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INVESTICIJŲ AUTOMATIZUOTŲ PATARIMŲ EFEKTYVUMO ĮVERTINIMAS	ASSESSMENT OF THE EFFICIENCY OF INVESTMENT ROBO-ADVISORY

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INTRODUCTION

Fintech, an abbreviation for "financial technology," alludes to the application of technology to provide financial services or products, or to make them more efficient. With a fast pace of evolution and development, the global fintech market has been on the rise in recent years. According to Vantage Market Research (2021), the industry is valued at USD 112.5 Billion as of 2021 and projected to grow up to USD 332.5 Billion by the year 2028, implying a Compound Annual Growth Rate (CAGR) of 19.8%.

Since its beginnings the use of this specialized financial technologies, and the subsequent coinage of the term “Fintech” under which these innovations would be categorized, financial market participants, regulators, specialists, experts and academia have shown a growing interest in know whether the application and productive use of such technologies would bring any benefit to the companies implementing such innovation, and probably in an ultimate stance to pass the innovation benefits to the final consumer, therefore shifting the way financial business deliver value to customers, and to their relevant shareholders.

One significant application of technological innovation on the financial industry is the emerging use of automated tools, algorithms and applied forecast technology to the retail investment management, the so called “Robo-Advisors” have become a new phenomenon in the wealth management sector. Robo-Advisors have gained popularity as cost-effective alternatives to traditional human advisors, especially for the new generations that as in other industries look for a full online and “smart solution” to initiate, execute and monitor the comprehensive investment portfolio processes and routine management. Even the once known as traditional financial institutions have also embraced Robo-Advisory services as part of their value offer.

The relevance of the topic

The relevance of this matter stems from the dynamic evolution of such financial technology (Fintech) and the witnessing of its substantial growth globally. The surging valuation of the Fintech market underscores its transformative impact on the financial services sector. The relevant stakeholders, including academia, are motivated to comprehend the tangible benefits, challenges, and implications of Fintech innovations. As Fintech reshapes financial services, the efficiency and real-world impact of its implementation in financial decision-making processes become pivotal areas of exploration.

Within the broader Fintech context, the focus on Robo-Advisory (RA) further amplifies the relevance of the chosen topic. As a subset of fintech, this is one of the applications that has raised critical questions about the efficiency and efficacy of automated approaches compared to traditional human-driven investment strategies. Understanding whether Robo-Advisors bring added value, efficiency, and improved decision-making processes to the financial asset management domain is a central inquiry in contemporary finance.

The significance of this research extends beyond the broader Fintech landscape to directly address the specific challenges and opportunities presented by Robo-Advisory services. As Robo-Advisors gain prominence in the financial industry, assessing their efficiency becomes crucial for market participants, investors, and the financial services sector at large. This research contributes to the ongoing discourse on Robo-Advisory by seeking to evaluate its impact on financial decision-making processes, efficiency metrics, and the overall value chain of asset management. The importance of understanding whether Robo-Advisors bring optimal allocations, improved risk-taking metrics, and streamlined decision-making processes aligns with the evolving dynamics of modern financial markets.

The level of exploration of the topic

Many of the sources and results for the recent Fintech disruptions have been explored, in regulatory contexts or, for example in the context of threats and impacts to the financial institutions (Stankevičienė & Kabulova, 2022). Fintech companies have been leveraging fundamental changes in the way data is created and processed (Gobbi, 2016) to provide more efficient financial services, expecting that those efficiency gains are transferred to customers who in turn, are expected to face lower switching costs because of the intensive use of remote distribution channels.

Schueffel (2016) comprehensively summarizes from different perspectives that Fintech is poised to have a multifaceted impact on the financial services industry, as evidenced by various sources (Ferreira et al., 2015; Heap and Pollari, 2015; Grebe et al., 2016; Gulamhuseinwala et al., 2015; Deloitte, 2016). This impact is expected to be comprehensive and enduring, with no aspect of the business being immune to change. Fintech is believed to influence various facets, including product offerings, services, and market segments. Operations, which involve essential functions such as middle- and back-office support, product servicing, and risk management, are expected to experience a significant transformation. Similarly, distribution channels, which include both online and physical avenues, as well as agents, financial advisers, and third-party intermediaries, will experience shifts. Moreover, Fintech is predicted to impact the overall customer experience, encompassing all interactions with service providers. It will also have implications on the economics of the industry, affecting aspects like revenue, costs, and profit margins. Ultimately, Fintech is expected to reshape the competitive landscape and the broader ecosystem of financial services, leading to fundamental changes in industry dynamics (Deloitte, 2016).

Nonetheless such tasks as the assessment of efficiency are far from being done, while the Fintech world is still developing, the number of innovations keep growing and new shades withing the span that ranges from traditional businesses to a purely automatized business appear and make difficult to assess them independently from the whole financial institutions system. On the other hand, a growing number of applications of financial innovations and technologies have placed fintech into different areas, spanning from KYC, fraud detection, risk management, to credit origination. Those technologies, moreover, do not work alone as many participants such as intermediaries place them in the most economically attractive terms in the form of partnerships, licensing of proprietary software, new products. In summary: we have information about this market, the companies, the innovations, and growth expectations. However, we are still lacking methodologies and data that could evaluate and compare the effects of Fintech relative to other financial services, this is what the current research aims to address.

The novelty of the work

The novelty of this thesis lies in its attempt to contribute to the knowledge and scientific framework for evaluating the efficiency of Fintech innovations, particularly in the domains of Robo-Advising. Unlike previous studies that may have explored certain aspects of Fintech, this research offers a holistic framework that spans theoretical considerations, classification proposals, literature review, and empirical methodologies.

The thesis begins by constructing a theoretical framework, which includes a thorough understanding of Fintech and proposes a classification system. It sets the stage for a more precise evaluation of Fintech innovations within a structured framework. Then, the research introduces a descriptive and comprehensive revision of evaluation frameworks, efficiency assessments and literature contribution on performance, the exhaustive collection of sources and approaches makes this work a solid consulting, recompilation, and base of further work on the topic.

By choosing Robo-Advising for case study, the thesis goes beyond a generic examination of Fintech. This targeted approach adds depth to the research, allowing for a more nuanced understanding of how Fintech influences specific financial services. A critical gap is addressed in the existing literature by focusing on efficiency measures, while there is ample discussion on the growth and potential of Fintech, there is a scarcity of studies that systematically evaluate its efficiency in comparison to traditional financial services. The research's emphasis on efficiency becomes particularly relevant in the context of substantial investments in Fintech and questions about its sustained value. This focus on practical implications enhances the applicability and significance of the findings in the current market dynamics.

The problem, aim and scope of the thesis

This work finds its motivation in the face of Fintech surge, especially in the realm of Robo-Advisors. However, amidst this rapid growth, there exists a notable gap in the literature—a lack of a structured framework to evaluate their efficiency. The existing literature and state of research still challenges to gauge the true impact and value proposition of these automated advisory systems compared to traditional financial services.

The aim of this work is to assess the efficiency of Robo-Advisory in comparison to traditional investment services. To achieve this aim, we set the following objectives:

- Conduct a thorough review of literature of concepts, classifications, and methodologies for assessing efficiency in order to be able find relevant guidelines to evaluate and measure the efficiency Robo-Advisory services in the context of financial decision-making processes.

- Develop a methodology and build a case study that allows us to compare and provide scientific evidence of the efficiency of such technologies in contrast of traditional financial services or relative to the overall market returns.
- Conduct the study with the use of different technologies, tools and algorithms; analyze and provide empirical evidence. Also, to be able to draw conclusions about our findings and discuss limitations and suggestions for further research.

The scope of this work does not limit to the understanding or recompilation of the theoretical underpinnings but also extends to the proposal of a classification system and evaluation framework that allows for current and future research on these topics. While fintech is found in many applications, particularly important questions that provide guidance on the direction of this research are: How could efficiency of financial technologies implementation be measured? Are these innovations truly enhancing the value chain of the provision of financial services, and if so to what extent? Should all innovations be measured the same? What could be a proper way to categorize fintech to measure efficiency? How these new services can be assessed and contrasted to the traditional way of providing financial services? Is technology bringing optimal allocations, risk taking metrics and the process of information? Are these technologies efficient in the rationalization and systematization of the decision-making process? Is the value creation justifiable enough for today's market size and investment inflows?

The structure and methods

In the initial phase of the research, a robust theoretical framework is constructed. This involves a comprehensive review of existing literature on Fintech, its definition, and classifications, also on Robo-Advisory services, efficiency models, and financial decision-making processes. The framework aims to establish definitions, classifications, and key characteristics that will be useful for constructing a methodology. A detailed literature review is conducted to understand the current academic proposals, methods, and scientific frameworks.

Then a methodology for finding evidence is constructed, based on the previously examined characteristics, concepts, and properties of the object of study. The building blocks for our methodology include the set-up of our case study, the construction of benchmark composites for analysis, the conceptual definition of our formulas and variables and the intended use of the data.

Then we proceed to explore our datasets, we transform the initial data to standardize it for correct and cohesive analysis, we resample the return data and we perform visual explanations of the variables that will be tested in our hypotheses. We use the most recent software for analysis: Python, Jupyter Notebooks and mathematical, statistical and data analytics libraries such as NumPy, MatplotLib, Pandas, SciPy, Seaborn and ScikitLearn.

The empirical results obtained from both the simulation-based and data-observed approaches are analyzed comprehensively. This involves using statistical tests, possibly including those from the scipy.stats library in Python, to draw meaningful insights regarding the efficiency of Robo-Advisory platforms. Python code snippets utilizing the scipy.stats library are incorporated into the research as annexes. These code segments are essential for implementing statistical tests and analyses, ensuring transparency and reproducibility of the research findings. The inclusion of code in the annexes facilitates a clear understanding of the computational aspects of the analysis.

1 CONCEPTUAL AND THEORETICAL BACKGROUND OF FINTECH AND ROBO-ADVISORY

1.1 Fintech definitions, impacts, taxonomy, and frameworks

1.1.1 Definition

The concept of Fintech probably dates to the early 1990s (Arner et al., 2015) when it was associated with the "Financial Services Technology Consortium," an initiative launched by Citigroup to foster collaboration in technological advancements within the financial industry.

Karakas and Stamegna (2017), in the context of policy analysis for the European Parliamentary Research Service (EPRS), considered Fintech as companies utilizing technology-based systems to either directly offer financial services and products or enhance their efficiency, Fintech encapsulates a wide array of innovative financial solutions.. However, in today's context, the concept of fintech is more broadly interpreted as any application of technology to financial services. As noted by Arner, Barberis & Buckley (2015) , this wider definition implies that Fintech is not an "inherently novel development" but rather a new stage or era of a continuous incremental evolution of the financial services industries paired with technology development.

We take another important conceptual interpretation from the International Monetary Fund's 2018 Bali Fintech Agenda (International Monetary Fund & World Bank, 2018) where fintech was deemed as the term denoting technological advancements that had the potential to revolutionize the delivery of financial services, catalyzing the emergence of novel business models, applications, processes, and products, In the same document a special remark on the symbiosis that exists between technology and finance, reminds us that though there may exists a formal definition or classification, Fintech implies a complex evolution in the combination of technology with processes, products, and applications.

After a thorough scientific review and study of the definition and genealogy of the term itself, Schueffel (2016) concludes that Fintech simply represents a recent financial sector that leverages technology to enhance various financial activities. Within his discussion, he asserts that this definition of Fintech represents a synthesis of various definitions found in the literature, striving to serve as both a precise and essential description while also having the potential to be a shorter, simpler, or more symbolic representation when applied in different contexts. It encompasses the notion that Fintech constitutes a new financial industry leveraging technology to enhance financial activities, impacting a wide array of financial services, from incremental technological improvements (e.g., APIs, device-independent technology) to disruptive innovations (e.g., Chat Bots, Blockchain, artificial intelligence). However, it excludes traditional, mainly mainframe and paper-based banking services delivered through human interfaces. This definition serves as a common baseline but may not fully capture the term's diversity across contexts. Furthermore, definitions change over time, reflecting evolving industry dynamics and technologies, and the term "new" in the definition is likely to evolve.

From these findings we can see that it is not an easy task to bound this concept, either historically, technologically or by the end byproduct. Fintech can be considered rather a continuum of market conditions, historical breakpoints and progressive developments and applications in the financial industry. It is however useful to draw classifications for the purpose of understanding and being able to further measure the impacts, efficiency, and risks of these innovations.

1.1.2 Classifications

Academic interest in Fintech has surged, leading to categorization efforts, debates on its nature as a product, business model, or disruptive mechanism, and attempts to develop a unified definition. Notably, (Mention, 2019) highlights the pivotal role of technology in this evolution, citing artificial intelligence, blockchain, smart contracts, and machine learning as key enablers.

Dermine (2016), for instance groups into three categories based on the banking services where technologies disrupted:

1. Banking services that involve mostly data processing. This is the example of payment processors and intensive operative data services.

2. Banking services that involve data analysis. This is the example of risk evaluation, corporative and investment advising, and state planning.

3. Banking services linked to the distinct structure and expertise of traditional banking, encompassing services that capitalize on the unique properties and capabilities of the banking balance sheet such as managing maturity mismatches.

On the other hand, FinTech start-up a classification has been explored based on non-functional characteristics (Gimpel et al., 2018). This taxonomy is designed to help understand Fintech better and the role of its start-ups in the financial sector. It consists of three main perspectives: *interaction*, *data*, and *monetization*, with each perspective having several dimensions and related characteristics. According to the authors' proposal:

Interaction Perspective: This perspective focuses on the interaction between Fintech companies and their customers. It includes the following dimensions:

- Personalization: Describes the level of customization of content and content presentation for users.
- Information exchange: Refers to how interactions between the start-up and their users are initiated (pull or push services).
- Interaction type: Captures the role of the start-up in interactions (direct interaction, intermediary, marketplace).
- User network: Represents how the services helps users to communicate.
- Role of IT: Differentiates technology's role in service encounters.
- Hybridization: Refers to the possibility of offering hybrid products (physical products integrated with digital services).
- Channel strategy: Describes the channels through which services are offered (digital exclusive or non-exclusive).

Data Perspective: This perspective characterizes how Fintech companies process data. It includes the following dimensions:

- Data source: Differentiates data sources used by start-ups (user data, peer data, public data).
- Time horizon: Describes the time frame of data used (historic, current, predictive).
- Data usage: Distinguishes between transactional and analytical data processing.

- Data type: Reflects the format and structure of processed data (structured or unstructured).

Monetization Perspective: This perspective focuses on how FinTech start-ups monetize their service offerings. It includes the following dimensions:

- Payment schedule: Differentiates between regularity of payments (transactional, subscription, or none).
- User's currency: Describes what users pay with (money, attention, data).
- Partner's currency: Represents how business partners pay for services (money, attention, data, or none).
- Business cooperation: Indicates whether the start-up operates independently or collaborates with partners.

