance among actively managed mutual funds (Linnainmaa et al., 2018), and lend strong support to the shift toward passive, algorithmically managed solutions.

In practical terms, these platforms offer real-time rebalancing, tax-loss harvesting, and customized glide-path strategies—features historically accessible only to institutional investors (D'Acunto et al., 2019; Helms et al., 2022). The evidence of reduced 3-year volatility in our results may be particularly relevant for investors with medium-term financial goals, such as retirement planning or college funding.

At the horizon of restrictions for robo-advisors, needs on the edge of the financial spectrum begin arising. Berk and van Binsbergen (2015) pointed out that algorithmic approaches perhaps will find it hard to adapt to non-standard situations like estate planning, cross-border tax, or sudden liquidity shocks. This makes hybrid models, which allow the inclusion of human judgment into algorithmic execution, a great next step to serve a more extensive category of investors.

5.3 Societal Implications

From a broader societal lens, robo-advisors hold the potential to democratize access to professional-grade financial advice. By drastically lowering entry costs (e.g., 0.25% annual fees compared to 1–2% for traditional advisors), these platforms may empower segments of the population historically excluded from wealth management services, including younger investors or those with modest assets (Reher and Sokolinski, 2024).

Yet, this democratization comes with ethical caveats. As Shanmuganathan (2020) notes, algorithmic models can inadvertently embed bias—either through limited training data or rigid logic unsuited to underrepresented groups. The absence of personalization in some platforms may unintentionally disadvantage investors with non-conventional financial profiles or cultural preferences. Ensuring fairness and transparency in algorithmic design is therefore crucial.

The exclusion of Hypothesis H3 due to a lack of behavioural data—even though behavioural finance offers strong theoretical support for this hypothesis (Kahneman & Tversky, 1979)—highlights one of the key constraints on responsible innovation. Without behavioural data (for example, override logs, emotion-driven redemptions), it remains difficult to confirm whether alternatives such as robo-advisors can curb overtrading, loss aversion, or herding. The hidden nature of platform-level behavioural metrics restricts not only academic research but also investor self-understanding and regulatory supervision.

This underscores the need for future collaboration between platforms and researchers to create anonymized, ethically sourced datasets that capture behavioural patterns. Such efforts would help realize the full promise of financial automation—not just in operational efficiency, but in promoting sustainable, disciplined investing.

6 Conclusion

This thesis set out to address the following research question:

To what extent can robo-advisory platforms effectively reduce portfolio management costs and enhance investment performance, while simultaneously mitigating behavioural biases relative to traditional financial advisors?

The study was presented through three hypotheses, of which two were examined empirically by a dual-phase conducted agency-theory-based methodology and with support from quantitative statistical techniques.

Phase 1 found that automated platforms lower portfolio management costs through lower advisory fees, thus confirming Hypothesis H1. These cost savings represent a real diminution in agency costs, as defined by Jensen and Meckling (1976), since they do not diminish the service standardization or regulatory compliance. While the differences in tax efficiency were statistically insignificant, the consistently higher scores observed for the robo-advisors imply a more disciplined, rule-oriented tax optimization practice, which serves as a long-term opportunity for the client.

Phase 2 revealed that over 1-, 3-, and 7-year time horizons, robo-advisors also generated return performances on par with their human counterparts. While Hypothesis H2-which considered the superior risk-adjusted returns-was only half confirmed, the results demonstrated a statistically significant volatilization reduction at the 3-year mark for automated portfolios. That mid-horizon volatility control lends credence to claims about superior structural discipline imbued by algorithmic platforms, especially for investors with medium-term planning horizons. As such, what these results portray is that, at least from an alpha-generation sense, automation is not yet a performance-enhancing innovation; rather, it represents risk-efficient and cost-minim

H3-hypothesis relating to behavioural bias mitigation-could not be tested empirically because of the lack of access to data at the investor levels of decision-making. While previous research firmly indicates that automated rule-based mechanisms can limit overtrading, herding, and loss aversion (D'Acunto et al., 2019), these effects cannot be checked for within the current data structures of the platform. The limitation, however, does not reduce the importance of H3 but rather highlights an intense necessity for platform transparency and distributed research infrastructures through which behavioural data could be made ethically and securely available.