In the same study, this classification is used to group 227 FinTech start-ups. For example, in the Interaction Perspective, the archetypes include "personalized isolated," "non-personalized isolated," and "socially connecting intermediate," which describe the degree of personalization and interconnectedness of user networks. In the Data Perspective, the proposal considers two archetypes: "standard processing" and "advanced analytics," differentiating start-ups based on their data processing methods. In the Monetization Perspective, the archetypes are "no money," "user-paid," and "business-paid," indicating how the start-ups monetize their services.

Arner (et al., 2015) on the other hand, describes a major topology in fintech as the classification of five major areas: finance and investment, operations and risk management, payments and infrastructure, data security and monetization, and customer interface.

Kabulova and Stankevičienė (2020), upon the review of multiple sources classify Fintech among four major dimensions linked to the underlying technology and consequently then expanding subclassifications to a specific innovation and the financial services where those technologies are used.

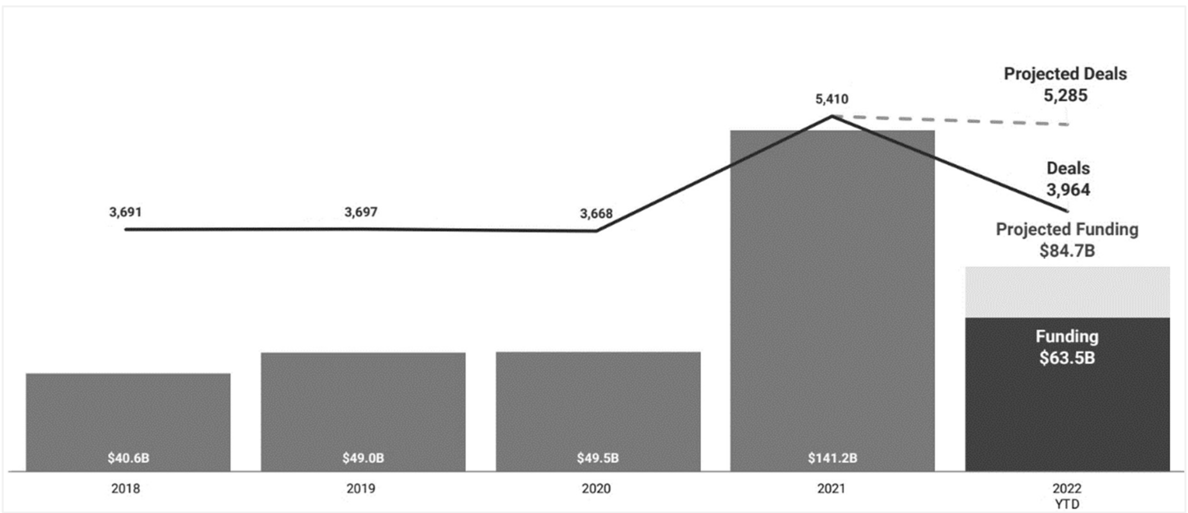
1.1.3 Impacts

As of the second quarter of 2022 the value of new funding for fintech was 63.5 billion USD worldwide (KPMG, 2022), last year showed a record historical funding of 141.2 billion USD (CB

Insights, 2022). The peak during last year, as well as the falling short of projected numbers during this year, amplify the motivation for this research and its relevance by raising further interrogations to address such as if the value of fintech will achieve the growth rates previously forecasted, if the innovation has encountered any loss of value, if the current estate justify the big amount of investment flows and if today's valuations are correctly justified by the value added.

Figure 1

Fintech funding globally and number of deals



Source: CB Insights, 2022.

As the technology is reshapes the financial services industry and gives rise to new competitors outside of the traditional sectors, new research emerges trying to find insights into this market disruption (Goldstein et al., 2019). The authors mention a body of research under the category of "transformation and disruption of financial services." The same resources are examined here with a focus on technology-based investment advisory services. Relevant to our approach, we present the findings of (Fuster et al., 2019), (Tang, 2019), and (D'Acunto et al., 2019).

In assessing the transformative impact of technology-driven lenders on the U.S. mortgage market mortgage, Fuster and others (2019) reveal several significant key insights. Firstly, FinTech lenders simplify the mortgage origination process, making it less vulnerable to capacity limitations and thereby improving the transmission of monetary policy to households during peak demand periods. Additionally, FinTech lending is linked to a higher likelihood of borrowers refinancing, particularly when it is advantageous for them. Notably, the study does not uncover any indications that FinTech lenders issue riskier loans or engage in less effective borrower screening. In fact, lower default rates compared to similar loans from other sources were seen in FHA mortgages that were originated by a Fintech lender.

For the future, the study anticipates a broader adoption of the *flagship* model where online applications and centralized, semi-automated underwriting. While online mortgage lending kept expanding, it remains uncertain whether traditional banks can compete effectively with specialist nonbank mortgage lenders in the long run. Banks possess distinct advantages such as low-cost deposit funding and branch networks for hybrid online and in-person interactions, but they may face challenges in adapting due to regulatory constraints and complex legacy processes.

According to the authors, from industry dynamics perspective, the transition to online lending could result in market concentration, tilting the advantage towards larger firms equipped with the resources to invest in technology.

From a consumer standpoint, the study suggests that technological diffusion in the mortgage market will expedite origination processes and improve refinancing decisions, ultimately benefiting U.S. households. However, the findings are situated within the context of the U.S. mortgage market at the time of the study, where FinTech lenders were primarily nonbanks. The potential implications as the model extends to deposit-taking banks and regulatory changes remain areas for further research. Additionally, the impact of FinTech on access to credit for borrowers requiring soft information or in-person communication with loan officers is a subject left for future investigation.

Now, on the competition dynamics perspective Tang H. (2019) finds that indicate that the impact of peer-to-peer (P2P) lending platforms on banks in the consumer credit market can be both substitutional and complementary, depending on the specific circumstances.

Substitution: Findings that P2P lending can serve as a substitute for bank lending when it comes to serving less credit-worthy bank borrowers came in the study. This implies that when banks tighten their lending criteria or reduce credit supply, some borrowers who would typically rely on traditional banks turn to P2P lending platforms as an alternative source of credit.

Complementarity: In the context of peer-to-peer (P2P) lending and traditional bank lending complementarity is observed when addressing small loan amounts. Specifically, P2P lending platforms and banks are not engaged in direct competition but rather collaborate to meet the credit needs of borrowers seeking smaller loan sums.

In contrast to Fuster's findings, the results of this study suggest that the credit expansion facilitated by P2P lending predominantly benefits borrowers who already have access to bank credit. This implies that P2P lending might not necessarily broaden credit access for underserved or unbanked populations; instead, it serves as an alternative credit source for those who can already secure credit from traditional banks.

The study's primary conclusion is that P2P lending exhibits a dual role, acting both as a substitute for and a complement to traditional bank lending in the consumer credit market. It emphasizes that the impact of P2P lending on banks is contingent on specific contextual factors, borrower profiles, and the lending criteria of traditional banks. Furthermore, the study affirms that a negative shock to bank credit supply, as evidenced by regulatory changes, leads to an upsurge in P2P lending volume. This supports the notion that P2P lending can function as an alternative credit source when traditional banks curtail their lending activities.

Lastly, we will discuss and contrast the findings of D'Acunto and others (2019) on an impact assessment of wealth-management Robo-Advisor on investors. The research centers on the introduction of a specific instance of Robo-Advisor, a technological platform that customizes portfolios based on investors' existing holdings and preferences.

Diversification Outcomes: The study aims to understand whether Robo-Advising can improve the diversification of investors' portfolios. It considers three hypotheses for why Robo-Advising might enhance diversification: (a) Human advisers might not fully understand diversification, leading to suboptimal advice. (b) The complexity of achieving diversification with multiple stocks might lead to inaction, and Robo-Advising simplifies the process. (c) Human advisers might prioritize client preferences over diversification.

*Diversification Benefits: I*nvestors with inadequate diversification increase the number of stocks in their portfolios after adopting Robo-Advising. Conversely, highly diversified investors do not undergo significant changes in their diversification levels. This suggests that Robo-Advising serves as a valuable tool for under-diversified investors, aiding them in optimizing and improving the diversification of their investment portfolios.

Performance Improvement: Under-diversified investors who adopt Robo-Advising show better performance in terms of market-adjusted returns. However, investors who were already diversified and adopt Robo-Advising trade more, but not always with better performance.

Behavioral Bias Reduction: The integration of Robo-Advising results in a decline in significant behavioral biases such as the disposition effect, trend chasing, and the rank effect among investors, irrespective of their initial diversification levels.

Increased Attention: Takes the accounts login as a measure of increased attention, indicating that Robo-Advising tools may encourage investors to monitor their portfolios more closely.

The study's findings suggest that the impact of Robo-Advising tools varies depending on investors' initial diversification levels. Under-diversified investors tend to benefit from improved diversification and performance after adopting Robo-Advising. However, highly diversified investors may not experience significant improvements in performance despite increased trading activity.

In conclusion, the reviewed studies shed light on the multifaceted impact of FinTech, P2P lending platforms, and Robo-Advisors in various financial contexts. These studies collectively highlight the nuanced effects of financial technology on various aspects of the financial industry. They underscore the potential benefits for investors and borrowers but also emphasize the need for continued research to understand the evolving landscape and address challenges associated with these technological advancements in finance.

1.1.4 Development of our framework for classification

Within this summarized classification we will construct our framework for analysis by adding one more scope in the classification: a label that shows the specific moment or process on the value chain that for each category and subcategory, and for each financial service, the innovation could be applied in, from the perspective of the financial services providers.

Figure 2

Classifications of Fintech

		Technology Innovation	**Financial Services**	**Application in the value chain**
	Artificial intelligence (AI) Big Data	Machine learning (ML) Predictive analytics Data analytic	Investment advice (robo-advising) Credit decisions Asset Trading	Enhacement of core business backoffice Enhancement of non core business backoffice Creation of a new product or service Decision of financial asset management
	Distributed computing	Distributed ledger (DLT) Blockchain Smart contracts	Digital currencies Back-office, recording Settle payments Automatic transactions	
Dimension of technology	Cryptography	Biometrics Cybersecurity	Identity protection Cybersecurity	
	Mobile access internet	Digital wallets Application programming interfaces (APIs) Mobile transactions Internet of things (IoT)	Crowd funding person-to-person transactions (P2P) Smartphone wallets Inter-operability and expandability	

Source: Kabulova & Stankevičienė, 2020 with input of the author.

Classifications could work as a comparative tool for the purpose of the classifier, such as regulatory or scientific (Karakas & Stamegna, 2018). Thus, this new proposed labeling is not intended to be strict in the sense that does not imply that categories are unique, exhaustive, or paired one to one with the technologies and innovations. Rather, Fintech comprises a great level of complexity and dynamic boundaries. For instance, in the analysis of Robo-Advisors, we might label them as technology applied to financial asset decision making, but by considering the aggregate of technologies across all the processes, as we will see later, some Robo-Advising become a whole new product for the consumer.

Below is a description of the categories proposed for subsequent analysis.

1. The enhancement of non-core back-office. Implies any technology applied to parts in the financial services provided other than the operatives of the financial service itself. This is the case of cryptography technology used for stronger authentication processes, the use of Machine Learning for fraud or money laundry detection and other regulatory aids.

2. Enhancement of core-business back-office. Implies the application of technology to the operatives of the financial service provided. This is related to Dermine's first category, as described by him as a heavily electronic data-processing service by banking institution. Here we may we consider core back-office as the data processing activities that generate an operative activity but do not provide any insight or analysis. This is the example of payment settling fintech's or activities within banks related to current accounts such as debit and credit.

3. The delivery of a new product or asset to the consumer. This is the case, for example, of the use of block chain technology to create a digital token. Or the creation of crowdlending applications, which by making use of web and mobile technologies, created a pool of assets and investors based on peer-to-peer lending, patronage or sponsoring. It is important to mention, however, that the users of the platform bear the risk of funding (Mollick, 2014), hence companies running the crowdfunding platform do not bear any credit risk, and do not advise the customer whether to fund a loan or not. The core activity is to provide an exchange platform and custody as a product.

4. The financial asset management decision. This includes the use of Machine Learning and automatized models for wealth management and the use of artificial intelligence for loan quality prediction (and therefore loan application acceptance or rejection).

This new label allows us to classify the technology in terms of where in the value chain of the delivery of financial services the technology is applied. We believe that by segmenting this way we may have an interesting starting point for assessing the impact, efficiency, or risk of the technology introduction.

1.2 Investment decision and Robo-Advisory

The financial asset management decision exists at the core of many business models and financial institutions. Examples are banks, pension funds, endowments, foundations, mutual funds, and hedge funds, which ultimately depend on the result of the fund managers and staff decisions. Knittel (Knittel et al., 2004) finds that the returns and consistency of managers relative to a benchmark, in the flow of assets among investment products. Naturally, the success of such institutions' goals may respond to a complete set of factors and processes involved, but risks management and performance of the assets held are the key metrics against which the business are evaluated, and the survival of the funds would depend on those metrics.

Traditionally, the analytical businesses of financial institutions such as banks and investment funds have required a great amount of highly specialized and technical workforce. More than that, business such as lending, asset management and structuring, constitute a legacy of decades of bank expertise, which at some point would constitute a high barrier of entry (Philippon, 2016). Nonetheless the recent years data explosion and innovation on data processing systems, have transformed the data analytics business rapidly, bringing new entrants to the market (Kelly, 2014). As rigid as the financial asset decision-making of banks and financial institutions would have been for years, the new data paradigm brought fundamental changes to these processes.

1.2.1 Conceptual definition and characteristics

Robo-Advisors are a specific application of fintech in the wealth management industry, specifically in the portfolio management decision-making processes. Robo-Advisors appeared as digital platforms that provided automated portfolio management services using quantitative algorithms (Beketov et al., 2018) based on inputs of the user (Fein, 2015) and rules. These platforms typically service individual investors with portfolio management and charge lower fees than a human advisor would do (Capital One Financial, 2022).

Robo-Advisors have been growing in popularity, with global assets under management (AUM) reaching $1.2 trillion in 2019 (Cerulli Associates, 2019).

Also on the customer side, they have gained popularity as cost-effective alternatives to traditional human advisors (Abraham et al., 2019). These online platforms utilize algorithms to develop and oversee investment portfolios for clients, expanding their services to encompass comprehensive portfolio management. Notably, traditional financial institutions, including major brokerage firms like Charles Schwab and asset managers like BlackRock, have also embraced Robo-Advisory services. Also, they rely on a client's investment goals and risk profile to formulate personalized investment strategies. By assessing factors such as the investment purpose, time horizon, and risk tolerance, these platforms offer recommendations on asset allocation using automated algorithms, often based on modern portfolio theory. This approach aims to maximize expected returns while considering the client's risk tolerance or minimize risk given a specific expected return level. The adaptability of portfolio allocation based on individual goals and risk preferences highlights the flexibility and customization that Robo-Advisors bring to wealth management, making them an appealing option for investors seeking efficient and personalized financial services.

Robo-Advisors are built upon certain principles, being one of the most relevant the passive or rule-based investment (Scherer & Faloon, 2017). Passive investment relies on the idea that no constant alpha is achievable in the market, hence no need for identifying mismatches in price of assets. The passive versus active investment debate is a long and widely studied issue: Brinson, Hood, and Beebower (1986) concluded in their research that the benefits of active management do not justify the costs. Renshaw and Feldstain (1995) remark that even a psychological benefit is embedded in following a familiar index such as the Dow Jones Industrial Average without having to pay the costs for advisory services.

Robo-Advisors also attaches to the financial market efficiency hypothesis, and the kernel of their ruled-based allocation system is directly compatible with the factorial model based passive investing. The five risk factors model (Fama & French, 2015) decomposed further the risk exposure of benchmark indexes, making theoretically easy to implement a rule-based strategy that places tilts on the desired risk exposures given certain views of the market or client needs. Notwithstanding, Robo-Advisors hardly make public the inner rules and principles on their systems, and the exact use of passive factorial models can be only inferred from the information available (see for instance: Ginmon Vermögensverwaltung GmbH, 2022). Alternatively, Park, Ryu, and Shin (2016) listed some of the Robo-Advisor strategies finding the Black-Litterman model as the most common.

The study of (Foerster et al., 2014) sheds light on the significant impact that financial advisors have on the investment choices of households. The findings highlight three key points. First, having a financial advisor tends to push clients towards taking more risks, with the share of risky assets increasing by approximately thirty percentage points when advised. Second, advisors do not customize their advice much based on individual client characteristics, with only 13% of the variation in risky asset share explained by factors like risk tolerance. Third, there are substantial variations in risk-taking among clients based on their specific advisor, indicating that advisor-specific effects play a crucial role.

Interestingly, despite the lack of personalized advice and the considerable impact of advisor-fixed effects (essentially luck of the draw) on portfolios, the cost of this one-size-fits-all advice is relatively high—averaging 2.7% of assets per year. The study suggests that, while advised investors end up with riskier portfolios, these additional risks do not translate into higher net returns for them. In fact, it is the advisors and mutual funds who capture the additional returns, raising questions about whether the fees paid to advisors are justified solely based on investment advice.

1.2.2 Current state of Robo-Advisory – Cases worldwide

In the course of this study, we conducted an extensive review encompassing a total of at least 135 companies operating under the label or registration as Robo-Advisors. The refinement of this list involved a careful examination of each company's proposal, estimated Assets under Management (AuM), and the clarity with which their methodology was articulated. The aim was to distill a set of core principles that could be generalized to understand the foundational aspects of the Robo-Advisory business.

Our focus narrowed down to the top-performing Robo-Advisory firms on a global scale. Notably, some of these firms have reached a mature stage, attracting significant investments from the Private Equity sector. Additionally, one exceptional case involved a Robo-Advisor that successfully underwent an Initial Public Offering (IPO) in 2021, signifying a pivotal moment in the industry's evolution. Drawing insights from the whitepapers, methodologies, and relevant literature of these leading Robo-Advisors, we synthesized a conceptual common ground. This synthesis encapsulates key principles that underpin the operational frameworks and philosophies shared by these prominent players in the Robo-Advisory landscape.

Table 1

Main Robo-Advisors Worldwide

Country	Name	Methodology	Methodological resource, whitepaper strategy description	Historical returns
USA	Betterment	Black-Litterman Factor model MPT	*https://www.betterment.com/resources/betterment-portfolio-strategy*	NO
Germany	Ginmons	Factor model	*https://www.ginmon.de/en/investment-strategy/*	NO
Spain	Indexa Capital	Markowitz Black-Litterman	*https://indexacapital.com/es/esp/model#asset-allocation*	NO
Japan	Wealth Navi	Markowitz Black-Litterman	*https://corp.wealthnavi.com/en/ir/library/disclosure*	YES
USA	Wealth Front	Markowitz Black-Litterman	*https://research.wealthfront.com/whitepapers/investment-methodology/*	YES
Canada	Wealthsimple	Non specified	*https://help.wealthsimple.com/hc/en-ca/articles/1500002680761-Classic-Investing-Our-investment-strategy*	SUMMARIZED
USA	Stash	Non specified	*https://www.stash.com/learn/stash-way-investing-philosophy/*	NO
Singapore	Syfe	Factor investing Smart beta	*https://www.syfe.com/investment-strategy*	BACKTESTED
Australia	Stockspot	Active MPT	*https://www.stockspot.com.au/about-us/philosophy/*	YES

Source: Author's with input from the indicated resources.

There are characteristics common to all RA's, generally their investment strategy revolves around transparency and a comprehensive understanding of portfolio composition. The primary objective is to provide clients with not just information about their portfolios but also the rationale behind investment choices. The strategy emphasizes generating returns while managing risk, particularly during market downturns, outperforming traditional portfolios.

Diversification is one of the key offerings on all of them, also a shared characteristic with retail funds and traditional investment services. Allocating investments across various regions to capitalize on outperforming regions and smooth out returns. Focusing on stocks with lower volatility to reduce portfolio risk without compromising long-term return expectations.

As for the investment strategies, each offer differs but most methodologies revolve around Markowitz, Black-Litterman and Factor models. provides a range of investment strategies, some of them have a sustainable variant. These strategies vary in the allocation of stocks, bonds, real estate, and commodities. The recommendation of a specific strategy is influenced by factors like experience in capital markets and investment horizon, tailoring the suggestion to be more equity-focused for those with long-term perspectives.

Embedded in the Robo-Advisory emerging industry is the use of ETFs (Exchange Traded Funds), they work as the backbone of the Robo-Advisors core offer and construction of strategy in modern portfolio management. Robo-Advisors, which are meant to be automated, leverage ETFs to construct diversified and cost-effective investment portfolios for clients. As mentioned before, part of the offer is algorithms to analyze an investor's risk tolerance, financial goals, and time horizon. The execution of this proposal involves the allocation of assets across various ETFs accordingly. But why the use of ETFs and not the assets directly? We summarize below the reasons for ETF use provided by most Robo-Advisor:

Diversification and Cost-Effectiveness: Robo-Advisors favor ETFs for diversification, offering exposure to various assets like stocks, bonds, or commodities to create a well-diversified portfolio, reducing risk. ETFs are cost-effective compared to traditional mutual funds, making them an attractive option for investors seeking efficient and low-cost portfolio solutions.

Algorithmic Portfolio Construction: Robo-Advisors use advanced algorithms to build and oversee investment portfolios by taking into the algorithm's factors such as risk tolerance, investment goals, and market conditions to decide how to allocate assets across various ETFs. The automated process of Robo-Advisors ensures a systematic and disciplined approach to managing portfolios.

Risk Management Focus: Robo-Advisors place significant emphasis on risk management. The algorithms employed by these platforms consider risk factors associated with ETFs, such as diversification, counterparty risk, liquidity risk, and trading-costs associated risk.

Intraday Trading and Market Liquidity: ETFs, being traded on exchanges like stocks, offer intraday trading capabilities. This intraday liquidity is a significant advantage, allowing investors to buy or sell ETF shares at market prices throughout the trading day. This feature aligns well with the automated and real-time nature of Robo-Advisors.

Liquidity of Underlying Assets: The liquidity of an ETF is closely tied to the liquidity of its underlying assets. Robo-Advisors consider the liquidity of the ETFs they include in portfolios, ensuring that the underlying assets can be efficiently bought or sold without significant price impact.

Enhanced Trading Efficiency: The liquidity of ETFs contributes to the overall efficiency of trading within Robo-Advisory platforms. Investors can experience lower bid-ask spreads and reduced trading costs compared to less liquid investment vehicles.

Another shared characteristic catches the attention and the potential for developing a research framework: the use of goal-oriented investing, a global trend in wealth management that arose particularly from the big inflow of retail investors to the financial markets. Goal-oriented investing, central to the strategies employed by Robo-Advisors and other modern investment platforms, diverges from conventional approaches by weaving individual financial aspirations seamlessly into investment portfolios. This method eschews the one-size-fits-all model, and traditional models for investing such as MVO, or risk-return frameworks delving into investors' specific objectives, be it saving for retirement, purchasing a home, funding education, or other milestones. In this personalized journey, investors undergo a profiling process, articulating their goals, timeframes, and risk tolerance, forming the bedrock upon which the Robo-Advisor creates a bespoke investment portfolio. The key is a dynamic, customized approach, tailoring asset allocation and diversification strategies to the unique risk parameters and time constraints associated with achieving identified goals.

These portfolios are not static entities; rather, they undergo periodic reassessment and rebalancing, adapting to changing market conditions and investors' evolving circumstances. Risk management takes on a personalized hue, recognizing that the risk tolerance for a retirement fund may differ markedly from that of a portfolio earmarked for short-term goals. Investors are equipped with tools and dashboards for ongoing progress tracking, allowing them to gauge how well their portfolios align with their financial objectives. Additionally, goal-oriented investing is not merely transactional; it incorporates an educational dimension, offering guidance on financial planning, goal setting, and investment strategy. The adaptability of this approach is crucial, recognizing life changes and ensuring that the investment strategy remains in harmony with shifting circumstances.

Finally, other few characteristics to mention, but where there is very little research are monitoring and rebalancing: Robo-Advisors continuously monitor the performance of investment portfolios. When necessary, automated rebalancing takes place to maintain the desired asset allocation. This proactive approach ensures that the portfolio aligns with the investor's goals and risk preferences over time; Transparency: a shared characteristic of Robo-Advisors since they often provide clear information about investment strategies, fees, and performance. Investors can easily access details about their portfolios and understand the rationale behind investment decisions made by the algorithm; and user interface: Robo-Advisors are designed to be have easy and simple interfaces directed to all levels of financial knowledge. Investors can typically set up and manage their accounts through intuitive online platforms or mobile applications, providing a seamless experience.

1.2.3 Research methodologies on Robo-Advisory

Different methodologies and approaches are taken when trying to measure the effectiveness of financial decisions, specifically in the context of financial asset decisions. A comprehensive review of authors and methodologies was performed, we started by broadly including the research on those assessments on, for example that grant a loan, as technically means buying a debt asset based on a financial institution's risk guidelines and appetite. Then more specifically on buying, selling investment financial assets on behalf of typically a retail client, after performing a knowledge survey about their risk preferences, time frame for investing and constraints.

Wozniewska, G. (2008), for example, conducted a study on the efficiency of commercial banks, specifically focusing on Polish banks. The research utilized the Data Envelopment Analysis (DEA) method, a non-parametric approach increasingly employed in measuring efficiency in well-established banking systems and put it in the contrast of efficiency analysis by financial indicators method. The DEA method, originally proposed by Charnes, Cooper, and Rhodes, evaluates efficiency by considering multiple inputs and outputs, measuring a unit's efficiency in relation to others in the study group.

The study adopted the value-added approach within the DEA method, where a bank's output is any activity consuming its resources. In this context, outputs included the volume of loans, deposits, and non-interest income, while inputs comprised assets and the number of employees. The efficiency evaluation considered various assumptions related to the economy of scale, including constant scale effects, variable scale effects, or non-increasing scale effects of performance. This study concludes that both methods yield corresponding results in evidence of positive efficiency.

In reviewing different fintech methodologies a relevant aggregation paper helped us navigate different methodologies. In their work Takeda & Ito (2021) conducted a search for relevant studies within the FinTech domain between February and April 2019, utilizing Elsevier's Scopus database then refining the results under their own thresholds, to finally present a final sample of 88 FinTech papers.

The papers were sorted into four categories: Type A explored how existing financial institutions utilized FinTech for additional value, Type B examined the use of FinTech by existing institutions to enhance efficiency, Type C focused on new players bringing fresh value, and Type D covered new entrants improving efficiency. New entrants were defined as companies entering the finance industry by leveraging FinTech technology.

The distribution of papers across these categories showed that Type C, which dealt with new entrants providing new value, was the most common, while Type B, concerning improved efficiency in existing financial institutions, was the least frequent. The author also organized the papers based on new value-added types, regions, and research methods. Notably, most papers on new value-added concentrated on exploring the provision of new value through new technologies. In terms of regions, Asia and the EU represented a significant portion of the studies, making up 59% of the total. The case study was identified as the most frequently used research method, applied in twenty-nine papers.

1.2.4 Efficiency from financial efficiency perspective

The primary role of functional markets is to allocate the capital resources to its best use, and under the price that rationally reflects all information and conditions. As described by Fama (Fama, 1970), in an ideal world price of assets would reflect fully their intrinsic characteristics and investors would choose exactly the assets that best represent their desire, risk appetite, and other constraints. Whether the markets reflect efficiency or not, and if so to what extent is a matter of modern debate and research. However, the acknowledge of the concept of efficiency in financial markets is a baseline to framework our efficiency assessment for the exact Fintech classification we are trying to assess efficiency on the financial technology that relates to the decision of financial asset allocation and management.

Given the definition explored before, we can conclude that efficiency would imply the correct allocation of resources into assets that would be most productive, and well-matched to predefined constraints. Naturally, a test of efficiency would involve wise allocation and correct pricing.

For the subjects of our analysis, an efficiency assessment would imply test for risk adjusted returns, of the Robo-Advising portfolio allocation vs. other funds of the same constraints, or in the case of the strongest efficiency of markets hypothesis, versus a stated benchmark beyond of which is believed there would be no room for what it is called abnormal returns. Nonetheless, as mentioned, Robo-Advising innovation finds itself in a state-of-the-art implementation. Being blurry regulated on those countries that have sandbox and principle-oriented regulation (Chikako Baba et al., 2020). While on the other hand, being heterogenous in the legal figure that it takes in those countries where the Robo-Advisor must fit an existing regulatory framework - rule based regulation. These differences in the current estate present challenges for the data collection in terms of the intended efficiency test.

On the other side, Woo et al., 2020 discusses the debate on market efficiency, citing numerous studies and perspectives. Notable scholars like Jensen, Lehmann, and Fama have argued for market inefficiencies, while Loughran and Ritter caution against certain testing methods. The review recognizes current research efforts, with recent investigations introducing predictive indicators for market returns, studying the influence of financial constraints on the long-term performance of companies, and delving into the positive correlation between housing and stock investment in Chinese cities. Simulation scenarios are also taken into account, including experiments that test models with gamma random errors and scrutinize market efficiency using stochastic dominance and the Omega ratio.

As per the study conclusions, while certain research affirms the efficiency of the market, discrepancies emerge in scenarios such as the influence of exchange rates on stock markets and the connection between oil prices and the stock prices of renewable energy. The study underscores the significance of persistent research efforts to reconcile these conflicts. Scholars employ techniques like cointegration, error-correction methods, and stochastic dominance tests to evaluate market efficiency across diverse contexts, including the Taiwan stock and futures markets, oil spot and futures markets, Hong Kong residential property market, and Shanghai gold market. The conclusion underscores the continual discourse regarding market efficiency and the potential existence of arbitrage opportunities.