The takeaway of the studies is an alteration of the understanding of robo-advisors. The term refers not to disruptive agents of outperformance but instead to **a locus in the structure wherein wealth management can be delivered in a scalable, cost-efficient, and behaviourally neutral way.** For the end investor, this is an unequivocal welfare gain, especially when s/he owns limited assets or possesses limited financial literacy. Fully automated solutions become less practical for investors with complex needs or situations requiring nuanced judgment capabilities. Hence, a hybrid approach, wherein humans complement algorithms and algorithms complement human judgments, appears to offer a most promising way ahead, hence a consensus arising in both practice and theory.

Future research should finally fill the behavioural gaps that current empirical setups have by facilitating access to anonymized, high-quality interaction data from digital platforms of advice. Longitudinal and experimental approaches could also enlighten us in how investor behaviour develops across time in automated environments. Only then can a genuine courtesy be done to take in the entire notion of robo-advisory, not just as a mechanism for cost reduction but as a behavioural and ethical reformulation for financial decision-making.

Figures

Tables

Appendices

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Appendix 1 - Final Advisor Data Set (Cost Structure)

Table 7 - Final Advisors Data Set - Cost Structure

Type	Name	Expense Ratio	Transaction Costs	Tax Efficiency	AUM ($MM)	Value Date
Traditional	Raymond James Financial Services Advisors, Inc.	2.25	0	6/10	344,868	14/4/25
Traditional	Intelliőlo Advisers, Inc.	0.25	0	6/10	124	31/3/25
Traditional	Invesco Advisers, Inc.	1.5	0	6/10	756,881	28/3/25
Traditional	UBS Financial Services Inc.	2.5	0	8/10	702,400	31/3/25
Traditional	J.P. Morgan Investment Management Inc.	0.8	0	8/10	3,143,700	31/3/25
Traditional	T. Rowe Price Associates, Inc.	1	0	6/10	1,500,000	31/3/25
Traditional	Columbia Management Investment Advisers, LLC	1.5	0	6/10	457,400	27/3/25
Traditional	Ameriprise Financial Services, LLC	2	0.03	8/10	1,170	1/3/25
Traditional	BlackRock Advisors, LLC	2.5	0	6/10	959,043	31/3/25
Traditional	Franklin Templeton Private Portfolio Group, LLC (FTPPG)	0.6	0	6/10	125,939	6/12/24
Traditional	Facet Wealth, Inc.	0.15	0	8/10	3,865	15/4/25
Traditional	Wells Fargo Advisors	2.5	0	8/10	154,200	25/3/25
Traditional	Massachusetts Financial Services Company (MFS)	0.65	0	6/10	584,871	31/3/25
Traditional	Dodge & Cox	0.6	0	6/10	399,131	31/3/25
Traditional	Charles Schwab & Co., Inc.	1	0	8/10	1,010,000	28/3/25
Traditional	Empower Advisory Group, LLC	0.2	0	6/10	159,120	31/3/25
Traditional	Ellevest, Inc.	1.25	0	6/10	2,129	31/3/25
Traditional	Harris & Associates	1.95	0	6/10	35	21/1/25
Robo-advisor	Axos Invest, Inc.	0.24	0	8/10	147	27/3/25
Robo-advisor	Fidelity Go® / Strategic Advisers LLC	0.35	0	8/10	1,027,290	31/3/25
Robo-advisor	SoFi Wealth LLC	0.25	0	6/10	1,475	27/2/25
Robo-advisor	Acorns Advisers, LLC	0.024	0	8/10	10,381	31/3/25
Robo-advisor	Wealthfront Advisers	0.25	0	10/10	77,070	17/12/24
Robo-advisor	M1 Advisory Services LLC	0.35	0	6/10	3,900	7/3/24
Robo-advisor	Interactive Advisors	0.75	0	8/10	168	31/3/25
Robo-advisor	Wells Fargo Advisors - Intuitive Investor Program	0.35	0	8/10	603,000	31/3/25