We previously mentioned about among some shared characteristics of the Robo-Advisor product offer is the use of Exchange Traded Funds (ETFs), recent findings indicate that portfolios managed by Robo-Advisors exhibit significantly better returns compared to non-Robo-Advisor portfolios (Zhang et al., 2023) in the context of use of selection recommendations in ETF portfolios, using Artificial Intelligence. This study evaluates 798 ETFs with the portfolio return formula and the random forest algorithm and the study reveals that while Robo-Advisors have some influence on average returns, their significance is not as pronounced as traditional metrics. However, they play a crucial role in risk management, with the empirical analysis identifying two key indicators — *maximum retracement* and the *decidability factor* — that significantly influence intelligent investments. These indicators serve as measures of risk, emphasizing Robo-Advisors' focus on risk factors in ETF funds and their implementation of effective risk management strategies.

Finally, research on the goal-oriented investing characteristic of the Robo-Advisors evidence the computational advantages of robust optimization over scenario-based models, especially in scenarios with numerous stages where the latter becomes computationally expensive and sensitive to scenario selection (Kim et al., 2022). Their research introduces a goal-based investing model grounded in robust optimization for personalized financial planning. The model addresses the intricate landscape of multiple financial goals with varying priorities. The robust multi-stage problem is then solved for each priority level, showcasing its model's adaptability.

2 METHODOLOGY FOR FINDING EVIDENCE OF EFFICIENCY OF ROBO-ADVISORS

The conceptual core of this research work has been revolving around creating a framework for developing a practical methodology that describes and evidences the efficiency of Robo-Advisor (RA) investing in comparison to human-led investment approaches. In a broader or more extrapolated sense, the research seeks to address a higher order question in academic discourse—whether financial innovations in the form of Financial Technology (FinTech) bring intrinsic value and efficiency when contrasted with traditional financial services.

Robo-Advisory, as described in the theoretical framework, particularly presents unique challenges. A key hurdle is the absence of a standardized methodology universally accepted as representative of Robo-Advisor practices, considering that by definition financial technologies represent rather a span of degree of use and application of technology on a certain area, process, or problem in financial services. Accordingly, unlike other financial models or defined products, the Robo-Advisor landscape lacks a single strategy or theoretical foundation, leading to a diverse range of strategies and implementations - this was exemplified and evidence during the description stage where several Robo-Advisory value-offers worldwide were summarized. This diversity necessitates a thorough exploration of the varied nature of Robo-Advisor methodologies.

Performance evaluation, evidence of efficiency or ratings of Robo-Advisor investing adds complexity. Unlike the conventional performance attribution framework used for active investment managers, Robo-Advisor principles naturally align with passive investment strategies by product design. This departure from traditional evaluation paradigms underscores the need for a nuanced approach to understand and appraise the unique attributes of Robo-Advisor investing.

Nevertheless, the intricacies of Robo-Advisor methodologies go beyond conventional evaluation paradigms like those governing Exchange Traded Funds (ETFs). While ETFs are typically assessed within the tracking error framework against specific indices, Robo-Advisors differ due to a greater complexity in the structuring of the products. Instead of aligning with a singular index, they build portfolios from a broad range of ETFs, constructing optimal investment portfolios that vary asset class weights based on different risk levels, as per the financial theory. This complexity underscores the need for a comprehensive and revised evaluation of Robo-Advisor investing.

2.1 Building blocks for the analysis: Wealth Navi's case study

The building blocks of this methodology start with the definition of certain variables for the analysis. To illustrate our approach, we will conduct a case study featuring a Robo-Advisor in the Japanese market: Wealth Navi. Notably, Wealth Navi stands out as the first publicly traded Robo-Advisor to undergo an initial public offering independently, without affiliations to a bank or another financial institution. While the disclosure of operational models and theoretical frameworks is not an exclusive attribute of publicly traded Robo-Advisors, the status of being a public company provides enhanced transparency. This transparency is reflected in comprehensive reporting on portfolio holdings, performance metrics, and clear disclosure regarding the construction of the automated portfolios, in our consideration we observed that such transparency makes the product more appealing, trustable, and "smart" from the customer perspective.

Wealth Navi, like many other global Robo-Advisors, adheres to the widespread practice of transparently communicating its methodology, risk assessment decisions, asset allocations, and other facets within the wealth management sphere. As evident in their white paper (2021), the company outlines a portfolio optimized for long-term asset formation, focusing on international diversified investments denominated in U.S. dollars. The white paper delves into the meticulous methodology for asset selection and the construction of five distinct portfolios, drawing on the theoretical foundations of Markowitz and Black-Litterman.

Within the framework of optimal portfolio principles, our Robo-Advisor object of study emphasizes the following key aspects, which indeed turn out to be common characteristics and foundational product blocks for the listed and studied Robo-Advisors:

Optimal Portfolio: Seeks to build an optimal portfolio that balances multiple securities with different price movements, aiming to mitigate risk through diversification. The objective is to achieve the highest return among portfolios with similar risk levels, thereby optimizing return acquisition efficiently.

International Diversified Investment: By extending investment targets beyond Japan [domestic] to a global scale, the portfolio leverages the economic growth of various countries worldwide. This strategy enhances the diversification effect, reducing risk and optimizing returns.

U.S. Dollar-Denominated: Recognizing the significance of efficiently increasing assets in U.S. dollars, the world's base currency, the Robo-Advisor conducts asset allocation optimization in U.S. dollars. Notably for this particular instance, there is no currency hedging against the Japanese yen.

Index Investing (Passive Investing): The company employs low-cost ETFs as investment targets, aligning with a passive investment approach. This strategy aims to track the average movements of each market, emphasizing cost-effectiveness through index investing.

This explicit delineation of principles and strategies provides clients with a comprehensive understanding of the wealth manager approach, contributing to transparency and informed decision-making in the realm of Robo-Advisory.

2.1.1 Security selection and the construct of the benchmark profiles for comparison

In implementing its investment strategy, the Robo-Advisor describes its focus on security selection and benchmark profile construction. The approach involves categorizing assets into six groups based on various characteristics like countries, regions, and types of securities (stocks and bonds) to minimize risk through diversified investment.

Wealth Navi opts for Exchange-Traded Funds (ETFs) as investment vehicles due to their advantages, particularly suited for retail investors. These advantages as described previously include being large-scale, ensuring liquidity, facilitating easy investment in foreign markets, and cost-effectiveness for index tracking.

The following table describes the ETF selection:

Table 2

Investment universe of the Robo-Advisor

Classification	Ticker	Name	ETF Manager	AuM	Risk (as of 2023)	Expected Return
Stocks	*VTI*	Vanguard Total Stock Market ETF	Vanguard	$324.58B	16.80%	7.10%
	VEA	Vanguard FTSE Developed Markets (excluding US) ETF	Vanguard	$114.74B	16.50%	7.00%
	VWO	Vanguard FTSE Emerging Markets ETF	Vanguard	$72.60B	17%	6.30%
Bonds	*AGG*	iShares Core U.S. Aggregate Bond Market ETF	Blackrock	$94.17B	4.80%	2.90%
	TIP	iShares US Inflation-Indexed Government Bond ETF	Blackrock	$19.89B	6.86%	3.10%
Alternative	*GLD*	SPDR Gold Shares	State Street Advisors	$56.26B	14.40%	3.40%
	IYR	iShares US Real Estate ETF	Blackrock	$2.86B	17.80%	6.30%

The rationale for the inclusion of the investment vehicles is the following:

VTI: Vanguard Total Stock Market ETF. Provides exposure to the entire U.S. equity market, aligning with the strategy of diversifying across the broad spectrum of U.S. stocks.

VEA: Vanguard FTSE Developed Markets (excluding US) ETF. Focuses on developed markets outside the United States, contributing to global diversification.

VWO: Vanguard FTSE Emerging Markets ETF. Concentrates on emerging markets, diversifying the portfolio with exposure to economies with higher growth potential.

AGG: iShares Core U.S. Aggregate Bond Market ETF. Offers exposure to the U.S. investment-grade bond market, adding a fixed-income component to the portfolio for risk mitigation.

TIP: iShares US Inflation-Indexed Government Bond ETF. Focuses on U.S. Treasury bonds indexed to inflation, providing a hedge against inflation.

GLD: SPDR Gold Shares. Introduces an allocation to gold, diversifying the portfolio and serving as a hedge against economic uncertainties.

IYR: iShares US Real Estate ETF. Offers exposure to the U.S. real estate market, further diversifying the alternative investment portion of the portfolio with real estate assets.

The Robo-Advisor provides in their methodology the grounds for constructing customer's portfolio using Mean Variance Optimization, and setting their five risk tolerance level portfolios starting with the minimum variance portfolio, and adjusted so that the third portfolio coefficient would correspond to the equilibrium portfolio, weights are constrained only by a minimum and maximum rules of the RA. The methodology yields five different combinations of weights for the ETF's.

Table 3

Initial portfolio weights

	VTI	**VEA**	**VWO**	**AGG**	**TIP**	**GLD**	**IYR**
Portfolio 1	11%	5%	5%	34%	34%	7%	5%
Portfolio 2	24%	11%	5%	24%	24%	7%	5%
Portfolio 3	34%	19%	7%	15%	15%	7%	5%
Portfolio 4	39%	29%	8%	5%	5%	8%	5%
Portfolio 5	39%	34%	12%	3%	3%	5%	5%

Source: Wealth Navi, 2021.

Based on this portfolio, the Robo-Advisor executes the management of assets for each client, keeping the investments as close as possible to the model portfolio. Once the investment enters the management and tracking phase, periodic rebalancing and adjustments occur. Notably, the exact details of the rebalancing process, such as mechanisms, formulas, or theoretical foundations, are not explicitly disclosed in Wealth Navi's documentation. They mention that rebalancing involves adjustments in weights and asset selection, although the selection of assets remains consistent over the operational years.

The presented background clearly shows some challenges for our analysis, especially when trying to perform comparison and evaluation of the methodologies used. The Robo-Advisor is not strictly adhering to a passive investment approach, since it employs Mean Variance Optimization (MVO), a characteristic mostly typical of active asset management, to select multiple Exchange Traded Funds (ETFs) for its portfolios, then the approach is complemented by periodic rebalancing.

However, it is crucial to recognize that Wealth Navi's strategy is not purely active either, given its buy-and-hold element, which does not change the strategic asset allocation over time.

In response to this, we crafted a composite benchmark portfolio for a logical and coherent comparison. Since Wealth Navi's portfolios cannot be straightforwardly compared to a single benchmark, we applied a formula to construct composite benchmarks. Subsequently, we ran a back test for returns, assuming no rebalancing, to establish a foundation for evaluating Wealth Navi's portfolio performance against the composite benchmark.

Equation 1

$$\text{Benchmark Composite}_i = \mathrm{A_j} * w_{ji}$$

Where the benchmark composite portfolio *BC* for the i^{th} risk level is constructed by assigning the initial weight for each specific asset.

2.1.2 Managed funds market benchmark

As previously highlighted, the strategic asset allocation for portfolio construction involves an asset selection component. The Robo-Advisor (RA) defines the asset universe, and the weights for this allocation are determined through an optimization engine, showcasing the "intelligent" aspect of the RA. These initial weights set by the engine are essential for the portfolio's performance.

In our evaluation, we aim to assess the efficiency of the engine's initial decisions. The benchmark constructed earlier allows us to compare against the same components of the portfolio. However, for a more comprehensive analysis, we need to consider what a typical investor might have chosen if not opting for the Robo-Advisor offer. To gather this comparative dataset, we will obtain the resampled returns of the fund markets listed in the Investment Trust Association of Japan.

The Investment Trust Association of Japan represents a collective body overseeing private investment trusts, public investment trusts, and alternative trusts. In our study, the focus will be on public investment trusts, which are relevant to small retail investors—the target audience for the Robo-Advisor offer. Analyzing the returns of these public investment trusts provides insights into the potential outcomes for investors who did not choose the Robo-Advisor option.

The statistical data provided by the association encompasses details related to publicly offered investment trusts, specifically focusing on asset increase/decrease status, product classification breakdown of stock investment trusts, and asset status by management company. The information includes establishment/cancellation amounts, capital increase/decrease, investment variations, and total net assets for distinct categories. Additionally, churn rates are calculated for monthly and yearly time series.

Further insights are provided into asset status by management company, principal status, and the composition of total net assets, including a breakdown by domestic and foreign currency denominations. The data covers various aspects such as the surplus capital and other securities, foreign currency-denominated total net assets, and their composition by currency. Specific breakdowns, such as the Euro breakdown, details of stocks included in trust assets by industry, and bond trading status, are also available. Additionally, the data includes information on beneficiary certificate recruitment status and distribution details by application amount and institution.

Based on this information we are able to define our next set of benchmarks for the Robo-Advisor performance. The available funds are:

Table 4

Japanese funds and aggregates

	Last number of funds
Stock Funds	5,817
Bond Funds	91
Total Blended	**5,908**
Stock Ex-ETFs	5,539
ETFs	278
Total Stock Funds	**5,817**
Closed Funds	93
Open Funds	5,724
Total Stock Funds	**5,817**
Long Term Bond	72
Money Market Fund	11
ETFs Bond Funds	8
Total bonds	**91**

Source: The Investment Trust Association of Japan, 2023.

The data provided by the Investment Trust Association of Japan allow us to track a time series of the balance of assets of the publicly traded investment funds at the country level. Although the data is intended to provide a balance picture at every month end of the funds, we can infer the returns of the aggregate group by applying the following formula:

Equation 2

$$\text{Total Return \%} = \frac{\mathrm{TA_t} - \mathrm{NF_t} + D_t}{\mathrm{TA_{t-1}}}$$

Where TA_t is the value of the Total Assets of the funds at time *t,* minus the net asset flows of the period, plus profit distributions paid to fund holders, divided by the total net assets of the previous period. Or equivalently:

Equation 3

$$\text{Total Return \%} = \frac{D_t + \Delta V_t}{TA_{t-1}}$$

Where the percentage return on any given period is calculated as the profit distributions paid during that period, plus the change in value of the assets in that specific period (management results), divided by the total net amount of assets of the previous period.

2.2 Hypothesis formulation

Once established the grounding principles, conceptual frameworks, and benchmark indicators, we are ready to propose the hypothesis of this work. Given the nature of our data, as well as the complexity of our research questions, several hypotheses will be presented and later developed.

We start by testing how the returns of the portfolio differ to those of the constructed benchmarks. Let us keep in mind that the constructed benchmarks are composites weighted by the weight vectors defined by the RA's methodology upon inception of the portfolios.

As our composites do not consider any rebalancing but rather a pure buy and hold strategy, a paired t-test of returns mean differences will be able to reveal whether the Robo-Advisor deviates from the weights or tactically adds (or destroy) value, away from the pure long play that an investor could have entered by following the same asset selection. This test, at the same time is the test performed for tracking error, typically used by ETF fund managers where they measure the NAV of the fund vs the index, to prove to what extent if any the passive investment would deviate from the benchmark. In the context of tracking error analysis, we would be comparing the differences between paired observations (portfolio returns and benchmark returns).