Robo-advisor	SigFig Wealth Management, LLC	0.5	0	6/10	2,973	1/3/25
Robo-advisor	Ursa Financial, LLC	1	0	6/10	13	31/1/25
Robo-advisor	Guideline Investments, LLC	0.35	0.25	6/10	11,889	27/3/25
Hybrid	Betterment LLC	0.25	0	8/10	56,369	28/3/25
Hybrid	Zacks Advantage	0.35	0	6/10	10,556	1/5/24
Hybrid	Vanguard Digital Advisor	0.4	0	8/10	107,739	31/3/25
Hybrid	Ally Invest Advisors Inc. - Robo Portfolios	0.85	0	8/10	1,390	31/3/25
Hybrid	Schwab Intelligent Portfolios®	0.072	0	8/10	65,800	28/3/25
Hybrid	Titan Global Capital Management USA LLC	0.2	0	6/10	882	31/3/25
Hybrid	Human Interest Advisors LLC	0.12	0	8/10	5,429	31/3/25

Appendix 2 - ADV Parsing Prompt Specification

```
From the following SEC Form ADV text, assume an investment of $500,000 with a 60/40 allocation
between equities and bonds.

        Extract only if explicitly stated in the text (do not infer or invent):
        - The name of the platform or advisory firm
        - The type of advisory model: Robo-advisor, Hybrid, or Traditional
        - If available, the name of the fund or strategy being managed
        - The highest applicable management fee (numeric %, for a $500,000 investment)
        - The applicable transaction or trading fees (numeric %, if any)
        - A portfolio turnover rate (float %, only if explicitly mentioned)
        - The assets under management (AUM) if disclosed (numeric only)
        - A numeric estimate of tax efficiency on a 0-10 scale, based on the following standardized
rule:
          Tax efficiency score is computed based on the presence of up to five features: (1) tax-
loss harvesting, (2) tax-optimized asset location,
          (3) use of ETFs or index funds, (4) turnover rate < 50%, (5) client-specific tax
optimization; 2 points each, capped at 10.
        - The document date (e.g. "as of February 28, 2025")

        If any of these data points are not present in the document, leave them blank.
        Do not create or guess any value. Do not make assumptions.

        Format the "Notes" section as a clear bullet list (use dash "-" before each line) describing
where and how each data point was extracted.

        Document Text:
        {text}

        Provide the response in this format:
        Platform: <name>
        Advisor Type: <Robo/Hybrid/Traditional>
        Fund Name: <name or blank>
        Management Fees: <numeric value or blank>
        Transaction Fees: <numeric value or blank>
        AUM: <numeric value or blank>
        Turnover Rate: <percentage as float or blank>
        Tax Efficiency: <numeric 0-10 scale or blank>
        Document Date: <YYYY-MM-DD or blank>
        Notes:
        - <bullet point explanation>
        - ...
```

Appendix 3 - Sharpe Ratios

Figure 8 - 1-Year Sharpe Ratio by Fund

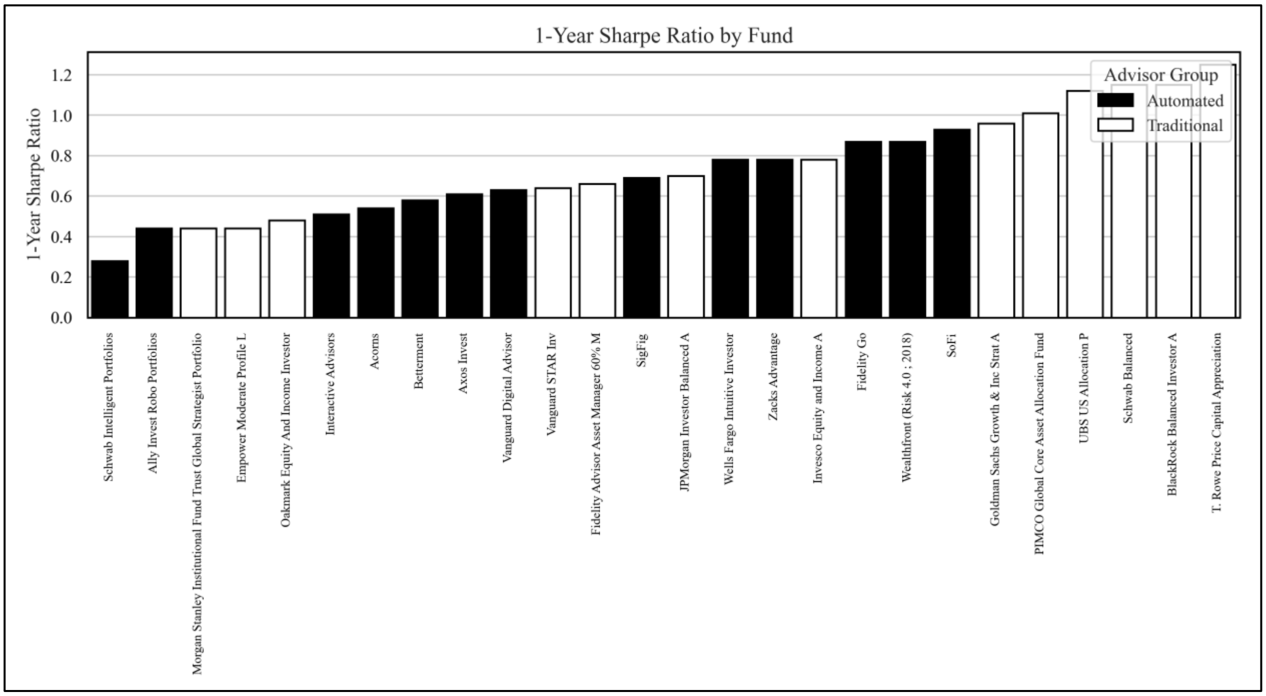