On the other hand, we also want to know if the Robo-Advisory tactical management represents an increase or decrease in volatility compared to the composite benchmark, or if we can confirm otherwise that the rob advisor effectively replicates the risk profile of the composite. For this matter we propose a F-Test for variances

Hypothesis 1. During the reporting period the returns of the Robo-Advisor were not significantly different from those of the ETF composite benchmark.

$$H_0\colon \mu_{robo} - \mu_{hold} = 0$$

Hypothesis 2. During the reporting period the variance (volatility) of the portfolio is equal to the variance of the benchmark.

$$H_0\colon \sigma^2_{robo} - \sigma^2_{benchmark} = 0$$

Alternatively, the H1 hypothesis suggests that suggests that the variance of the portfolio is greater than the variance of the benchmark, indicating that, on average, the portfolio is riskier.

$$H_1\colon \sigma^2_{robo} \; > \; \sigma^2_{benchmark} = 0$$

The same logic that we applied to the constructed composite benchmarks, could be applied to compare the Robo-Advisor's performance versus those of the Japanese market. With this test we intend to evaluate another aspect of the Robo-Advisor offer: the strategical asset decision, in the light of the fact that our previous test only evidenced the tactical management but not the asset selection (active) portion of Wealth Navi's strategy. As previously proposed, this would give us a clear answer to the question: Would the investors be better off if they had simply invested their money into funds? Is there any addition to the value offered in financial services by introducing a Robo-Advisor or would it be a sub-optimal product?

Hypothesis 3. During the reporting period the returns of the Robo-Advisor were not significantly different from those of the Japanese funds.

$$H_0\colon \mu_{robo} - \mu_{funds} = 0$$

For this matter we propose a paired t-test for each of the portfolio-fund pairs at distinct levels of significance

3 EMPIRICAL RESULTS FOR ROBO-ADVISOR PERFORMANCE

3.1 Robo-Advisor performance and volatility versus Benchmark Composite

In conducting our empirical analysis, three distinct datasets form the foundation of our examination. The primary dataset encapsulates the price index of the Robo-Advisor (RA) across its risk portfolios, reported in both JPY and USD, initiating from one hundred units of currency in January 2016, with monthly observations. Complementary to this, historical adjusted monthly returns for each Exchange-Traded Fund (ETF) within the Robo-Advisor investment universe were extracted and resampled to align with the Robo-Advisor data, constructing a series of ETF returns. The construction of benchmark composites ensued through the application of the benchmark construction formula, resulting in ninety-four time series observations for each composite, synchronized with the Robo-Advisor returns and commencing from a baseline of one hundred units. For the purpose of our analysis, necessitating return data, a monthly returns dataset was derived with 93 points.

Concurrently, the second facet of our investigation encompasses return data garnered from the Investment Trust Association of Japan (ITA) for each funds grouping, yielding a total of eight distinct benchmark comparisons. The representation of the datasets is summarized in the table below:

Table 5

Data sets

	Data Set	Number of Observations	Frequency	Portfolios/Benchmarks
1	Robo-Advisor Price Index	93	Monthly	5
2	ETF Returns	93	Monthly	5
3	Benchmark (ITA)	93	Monthly	8

The descriptive analysis of Data Set 1, which pertains to the Robo-Advisor Price Index returns across its risk portfolios, is summarized in the table below:

Table 6

Descriptive statistics of the Robo-Advisor return

	1	**2**	**3**	**4**	**5**
N	93	93	93	93	93
Mean	0.25%	0.39%	0.50%	0.60%	0.64%
Standard deviation	1.86%	2.36%	2.92%	3.41%	3.75%
Minimum	-7%	-7%	-9%	-11%	-13%
25%	-0.54%	-0.55%	-0.44%	-0.50%	-0.61%
50%	0.57%	0.80%	0.89%	0.98%	1.08%
75%	1.26%	1.42%	1.85%	2.23%	2.62%
Maximum	4.40%	5.87%	7.92%	9.43%	10.59%

Looking at the mean returns, we see a clear upward trend from Portfolio 1 to Portfolio 5, ranging from 0.0025 to 0.0064. This suggests that, on average, returns increase as we move across the risk spectrum. The standard deviation, which gives us an idea of how much the returns vary, follows a similar pattern, with Portfolio 5 showing the highest volatility.

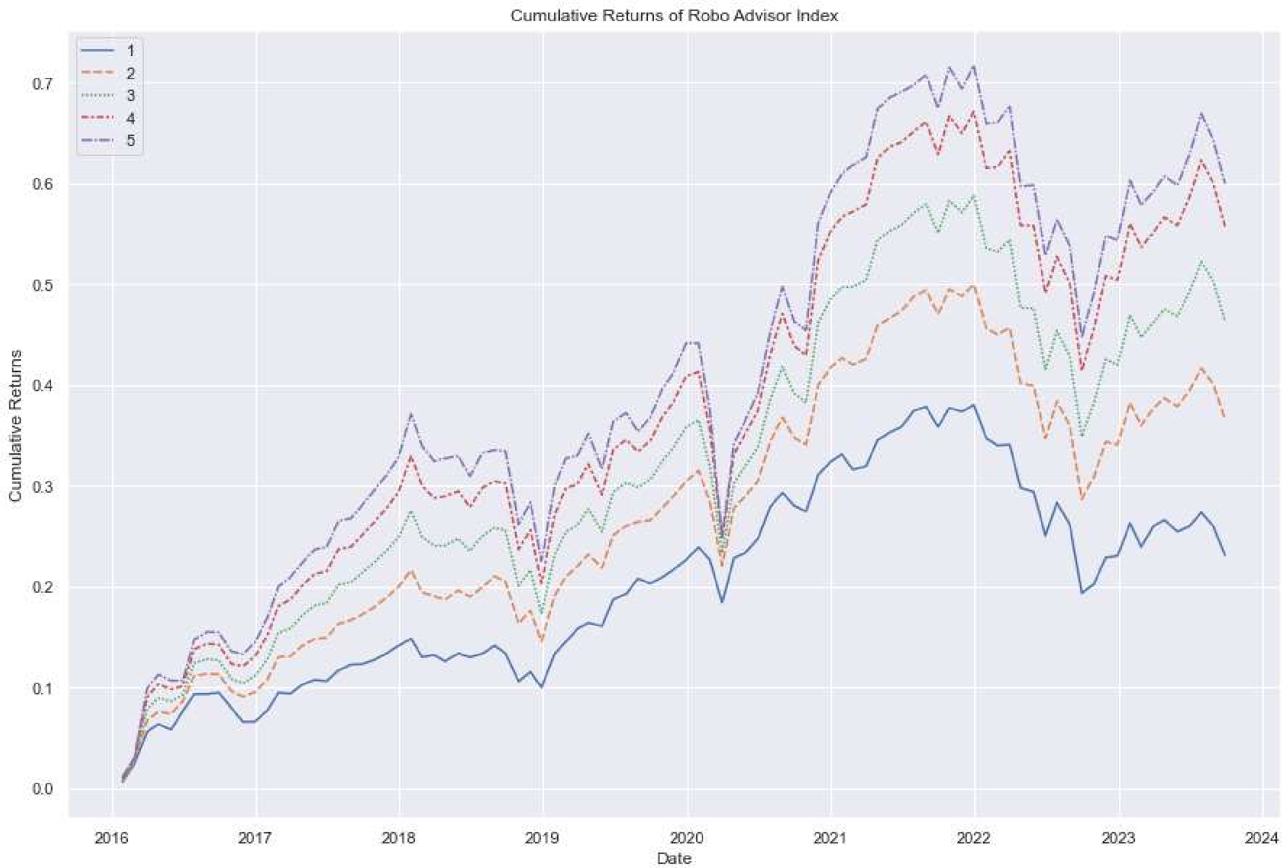
As for minimum and maximum returns, we notice both negative and positive extremes. Negative returns indicate periods of not-so-great performance, while positive maximum returns, especially in Portfolio 5, hint at the potential for significant gains.

The percentiles (25th, 50th, 75th) provide additional insights. The 25th percentile gives us a sense of the lower end of returns, the median represents the middle point, and the 75th percentile shows the upper end. These percentiles add depth to our understanding of how returns are distributed across different levels.

Visually is easier to identify the trends and patterns for the time series of returns:

Figure 3

Robo-Advisor Portfolio's returns



The trend of the portfolio returns shows great correlation, at the time that shows congruence with the intended risk-return level of the portfolios. We can visually identify, from a first perspective, that the cycles are more visible on the higher risk portfolios, but downturns seem to be less drastically different. The statistical properties are summarized below in the form of returns and standard deviation.

One of the lowest downturns in the cumulative returns occurred around March 2020, coinciding with the global market downturn at the onset of the COVID-19 pandemic. The highest points are typically observed at the end of each calendar year, indicating potential positive year-end performance. From January 2016 to mid-2018, the cumulative returns show a generally upward trend, with periodic fluctuations. There's as well a noticeable dip in late 2018, reflecting the increased market volatility during that period, however we can observe that relative to highest points the “crisis” downturn behaves very different than the “volatility” downturn, in other words, the “crisis” downturn pulled all portfolios to a certain dip, being the riskier portfolios the most affected but we saw from the strong recovery previous after the COVID crisis, the recovery of the riskier portfolios was exponential. This overall follows the general expectations of the market and hints that the Robo-Advisor portfolio returns might effectively being sensible to the systematic conditions and to be tightly synchronized with the market general behavior.

Table 7

Summary results of the Robo-Advisor

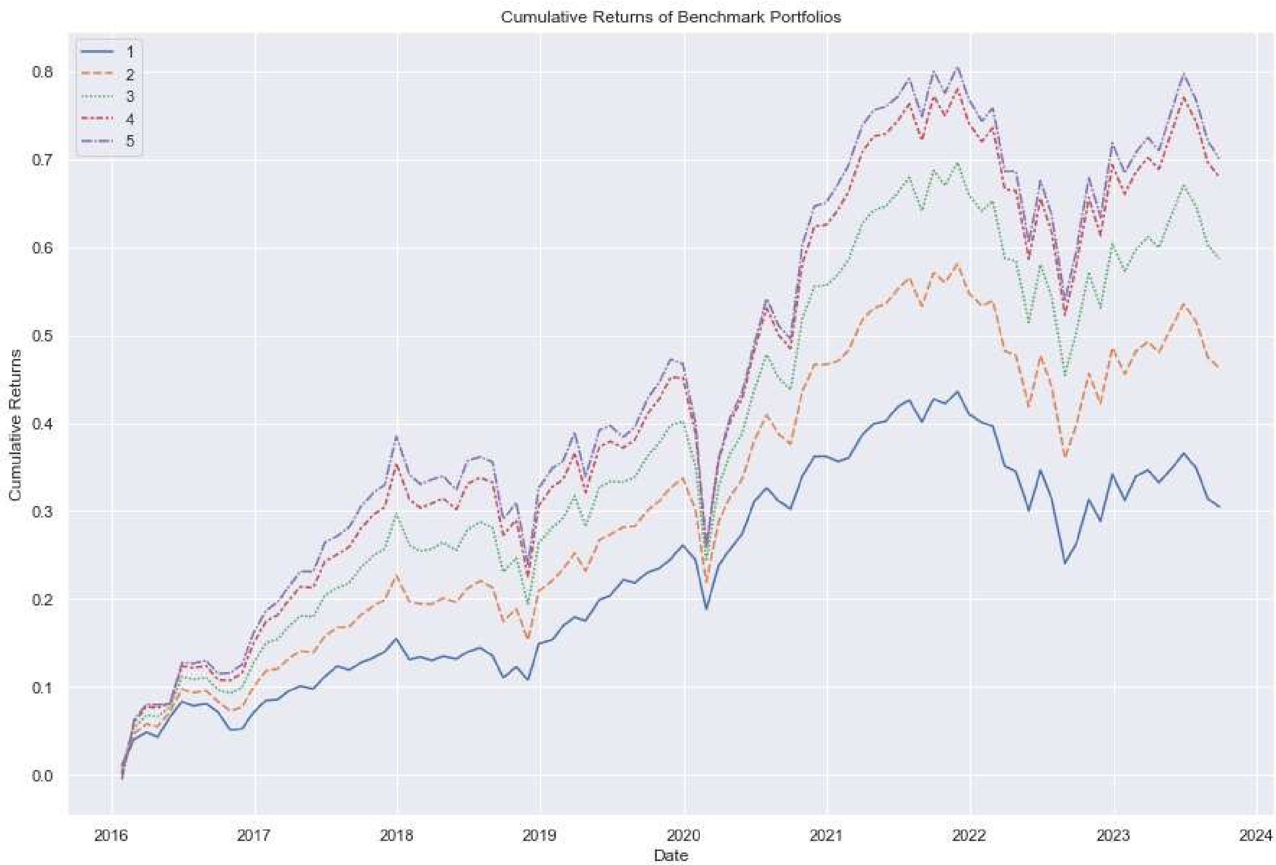
Portfolio	Annualized Returns	Annualized Standard Deviation	Sharpe Ratio
1	3.0%	6.43%	0.4630
2	4.7%	8.19%	0.5760
3	6.0%	10.11%	0.5911
4	7.2%	11.81%	0.6082
5	7.7%	12.98%	0.5954

As we clearly see from the summary statistics, there is a consistent increase in the standard deviation from Portfolio 1 to Portfolio 5. This suggests that, as the portfolios pursue higher returns, they also exhibit higher volatility. Portfolio 5 has the highest standard deviation, indicating the highest level of risk. While Portfolio 4 has the highest returns, it doesn't have the highest Sharpe ratio, indicating that Portfolio 5, despite having slightly lower returns, might be more efficient in terms of risk-adjusted returns.

Same analysis is done for the returns of the composite portfolios, plotting is done and summary statistics:

Figure 4

Benchmark returns



The benchmark exhibited positive returns throughout the year, reaching its peak at the end of December. Portfolios 2, 3, 4, and 5 outperformed the benchmark, especially Portfolio 5, which displayed a distinctive upward trajectory. All portfolios experienced positive growth, with Portfolio 5 standing out as the top performer. Coherent with the market, the benchmark composite faced the greatest downturn in March 2020, indicative of the global financial market challenges associated with the COVID-19 pandemic. Portfolios 2, 3, 4, and 5 exhibited similar trends, but the impact varied greater for the riskier composites. Interestingly, the most conservative composite shows a clear highest point at the end of 2021 before the market downturns due to inflation and rate hikes, but the recovery was not significant by mid-2023. Contrasting this, the higher risks portfolios show their highest point in June 2023, instead of December 2021

On a vis-à-vis basis, portfolio and composite returns are visually almost identical, also confirmed by the statistical properties. Also, examining the specific data points Portfolios 1 and 2 outperformed the benchmark during the 2020 downturn, potentially due to a more conservative or defensive strategy in rebalancing. We see, however, in the composite a slightly greater risk adjusted incremental return over the one in the portfolio.