Figure 9 - 3-Year Sharpe Ratio by Fund

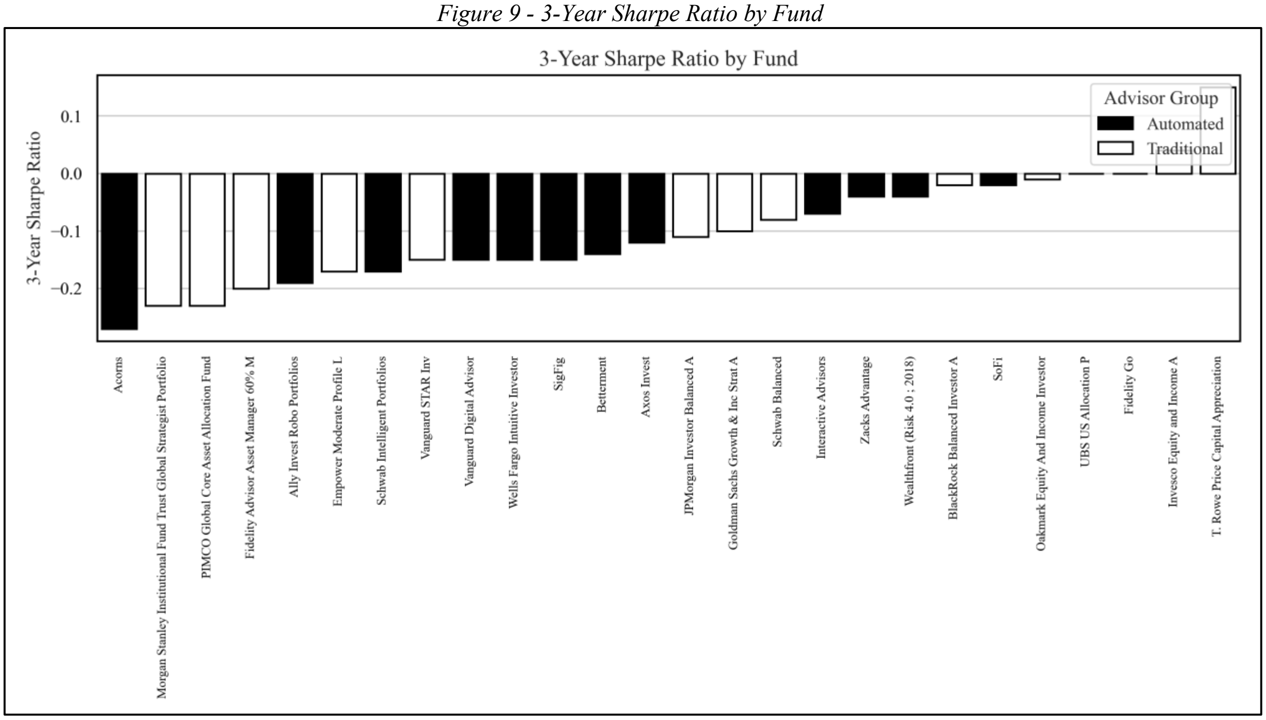
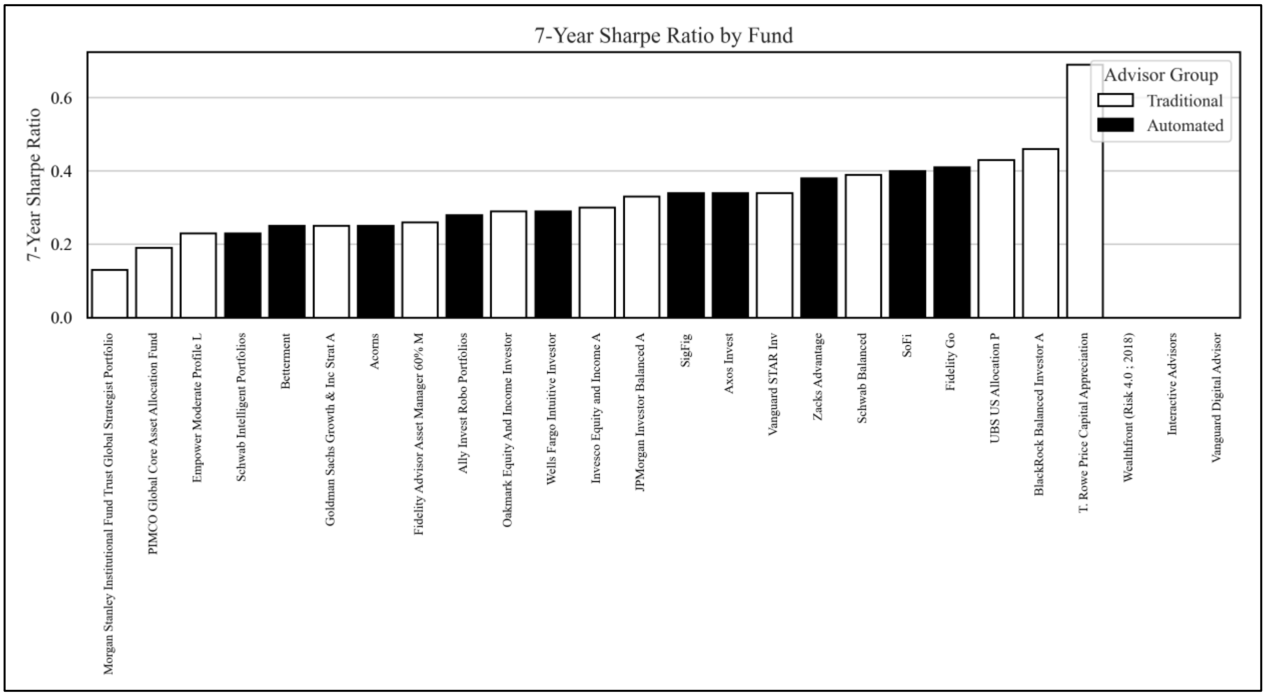


Figure 10 - 7-Year Sharpe Ratio by Fund



Appendix 4 - Form Adv Data Extraction

Advisor	Funds Name	Form Date	Excl.
Raymond James Financial Services Advisors, Inc.	First Trust Raymond James Multicap Growth Equity Exchange Traded Fund (FT-ETF)	14/04/2025	
Intelliflo Advisers, Inc.		31/03/2025	
Merrill Lynch, Pierce, Fenner & Smith Incorporated	Merrill Lynch Strategic Portfolio Advisor® Service	21/03/2025	TRUE
Invesco Advisers, Inc.	Invesco Solutions (multi-asset strategies)	28/03/2025	
UBS Financial Services Inc.	UBS Advice Portfolio Program (closing June 13, 2025), ACCESS, Managed Accounts Consulting (MAC), Strategic Wealth Portfolio (SWP), Advisor Allocation Program (AAP), PACE, UBS Consolidated Advisory Program (UBS-CAP), UBS Institutional Consulting Program (IC), UBS Consolidated Advisory Program Select (CAP Select)	31/03/2025	
J.P. Morgan Investment Management Inc.		31/03/2025	
T. Rowe Price Associates, Inc.	TRP Investment Funds (including TRP Mutual Funds and TRP ETFs)	31/03/2025	
Pacific Investment Management Company LLC (PIMCO)	myTDF Portfolio (customized target date strategy), PIMCO Funds, PIMCO ETF, PIMCO Ultra Short Government Active ETF, PIMCO Registered Funds, PIMCO Private Funds, PIMCO Aurora LLC (service provider), PIMCO Funds: Global Investor Series plc, PIMCO Variable Insurance Trust, PIMCO Equity Series, PIMCO Equity Series VIT, PIMCO ETF Trust, PIMCO Managed Accounts Trust, PIMCO interval funds, PIMCO Prime Real Estate GmbH, PIMCO Prime Real Estate Asia Pacific Pte. Ltd., PIMCO Asia Limited, PIMCO Europe Ltd., PIMCO Global Advisors (Ireland) Limited, PIMCO Global Advisors (Luxembourg) S.A., PIMCO Canada Corp., PIMCO Asia Pte Ltd., PIMCO Europe GmbH, PIMCO Latin America Administradora de Carteiras Ltda., PIMCO Australia Pty Ltd., PIMCO Australia Management Limited, PIMCO Taiwan Limited, PIMCO Investment Management (Shanghai) Limited	31/03/2025	TRUE
Columbia Management Investment Advisers, LLC	(multiple funds and strategies named, e.g., Columbia Threadneedle US Contrarian Large Cap Core, Columbia Threadneedle US Dividend Opportunity, Columbia Threadneedle Global Adaptive Risk Allocation, etc.)	27/03/2025	
Ameriprise Financial Services, LLC	Signature Wealth Investment Manager (for Signature Wealth Program)	01/03/2025	

BlackRock Advisors, LLC	US Unconstrained Equity, Global Unconstrained Equity, Private Investors, Dual Contract SMA Program, Premium Access Strategies (various fixed income, equity, balanced strategies)	31/03/2025	
SmartAsset		19/03/2025	TRUE
Franklin Templeton Private Portfolio Group, LLC (FTPPG)	Mutiples Funds	06/12/2024	
Facet Wealth, Inc.	Facet Direct Indexing, Facet Alternative Income Strategy, Tax-Sensitive Fixed Income Strategy (TSFI), Short Term Strategy, ESG portfolio, High-Yield Account	15/04/2025	
Wells Fargo Advisors	Personalized Unified Managed Account (Personalized UMA), FundSource Optimal Blends, Private Advisor Network, Customized Portfolios	25/03/2025	
Massachusetts Financial Services Company (MFS)	MFS ETFs (also referred to as MFS Funds, MFS Private Funds, MFS UCITS Funds, collectively “MFS Global Funds”)	31/03/2025	
Dodge & Cox	Dodge & Cox Stock Fund, Dodge & Cox Global Stock Fund, Dodge & Cox International Stock Fund, Dodge & Cox Emerging Markets Stock Fund, Dodge & Cox Balanced Fund, Dodge & Cox Income Fund, Dodge & Cox Global Bond Fund, Dodge & Cox Worldwide Funds plc (umbrella with four sub-funds)	31/03/2025	
Charles Schwab & Co., Inc.	Schwab Managed Account Services™ (Select, Connection, SMP), Schwab Managed Portfolios™ (SMP), Selective Portfolios, UMP Program	28/03/2025	
Empower Advisory Group, LLC	Empower Managed Portfolios	31/03/2025	
Ellevest, Inc.	Ellevest Global Intentional Impact Portfolios - Gender Equality; Ellevest Global Intentional Impact Portfolios - Climate Action	31/03/2025	
Harris & Associates		21/01/2025	
Zoe Financial, Inc. Wealth Platform	Model Portfolios (generic, no specific fund name given)	31/01/2025	TRUE
Axos Invest, Inc.		27/03/2025	
Fidelity Go® / Strategic Advisers LLC	Fidelity Flex® mutual funds	31/03/2025	
SoFi Wealth LLC		27/02/2025	
Acorns Advisers, LLC	Core Portfolio, Environmental, Social and (Corporate) Governance (“ESG”) Portfolio, Custom Portfolio	31/03/2025	
Fidelity Managed FidFolios	U.S. Large Cap Strategy, Dividend Income Strategy, International Strategy, U.S. Large Cap Index Strategy, International Index Strategy, U.S. Total Market Index Strategy, U.S. Low Volatility Index Strategy, Environmental Focus Strategy	31/03/2025	TRUE
Betterment LLC	Betterment Constructed Portfolios	28/03/2025	