Table 8

Summary results of the Benchmark

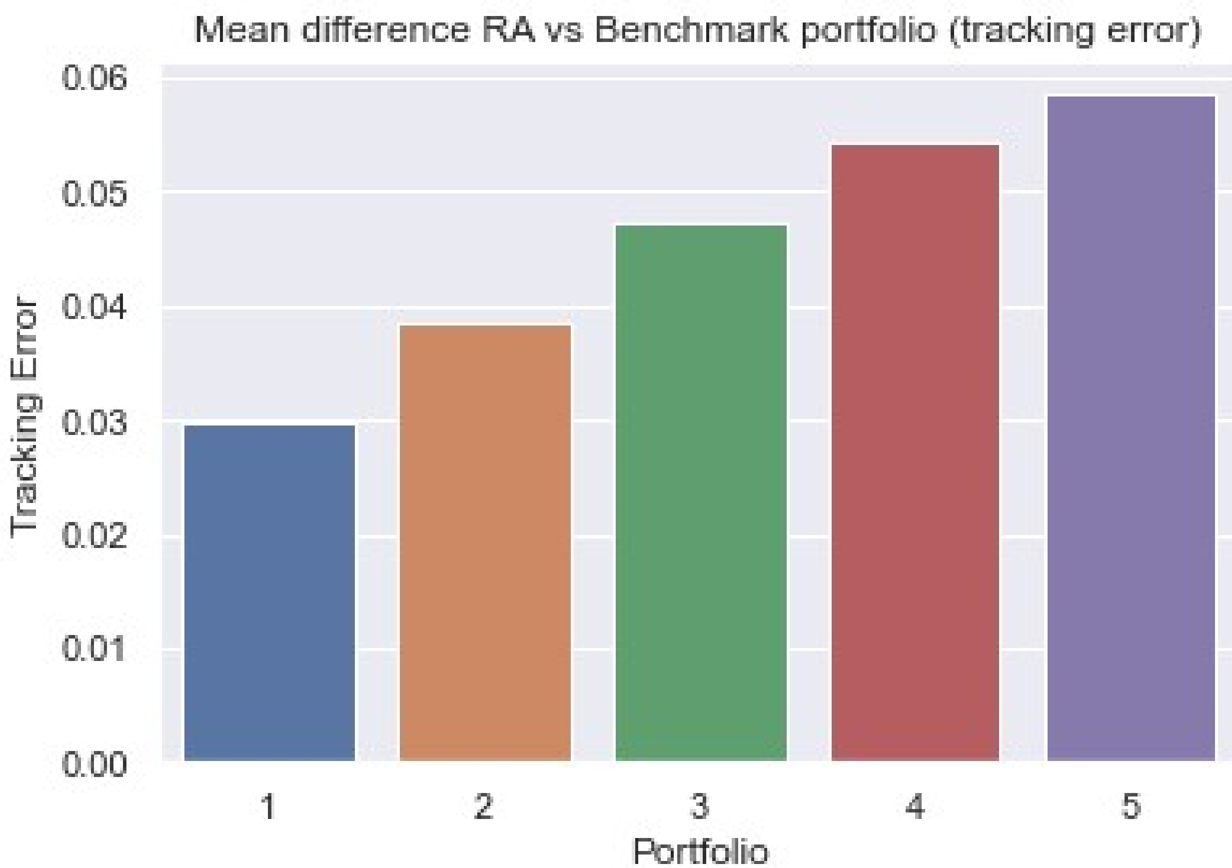
Benchmark	Annualized Returns	Annualized Standard Deviation	Sharpe Ratio
1	3.9%	7.68%	0.5123
2	6.0%	9.95%	0.5996
3	7.6%	12.12%	0.6247
4	8.8%	13.86%	0.6327
5	9.0%	14.75%	0.6126

We can conclude that the benchmark composite's performance aligns with the higher-risk portfolios (4 and 5) in terms of annualized returns and Sharpe ratio. This suggests that the benchmark composition likely incorporates riskier assets. During the market downturn in 2020, the benchmark experienced a significant drop, similar to the performance of higher-risk portfolios. This emphasizes the impact of market conditions on both the benchmark and riskier portfolios.

To further advance in our initial data exploration, we pair and resample to match the portfolio returns and the benchmark composite returns to then find the difference between each, this essentially creates a time series of what would be known as tracking error for pure passive investments which would not be unprecise in this case considering that the strategy of the Robo-Advisor is essentially a buy and hold strategy and we want to capture in this analysis the passive side of the investment with the asset allocation defined as given.

Figure 5

Mean return differences Robo-Advisor vs. Benchmark

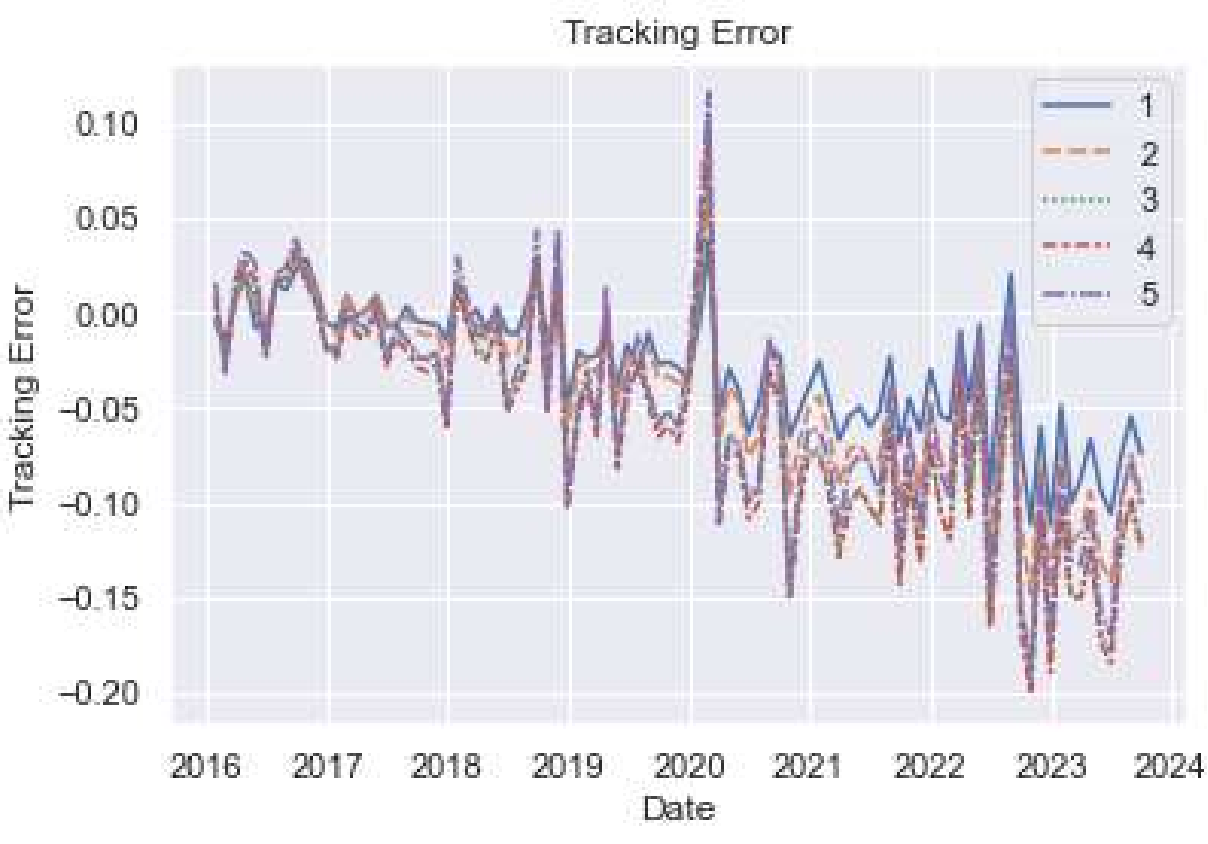


By looking at the results of tracking error, we see naturally that tracking error is correlated to the risk level profile. Portfolios with higher risk show more pronounced tracking errors. The likely explanation here is that riskier portfolios tend to have a significant reliance on stock ETFs, demanding more frequent rebalancing over time. This leads to a gradual divergence between a fixed-weight strategy and one that is consistently rebalanced, especially in portfolios with a hefty stock allocation.

Adding a temporal perspective to the mix, the tracking error dynamics became clearer, as illustrated in the tracking error graph. As time passed, tracking error not only increased but also showed a subtle trend of becoming negative. Although not drastically, this suggests that during the study period, the Robo-Advisor's rebalancing strategy might have resulted in slightly lower returns compared to the fixed-weighted composites.

***Figure* 6**

Tracking error Robo-Advisor vs. Composite



The time series data represents the tracking errors of five different portfolios compared to a benchmark. Tracking error measures, the standard deviation of the differences between the portfolio returns and the benchmark returns. Our preliminary interpretations conclude the following:

In January 2016, Portfolio 5 exhibited a tracking error of 1.612% relative to the benchmark, the highest among the five portfolios. This suggests that Portfolio 5 had the most significant deviation from the benchmark during this period. Over the next few months, Portfolio 5 continued to have relatively high tracking errors, indicating persistent divergence from the benchmark. By the end of September 2016, Portfolio 5 still had the highest tracking error, highlighting its consistent deviation.

Between November and December 2018, Portfolios 4 and 5 experienced a notable increase in tracking errors, reaching -10.343% and -10.143%, respectively. This suggests a significant deviation from the benchmark during this period, indicating potential challenges or risks associated with the investment strategies of these portfolios. The negative sign implies that the portfolios underperformed the benchmark during these months. This could be attributed to various factors, such as market volatility, economic events, or specific risks associated with the assets held in these portfolios.

As for the lower risk portfolios 1, 2 and 3 we observed that during January to March 2017, Portfolios 1, 2, and 3 demonstrated positive tracking errors, ranging from 0.718% to 1.037%. This indicates that these portfolios outperformed the benchmark slightly. It suggests that the investment strategies employed by these portfolios were successful in generating returns above the composite benchmarks. This could be attributed to successful rebalancing strategies of the Robo-Advisor, but also let us keep in mind that positive tracking error is mostly present as a random component.

In contrast for example, during April to June 2018, Portfolios 1, 2, and 3 experienced a decline in tracking errors, reaching as low as -1.658%. This suggests a period where these portfolios underperformed the benchmark. It is part of our research recommendation to investigate the reasons behind this underperformance. Underlying reasons could be poor rebalancing model of the Robo-Advisor, or overall higher costs relative to the pure benchmark hold strategies.

Now we present the correlation matrix of the returns, in order to briefly explore the relations between the portfolios:

Figure 7

Robo-Advisor portfolios correlation matrix

The correlation coefficients between all pairs of portfolios (1 to 5) are very high, ranging from approximately 0.895 to 1.000.

Portfolios 4 and 5 exhibit an exceptionally strong positive correlation of 0.998, indicating an almost perfect positive linear relationship. Similarly, Portfolios 3 and 4, as well as 3 and 5, also demonstrate extremely high correlations.

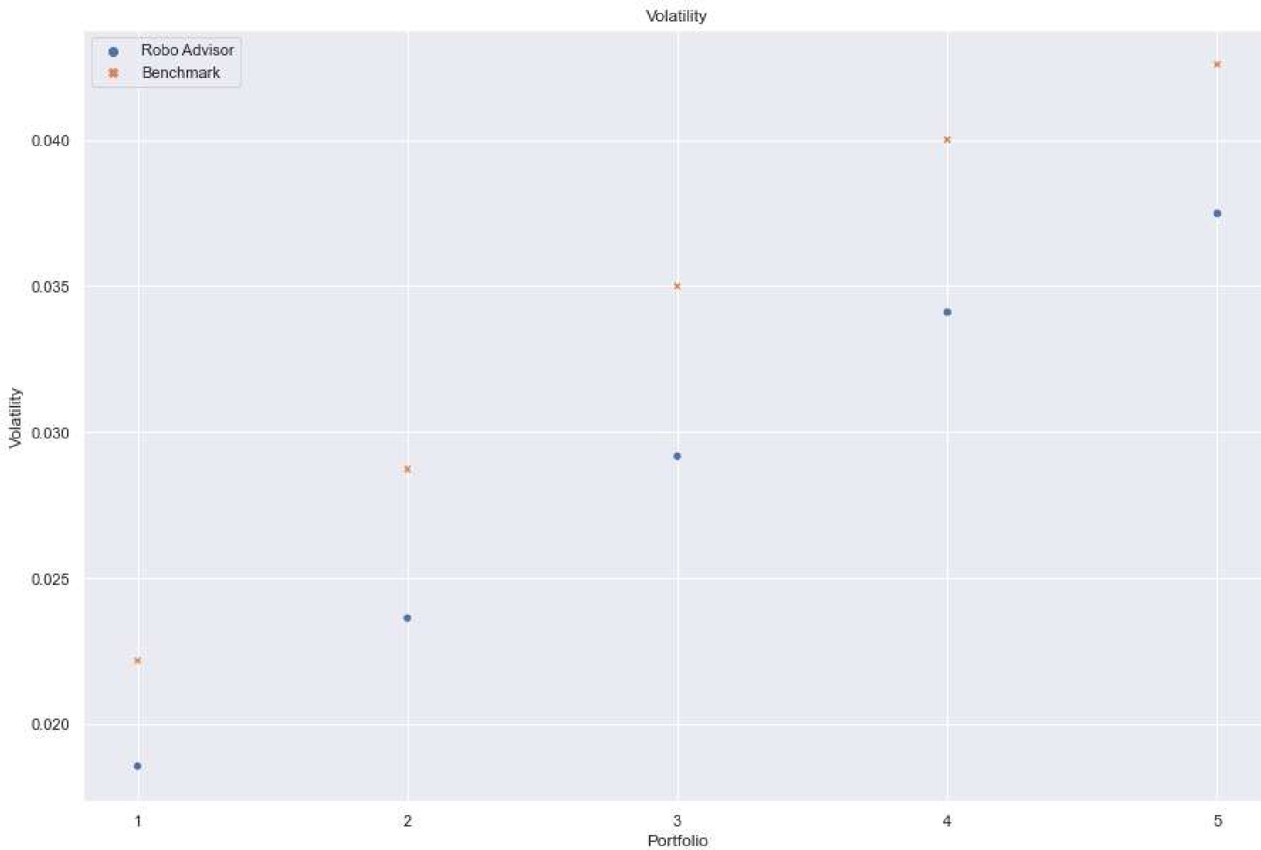
High positive correlations suggest that the Robo-Advisor portfolios tend to move together in the same direction. When one portfolio experiences gains or losses, the others are likely to follow suit.

For informed investors, it is a crucial piece to account for such high correlations, as it implies that diversification benefits might be limited. If the portfolios are highly correlated, the risk reduction achieved through diversification is not as effective because the portfolios are influenced by similar market factors. Potential reasons for high correlations might come from the previous explanation of how portfolios are constructed based on the Robo-Advisor's methodology. A limited selection of ETFs makes similar assets or follow comparable investment strategies, leading to synchronized movements. Also, common economic factors or market trends could be impacting the performance of all portfolios, contributing to the high positive correlations. During periods of market volatility or economic shifts, the high correlations indicate that all portfolios are likely to be affected similarly.