Wealthfront Advisers	Wealthfront Risk Parity Fund (WFRPX)	17/12/2024	
M1 Advisory Services LLC		07/03/2024	
Interactive Advisors	Interactive Advisors Multi-Manager Funds	31/03/2025	
Wells Fargo Advisors	Intuitive Investor Program	31/03/2025	
SigFig Wealth Management, LLC		01/03/2025	
Fundrise Advisors, LLC	Fundrise Real Estate Interval Fund, LLC; Fundrise Income Real Estate Fund, LLC; Fundrise Growth Tech Fund, LLC; Fundrise Equity REIT, LLC; Fundrise Growth eREIT II, LLC; Fundrise Growth eREIT III, LLC; Fundrise Development eREIT, LLC; Fundrise Growth eREIT VII, LLC; Fundrise Balanced eREIT II, LLC; Fundrise West Coast Opportunistic REIT, LLC; Fundrise East Coast Opportunistic REIT, LLC; Fundrise Midland Opportunistic REIT, LLC; Fundrise eFund, LLC; Fundrise Opportunity Fund, LP; Fundrise Opportunistic Credit Fund, LLC	10/03/2025	TRUE
Ursa Financial, LLC	Recommended Stock List	31/01/2025	
Guideline Investments, LLC		27/03/2025	
Zacks Investment Management, Inc.	Zacks Advantage	01/05/2024	
Vanguard Advisers, Inc.	Vanguard Digital Advisor, Vanguard Personal Advisor	31/03/2025	
Ally Invest Advisors Inc.	Robo Portfolios (Core, Income, Socially Responsible, Tax-Optimized), Invest Simply, Personal Advice (Foundational, Impact, Thematic Portfolios), Guided Advice	31/03/2025	
Charles Schwab & Co., Inc.	Schwab Intelligent Portfolios® / Schwab Intelligent Portfolios Premium®	28/03/2025	
Morgan Stanley Smith Barney LLC	Core Portfolios Program (Investment Strategies composed of ETFs)	28/03/2025	TRUE
Titan Global Capital Management USA LLC	Titan Crypto, Automated Bonds, Automated Equities, ARK Venture Fund	31/03/2025	
Morgan Stanley Smith Barney LLC	Performance-Seeking Portfolio, Impact Portfolio, Market-Tracking Portfolio (core portfolios); plus various thematic portfolios (e.g., Inflation Conscious, Global Frontier, Emerging Consumer, Robotics + Data + AI, Defense & Cybersecurity, Genomics & Bio-Medicine, Climate Action, Gender Diversity)	28/03/2025	TRUE
Human Interest Advisors LLC	Model Portfolios	31/03/2025	