Finally, in our preliminary assessment, we aim to evaluate the annual volatility of both portfolio returns and market returns. Utilizing the standard deviation of returns as a volatility metric, we create pairs of annual volatility data points for further analysis. The objective is to visually represent the relationship between the volatility of the portfolio and that of the market over time. By plotting these pairs, we can discern patterns, trends, or correlations that may offer valuable insights into the behavior and performance of the portfolio in relation to the broader market. This graphical representation will serve as an initial step in understanding the volatility dynamics and potential risk exposures associated with the portfolio.

Figure 8

Portfolio and Benchmark annual volatilities



Each point in the graph represents the standard deviation of returns, reflecting the volatility of each portfolio (Robo-Advisor and Benchmark) over the specified periods. Generally, the Robo-Advisor portfolio appears to have lower volatility compared to the benchmark in each corresponding year. This suggests that, based on the initial visualization, the Robo-Advisor's portfolio would be showing a tendency to be less volatile than the benchmark across these specific timeframes. As explained before, part of the core offer and appeal to investors is the consideration of lower volatility desirable as it signifies a more stable investment performance. We would need, however, to test this statistically for significance.

Then we proceed to perform the hypothesis testing, using our paired mean test. The results of the test are described below:

Table 9

Test results H1

Portfolio	Test Statistic	P-value	Significance Level (0.05)	Significance Level (0.01)
1	-0.2565	0.7981	Fail to reject null	Fail to reject null
2	-0.259	0.7962	Fail to reject null	Fail to reject null
3	-0.2705	0.7874	Fail to reject null	Fail to reject null
4	-0.2324	0.8167	Fail to reject null	Fail to reject null
5	-0.1783	0.8589	Fail to reject null	Fail to reject null

In all cases, at both the 0.05 and 0.01 significance levels, we fail to reject the null hypothesis. This suggests that there is not enough evidence to conclude that the mean returns of the portfolios are different from the benchmark. And therefore, the rebalancing or tactic portfolio does not create a statistically significant difference from holding the ETFs with their initial weight.

Proceeding with the analysis, we conducted tests to assess differences in volatilities between the Robo-Advisor (RA) returns and the benchmark returns. The null hypothesis assumes equal or lower volatility in the RA, given the absence of significant tactical deviation and the slightly lower returns observed in the previous analysis. Accordingly, the alternative hypothesis posits that the standard deviation of the Robo-Advisor returns is greater than that of the benchmark. The results are summarized as follows:

Table 10

Test results H2

Portfolio	F-Statistic	P-value	Significance Level (0.05)	Significance Level (0.01)
1	0.7007	0.9551	Fail to reject null	Fail to reject null
2	0.6770	0.9686	Fail to reject null	Fail to reject null
3	0.6950	0.9587	Fail to reject null	Fail to reject null
4	0.7264	0.9365	Fail to reject null	Fail to reject null
5	0.7748	0.8885	Fail to reject null	Fail to reject null

At both the 0.05 and 0.01 significance levels, we fail to reject the null hypothesis for all portfolios, suggesting that the volatilities of Robo-Advisor returns are not significantly different from those of the benchmark. Considering that the F-statistic represents the ratio of variances, indicating how much the variances of the two groups differ.

3.2 Robo-Advisor performance and volatility versus Japanese fund market

In the final phase of our study, we delve into how well Robo-Advisors perform compared to the Japanese fund market. By specifically focusing on the strategic asset management decision. We discovered before that on the tactical level, no evidence was found at the return and risk level versus the case on which the investor would have held long the assets with fixed weights initially. On that first stage our financial management decision was given. However, this step is crucial because just looking at returns does not tell the whole story. We want to see if Robo-Advisors are not just making money but doing it in a smart and safe way.

Table 11

Summary results Japanese Funds

Benchmark	Annualized Returns	Annualized Standard Deviation	Sharpe's Ratio
Blended funds	9.05%	10.30%	0.8785
Stock funds	10.13%	11.57%	0.8755
Bond funds	0.00%	0.00%	1.4215
Stock ex-ETF's	9.85%	10.67%	0.9231
Closed funds	0.66%	4.71%	0.1407
Open funds	10.20%	11.64%	0.8765
ETF's	10.06%	14.77%	0.6812
Long term bond	0.01%	0.01%	1.1894
Money reserve funds	0.00%	0.00%	1.9521

Our fund market approach for strategic asset allocation decisions data presents an interesting and different analysis for our research. The initial summary reveals a diverse landscape of financial instruments, each characterized by distinct annualized returns, standard deviations, and Sharpe ratios.

Notably, stock funds and open funds exhibit higher annualized returns at 10.13% and 10.20%, respectively, emphasizing their potential for generating positive returns for investors. However, it is essential to weigh these returns against the associated risks, as reflected in their standard deviations and Sharpes' ratios.

The blended funds category with a Sharpe ratio of 0.8785 stands out as an interesting balance between returns and risk, suggesting a relatively favorable risk-adjusted performance. Notably, this data sheds some light on better Sharpes' ratios in many of the portfolios. On the other hand, the performance of bond funds and long-term bonds, with zero annualized returns, prompts a closer examination, as their Sharpe ratios indicate positive risk-adjusted returns. This apparent discrepancy warrants a deeper dive into the nature of these funds and the factors contributing to their risk-return profiles.

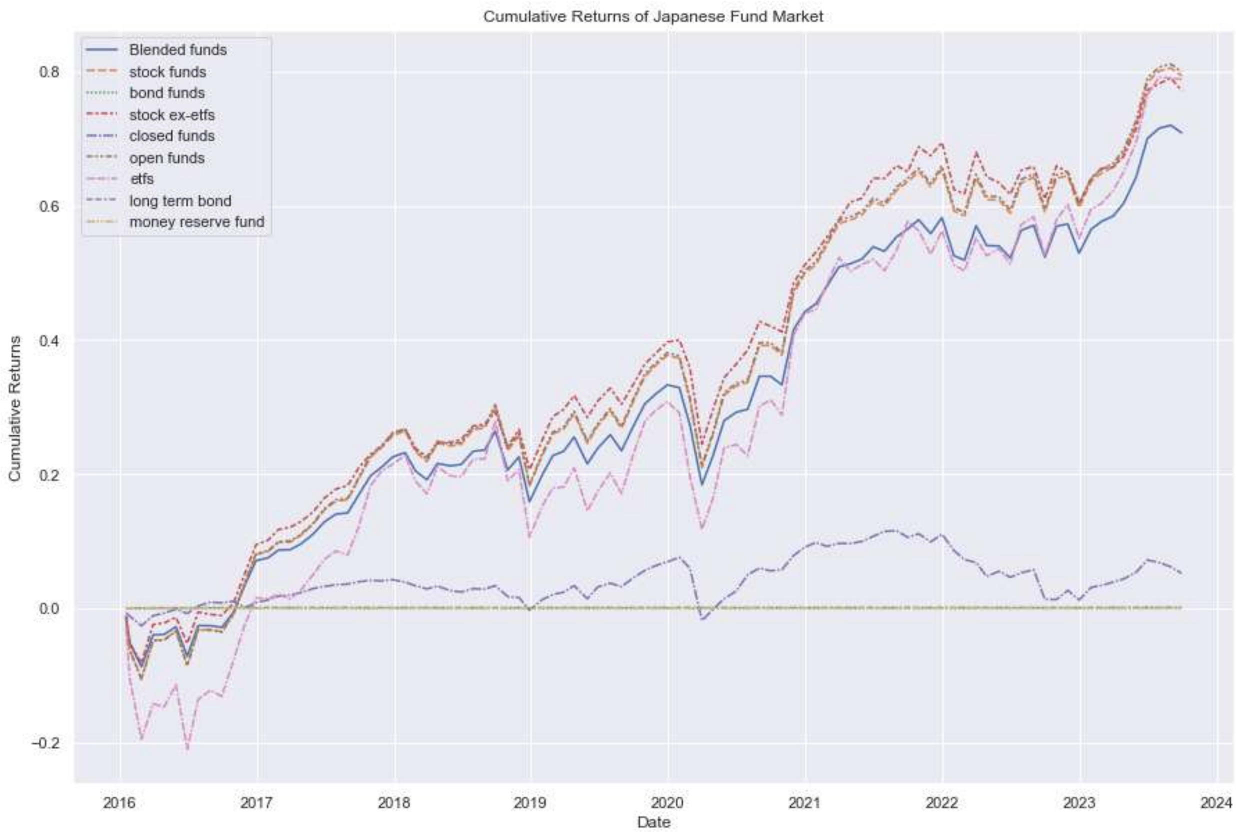
The data also highlights the diversity within equity investments, with stock ex-ETFs, closed funds, and ETFs demonstrating varied performance metrics. Notably, money reserve funds exhibit a high Sharpe ratio of 1.9521, indicating potentially attractive risk-adjusted returns, although their zero annualized returns should be further investigated. Overall, this preliminary data provides a nuanced understanding of the benchmarks, setting the stage for more in-depth analyses to uncover underlying trends and inform subsequent evaluations of Robo-Advisor performance against these benchmarks.

Blended funds and stock funds, with relatively higher cumulative returns, appear to be favorable investment choices over the observed period. Bond funds, while having a minimal cumulative return, still contribute positively to investors' portfolios. Stock ex-ETFs demonstrate positive cumulative returns, aligning with the performance of traditional stock funds. The cumulative returns offer a comprehensive measure of growth, aiding investors in evaluating the long-term profitability of each fund category.

In summary, our condensed data suggests variation in the returns of different fund types. Stock-related funds (blended funds and stock funds) exhibit higher average returns with higher variability. Bond funds and stock ex-ETFs show lower variability, and the latter has a higher maximum return. Further descriptive data will be presented for analysis, such as the cumulative returns representation, in order to be able to distinguish basic trends among the funds:

Figure 9

Cumulative returns Japanese funds



The cumulative returns data provides a comprehensive view of the performance of various funds over time.

The cumulative returns for blended funds started negative but gradually increased over time. There were periods of decline, such as in early 2016 and mid-2016, but overall, the trend has been positive. Despite its volatility, the fund has shown resilience, bouncing back from market downturns.

The stock funds exhibit a similar pattern to blended funds, with a steady increase in cumulative returns. The fund experienced downturns during market corrections but recovered, indicating the potential for long-term growth. Blended and stock funds show remarkably close results overall.

On a different asset level, bond funds show relatively stable and low cumulative returns, consistent with the conservative nature of fixed-income securities. The fund provides stability and serves as a risk-averse investment, especially during periods of market volatility.

As for the stock returns without considering ETFs, they follow the general market trend, showing growth over time. The fund's performance is influenced by the stock market, with periods of volatility reflecting broader market conditions.

Stock-related funds are more sensitive to market fluctuations, evident in their periodic declines and recoveries. Blended funds, combining various assets, demonstrate a balanced approach that helps mitigate risks during market downturns. On the other side bond funds provide stability and are less affected by market volatility, making them suitable for risk-averse investors. Each fund type responds differently to market conditions, emphasizing the importance of diversification in constructing a resilient portfolio. Also, the graphs of the funds evidence our challenge in trying to assess the funds compared to Robo-Advisory, as each show unique risk return characteristics.

As we did with the Robo-Advisor portfolio data, we will perform a correlation analysis to gain another comparison point for risk analysis before proceeding to the statistical tests.

***Figure* 10**

Japanese funds correlation matrix

We can immediately see from the graph that there's an extremely high positive correlation of about 0.9997 between blended funds and stock funds. This suggests that these two types of funds move almost identically, indicating a strong positive relationship, as expected due to the similar components. Bond funds show a weak negative correlation with blended funds, stock funds, stock ex-ETFs, and open funds. This implies a tendency for bond funds to move in the opposite direction, to a limited extent, compared to these other fund types. Then, stock ex-ETFs exhibit a very high positive correlation with blended funds, stock funds, and open funds, indicating a close alignment in their movements. The correlation with long-term bonds is positive but weaker. And closed funds have a positive correlation with all other fund types, with the highest correlation observed with stock ex-ETFs and open funds. This suggests a general positive relationship, especially with equity-related funds. As expected, ETFs show strong positive correlations with blended funds, stock funds, stock ex-ETFs, and open funds, indicating synchronized movements. Long-term bond funds have weak to moderate positive correlations with most other fund types, except for a notably weak correlation with ETFs. The money reserve funds show a strong positive correlation with bond funds and a moderate positive correlation with long-term bond funds. There is a notable negative correlation with stock and ETF-related funds, indicating potential diversification benefits.

This is not unfamiliar with what we analyzed on the Robo-Advisors' portfolios before. In both cases, there are strong positive correlations within each set of funds or portfolios, suggesting a similar directional movement. However, the Japanese funds seem to have more diverse correlations, including some negative correlations, while the Robo-Advisor portfolios exhibit consistently high positive correlations. This led us to conclude that investors in Japanese funds may find more diversification opportunities due to occasional negative correlations, particularly with bond and money reserve funds. Robo-advisor portfolios, as indicated by the previous correlation matrix, tend to move closely together, emphasizing the importance of careful risk management and diversification strategies.

Now we proceed to the statistical tests. The results are described below:

Table 12

Test results Robo-Advisor vs Japanese Funds

Portfolio	F-Statistic	P-value	Significance Level (0.05)	Significance Level (0.01)
Portfolio 1	-1.2340	0.2203	Fail to reject null	Fail to reject null
Portfolio 2	-1.0887	0.2791	Fail to reject null	Fail to reject null
Portfolio 3	-1.1414	0.2567	Fail to reject null	Fail to reject null
Portfolio 4	-1.1159	0.2674	Fail to reject null	Fail to reject null
Portfolio 5	-1.1911	0.2367	Fail to reject null	Fail to reject null

The test statistics and p-values were obtained for each portfolio in comparison to the Japanese Fund Market. At both 0.05 and 0.01 significance levels, the results consistently indicate a failure to reject the null hypothesis. This suggests that, similar to the previous tactical level analysis, there is no significant difference in the performance of Robo-Advisor portfolios and the Japanese Fund Market in terms of strategical asset management decisions. These findings reinforce the importance of looking beyond mere returns and evaluating the smart and safe aspects of financial management decisions made by Robo-Advisors.

CONCLUSIONS AND RECOMMENDATIONS

Based on exploring the literature on Financial Technologies and Robo-Advisory concepts, taxonomy and classification as grounds for developing a framework for evaluation, the first conclusion points to the fact that Financial Technology is not a defined set but rather a span of different applications, approaches and solutions of technology applied to financial services, Fintech is rather a constant progressive development of applied technology to the financial industry.

A second instance in literature review led to point out a multiphase and multifactor industry, where countless classifications and combinations were considered. Own classification framework was constructed, based on where the technology was being applied on the value chain of the financial products, providing clarity amid the ever-expanding landscape of financial innovations. This led to narrow possibilities for methodological construction.