Appendix 5 - Project Tree Python

```
afas_masterthesis_essca/
├── .env.example
├── .gitignore
├── costs_analysis/
│   ├── analysis.py
│   ├── data/
│   │   ├── adv_form/
│   │   │   └── processed/
│   │   │       ├── Acorns Advisers, LLC.pdf
│   │   │       ├── Ally Invest Advisors Inc..pdf
│   │   │       ├── Ameriprise Financial Services, LLC.pdf
│   │   │       ├── Axos invest.pdf
│   │   │       ├── betterment_adv.pdf
│   │   │       ├── BlackRock Advisors, LLC.pdf
│   │   │       ├── Charles Schwab Investment Advisory, Inc. traditional.pdf
│   │   │       ├── Charles Schwab Investment Advisory, Inc..pdf
│   │   │       ├── Columbia Management Investment Advisers, LLC.pdf
│   │   │       ├── Dodge & Cox.pdf
│   │   │       ├── Ellevest, Inc..pdf
│   │   │       ├── Empower Advisory Group, LLC.pdf
│   │   │       ├── Facet Wealth Inc..pdf
│   │   │       ├── Fidelity Go.pdf
│   │   │       ├── Fidelity Traditional.pdf
│   │   │       ├── Franklin Advisers, Inc..pdf
│   │   │       ├── fundrise.pdf
│   │   │       ├── Guideline, Inc..pdf
│   │   │       ├── Harris Associates L.P..pdf
│   │   │       ├── Human Interest Advisors LLC.pdf
│   │   │       ├── Interactive brokers.pdf
│   │   │       ├── Invesco Advisers, Inc..pdf
│   │   │       ├── J.P. Morgan Investment Management Inc..pdf
│   │   │       ├── Jemstep, Inc..pdf
│   │   │       ├── M1 Finance LLC.pdf
│   │   │       ├── Massachusetts Financial Services Company.pdf
│   │   │       ├── meryl.pdf
│   │   │       ├── morgan stanley access.pdf
│   │   │       ├── Morgan Stanley Wealth Management.pdf
│   │   │       ├── Pacific Investment Management Company LLC.pdf
│   │   │       ├── Raymond James Financial Services Advisors, Inc..pdf
│   │   │       ├── sigfig.pdf
│   │   │       ├── SmartAsset Advisors, LLC.pdf
│   │   │       ├── SoFi Wealth LLC.pdf
│   │   │       ├── T. Rowe Price Associates, Inc..pdf
│   │   │       ├── titan.pdf
│   │   │       ├── UBS Financial Services.pdf
│   │   │       ├── Ursa.pdf
│   │   │       ├── v.pdf
│   │   │       ├── Vanguard Digital Advisor.pdf
│   │   │       ├── Wealthfront Advisers LLC.pdf
│   │   │       ├── Wells fargo intuitive.pdf
│   │   │       ├── Zacks Investment Management, Inc..pdf
│   │   │       └── Zoe Financial, Inc..pdf
│   │   ├── portfolios_export.xlsx
│   │   └── portfolios_reprocessed.csv
│   ├── export.py
│   ├── import_reprocess.py
│   ├── main.py
│   ├── Portfolio_Analysis_final.xlsx
│   ├── Portfolio_Analysis.xlsx
```

```
│   └── results/
│       ├── cost_analysis_result_1746966208.096406.xlsx
│       └── plots/
│           ├── expense_ratio_by_advisor_group.png
│           ├── log_aum_by_advisor_group.png
│           ├── tax_efficiency_by_advisor_group.png
│           └── transaction_costs_by_advisor_group.png
├── data/
│   ├── backups/
│   │   └── portfolio_data_save.db
│   └── portfolio_data.db
├── performance_analysis/
│   ├── combine_performance.py
│   ├── compute_annualized_results.py
│   ├── compute_sharpe_rtios.py
│   ├── data/
│   │   ├── index.csv
│   │   ├── performance_combined/
│   │   │   └── combined_performance_stats.csv
│   │   └── performance_traditional/
│   │       ├── traditional_annual_returns.csv
│   │       ├── traditional_monthly_returns.csv
│   │       ├── traditional_performance_stats.csv
│   │       └── traditional_prices.csv
│   ├── download_returns.py
│   ├── fetch_summary_info.py
│   ├── final_analysis.py
│   ├── results/
│   │   └── phase2_analysis_20250511.xlsx
│   └── test_yfinance_import.py
├── README.md
├── test.py
└── utilities.py
```