Some other conclusions arose in the course of the research of the Robo-Advisory market. It was concluded that shared characteristics and identities exist for the current estate of Robo-Advisory. Among them are: Robo-Advisors are by definition not active investments; however, a strategical asset allocation component exists and therefore they are not purely passive strategies. Robo-Advisors also share common practices such as the use of ETFs for investment management, the use of goal-based investment management (in contrast to mean-variance or other traditional optimizations), the use of auto or algorithmic rebalancing, enhanced transparency and reporting and friendly user interfaces directed to a retail audience.

The original evaluation framework was developed and business case was constructed. It was concluded that the returns of the object of study Robo-Advisor could be decomposed in a tactical component which was related to the auto-rebalancing technology and an active component which would help to evaluate the asset allocation decision (powered by technology as well) on a strategical level.

On the conduction of the tests, it was concluded that the comprehensive series of tests conducted throughout this research provide valuable insights into the performance and efficiency of Robo-Advisors in comparison to various benchmarks and markets. At the tactical level, where the focus was on return and risk aspects, the analysis of portfolios under different market conditions revealed no substantial evidence to reject the null hypothesis. This suggests that, on the tactical front, Robo-Advisors do not significantly outperform or differ from the simple strategy of holding assets with fixed weights over time. The findings underscore the importance of evaluating not just returns but also the strategies employed by Robo-Advisors in navigating diverse market conditions. Similar findings are drawn from the risk perspective, no significant evidence exists for differences in variance.

Shifting the focus to the strategic level, specifically comparing Robo-Advisor portfolios with the Japanese Fund Market, the results consistently indicate a failure to reject the null hypothesis. This implies that there is no statistically significant difference in the asset management decisions made by Robo-Advisors in comparison to the Japanese Fund Market on a risk adjusted basis. These results align with the tactical level findings, emphasizing the need to delve deeper into the decision-making processes and risk management strategies employed by Robo-Advisors. The overall lack of rejection of the null hypothesis at both tactical and strategic levels prompts a deeper examination of the value proposition and efficiency of Robo-Advisors in the broader financial landscape.

While the tests contribute valuable statistical evidence, it is essential to note that the interpretation of these findings should consider the dynamic nature of financial markets and the evolving landscape of Robo-Advisory services. The research presented here lays a foundation for understanding the performance of Robo-Advisors, but ongoing scrutiny and further research are crucial to comprehensively assess the long-term implications and evolving dynamics of these innovative financial tools in a rapidly changing financial landscape.

The empirical results, while not groundbreaking, do open avenues for valuable recommendations in further research. It is crucial to emphasize that this study primarily focused on risk and return data evaluation, consistent with the methodologies described by Woo et al. (2020). However, this might present a partial perspective, and there is a compelling need to extend the analytical lens to encompass other critical dimensions such as product design, diversification strategies, channel dynamics, and customer experiences. Diversifying the evaluative criteria beyond risk and return could offer a more comprehensive understanding of the effectiveness and impact of Robo-Advisors, such as that explored by D’Acunto et al. (2019).

On other side, the development of this research relied highly on data availability. For instance, the aggregated funds data provided by the Japanese Fund Association, might need to be decomposed and examined for survivorship bias, or other drawbacks that might influence on the results. On further research, the recommendation is to expand the scope of the data, or if a source for detailed return data exists for benchmark returns, it should be used and re-tested.

Lastly, the evaluation of efficiency concerning markets represents just the initial facet of what could evolve into a comprehensive methodology for measuring, evaluating, and assessing efficiency, ultimately leading to value addition. Future research endeavors should aspire to integrate a more holistic approach, wherein various aspects are aggregated, allowing for more complex models that could and might even reveal divergent results on the different studied aspects, for further contribute to a more thorough comprehension of the landscape in which Robo-Advisors operate.

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SUMMARY IN ENGLISH

ASSESSMENT OF THE EFFICIENCY OF INVESTMENT ROBO-ADVISORY

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Master Thesis

Finance and Banking Programme

Faculty of Economics and Business Administration, Vilnius University

Supervisor Prof. Dr Jelena Stankevičienė

Vilnius, 2024

78 pages, 12 tables, 10 figures, 43 references.

The purpose of this master thesis is to assess the efficiency of Robo-Advisors, particularly in comparison to diverse benchmarks and markets, as well as on different components of their returns and risks.

The work consists of three main parts; the conceptual and theoretical background of Fintech and Robo-Advisors, the development of a methodology for this task, and the empirical results obtained. Conclusions and further recommendations are also provided for this work.

The theoretical framework reviews and analyze the existing research and conceptual backgrounds on the topic, it starts by reviewing conceptual definitions, characteristics of Fintech and Robo-Advisory, taxonomy and evolution, it later provides the groundwork for a classification. Then, a comprehensive documental review is performed on the current state of Robo-Advisory, by summarizing the characteristics of worldwide companies that provide such services. Finally, methodologies for efficiency evaluation are reviewed, commented, and contrasted, the later research works find initial evidence of enhancements in efficiency.

In the second part a new methodology for efficiency assessment is proposed, we start by describing the case study of a prominent Robo-Advisor in Japan, we describe the available data and the decomposition of the returns into a tactical and strategical component for return, as well as the risk metrics for evaluation. We also describe the methodology for constructing a composite benchmark for the first part of the return evaluation and the structure of the data taken from the Japanese Fund Association for the latter part of the return evaluation.

The third part provides the results for our tests: The comprehensive analysis of Robo-Advisors in this study focused on both tactical and strategic levels, revealing that, under diverse market conditions, these tools did not significantly outperform a straightforward fixed-weight asset holding strategy. The study emphasizes the importance of considering not only returns but also understanding the strategies employed by Robo-Advisors in navigating dynamic market scenarios. The lack of rejection of the null hypothesis at both levels prompts further exploration into the value proposition and efficiency of Robo-Advisors in the broader financial landscape. Additionally, the comparison with the Japanese Fund Market indicated no statistically significant differences in asset management

decisions, emphasizing the need for a deeper understanding of the decision-making processes and risk management strategies employed by Robo-Advisors. The study lays the foundation for future research recommendations, suggesting a broader focus on aspects like product design, diversification, channel dynamics, and customer experiences to comprehensively understand the evolving dynamics of these innovative financial tools in rapidly changing markets.

SUMMARY IN LITHUANIAN

INVESTICIJŲ AUTOMATIZUOTŲ PATARIMŲ EFEKTYVUMO ĮVERTINIMAS

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Magistro baigiamasis darbas

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Darbo vadovė prof. dr. Jelena Stankevičienė

Vilnius, 2024

78 puslapiai, 10 paveikslų, 12 lentelių, 43 šaltiniai.

Šio magistro darbo tikslas yra įvertinti investicijų automatizuotų patarimų efektyvumą, lyginant su kitais finansiniais instrumentais bei skirtingomis grąžos ir rizikos dedamosiomis.

Darbas susideda iš trijų pagrindinių dalių. Pirmoje dalyje, pateikiama FinTech ir investicijų automatizuotų patarimų konceptuali analizė ir teorinis pagrindimas. Antroje dalyje pasiūloma originali metodologija įvertinti investicijų automatizuotų patarimų efektyvumą. Trečioje dalyje, remiantis Japonijos finansų rinkų duomenimis, įvertinamas investicijų automatizuotų patarimų efektyvumas lyginant su kitų finansinių instrumentų efektyvumu bei nepastovumu. Darbo pabaigoje pateikiamos išvados ir rekomendacijos.

Teorinėje darbo dalyje analizuojamas esamas FinTech ir investicijų automatizuotų patarimų tyrimų laukas, pradedant nuo sąvokų apibrėžimų, FinTech ir investicijų automatizuotų patarimų charakteristikų, jų klasifikacijų ir raidos. Toliau atliekama išsami investicijų automatizuotų patarimų esamos situacijos analizė, apžvelgiamos visame pasaulyje tokią paslaugą teikiančių įmonių charakteristikos. Teorinės dalies pabaigoje išsamiai apžvelgiamos ir palyginamos efektyvumo vertinimo metodikos, atkreipiant ypatingą dėmesį į efektyvumo didinimo dedamąsias.

Antrojoje darbo dalyje pasiūloma originali investicijų automatizuotų patarimų efektyvumo vertinimo metodika, apžvelgiamas Japonijos investicijų fondo investicijų automatizuotų patarimų atvejis, paruošiamas vertinimui duomenų masyvas, išskiriant grąžos taktinę ir strateginę dedamąją bei rizikos metrikas. Taip pat aprašoma apibendrinamojo rodiklio sudarymo metodologija pirmajai grąžos vertinimo daliai ir, remiantis Japonijos investicijų fondų asociacijos duomenų struktūra, antrajai grąžos vertinimo daliai.

Trečiojoje dalyje pateikiami tyrimų rezultatai. Išsami investicijų automatizuotų patarimų analizė šiame tyrime apėmė tiek taktinį, tiek strateginį lygmenis, parodant, kad esant įvairioms rinkos sąlygoms šie įrankiai nėra reikšmingai efektyvesni nei paprasta fiksuotų svorių turto investavimo strategija. Tyrimo rezultatai parodė, kad svarbu ne tik atsižvelgti į grąžas, bet ir suprasti strategijas, kurias naudoja investicijų automatizuotų patarimų įrankiai, kurdami dinamiškus rinkos scenarijus. Nulinės hipotezės atmetimo trūkumas sukelia abejones dėl investicijų automatizuotų patarimų vertės pasiūlymo ir efektyvumo bei reikalauja tolimesnių tyrimų platesniame finansų rinkų kontekste,

atsižvelgiant į šių įrankių sprendimų priėmimo procesus ir rizikos valdymo strategijas. Be to, palyginimas su Japonijos investicinių fondų rezultatais parodė, kad nėra statistiškai reikšmingų skirtumų tarp turto valdymo sprendimų, priimtų remiantis investicijų automatizuotų patarimų įrankiais ir Japonijos investiciniais fondais atsižvelgiant į riziką. Remianti gautais rezultatais, galima išskirti tokias ateities tyrimų kryptis: atlikti gilesnius tyrimus atsižvelgiant į investicijų automatizuotų patarimų įrankių sprendimų priėmimo projektavimą, diversifikaciją, kanalų dinamiką, klientų patirtis, siekiant išsamiai suprasti šių inovatyvių finansinių įrankių tobulėjančias charakteristikas sparčiai kintančiose finansų rinkose.

ANNEXES

Annex 1 – Code snippets for data exploration and analysis

In [1]:
```
# importing libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
import statsmodels.api as sm
import statsmodels.formula.api as smf
```

In [2]:
```
# reading the robo-advisor returns

ra_index = pd.read_csv('wn-returns.csv', index_col = 'Date')
ra_index.index=pd.to_datetime(ra_index.index)
ra_index.dropna(inplace=True)
```

In [3]:
```
ra_index.head()
```

Out[3]:

Date	1	2	3	4	5
2016-01-19	100.00	100.00	100.00	100.00	100.00
2016-01-29	100.61	100.59	100.75	100.95	101.08
2016-02-29	102.47	102.79	102.87	103.12	103.11
2016-03-31	105.66	106.81	107.95	109.19	110.11
2016-04-29	106.47	107.78	109.19	110.64	111.64

In [37]:
```
ra_index.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 94 entries, 2016-01-19 to 2023-09-29
Data columns (total 5 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   1       94 non-null     float64
 1   2       94 non-null     float64
 2   3       94 non-null     float64
 3   4       94 non-null     float64
 4   5       94 non-null     float64
dtypes: float64(5)
memory usage: 4.4 KB
```

In [38]:
```
# ra index returns dataset
ra_returns = ra_index.pct_change().dropna()
```

In [39]:
```
ra_returns.describe()
```

Out[39]:

	1	2	3	4	5
count	93.000000	93.000000	93.000000	93.000000	93.000000
mean	0.002481	0.003929	0.004978	0.005987	0.006442
std	0.018557	0.023631	0.029171	0.034098	0.037482
min	-0.067643	-0.072421	-0.086768	-0.107669	-0.125964
25%	-0.005448	-0.005458	-0.004402	-0.004971	-0.006091
50%	0.005666	0.008016	0.008864	0.009787	0.010800
75%	0.012568	0.014235	0.018450	0.022267	0.026185
max	0.043969	0.058688	0.079151	0.094286	0.105940

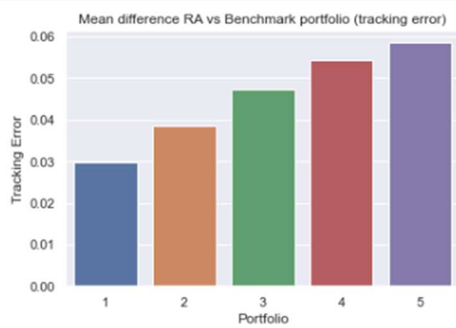
In [41]:
```
# calculating the annualized returns, standard deviation and sharpe ratio of the robo-advisor index, summarized in a dataframe

ra_annualized_returns = ra_returns.mean() * 12
ra_annualized_std = ra_returns.std() * np.sqrt(12)
ra_sharpe_ratio = ra_annualized_returns / ra_annualized_std

ra_metrics = pd.DataFrame([ra_annualized_returns, ra_annualized_std, ra_sharpe_ratio], index=['Annualized Returns', 'Annualized S
```

In [42]:
```
ra_metrics
```

Out[42]:

	Annualized Returns	Annualized Standard Deviation	Sharpe Ratio
1	0.029767	0.064285	0.463044
2	0.047152	0.081861	0.575997
3	0.059734	0.101050	0.591130
4	0.071845	0.118118	0.608246
5	0.077305	0.129840	0.595383

In [52]:
```
tracking_error = np.std(ra_returns - benchmark_returns)
tracking_error.index
sns.set(style="darkgrid")
sns.barplot(x=tracking_error.index, y=tracking_error.values)
plt.title('Mean difference RA vs Benchmark portfolio (tracking error)')
plt.xlabel('Portfolio')
plt.ylabel('Tracking Error')
plt.show()
```



In [53]:
```
# plotting tracking error
sns.set(style="darkgrid")
sns.lineplot(data=ra_returns.cumsum() - benchmark_returns.cumsum())
plt.title('Tracking Error')
plt.xlabel('Date')
plt.ylabel('Tracking Error')
plt.show()
```

Annex 2 – Composite construction

In [45]:
```
benchmark_tickers = benchmark_prices.columns

benchmark_tickers
```

Out[45]:
```
Index(['VTI', 'VEA', 'VWO', 'AGG', 'TIP', 'GLD', 'IYR'], dtype='object')
```

In [46]:
```
# weights vectors
portfolio1_weights = np.array([0.109, 0.05, 0.05, 0.675/2, 0.675/2, 0.066,0.05])
portfolio2_weights = np.array([0.241, 0.105, 0.05, 0.485/2, 0.485/2,0.069,0.05])
portfolio3_weights = np.array([0.335, 0.189, 0.066, 0.29/2,0.29/2, 0.07,0.05])
portfolio4_weights = np.array([0.39, 0.29, 0.078, 0.109/2,0.109/2, 0.083,0.05])
portfolio5_weights = np.array([0.39, 0.339, 0.121, 0.05/2,0.05/2, 0.05,0.05])

# verifying if the weights sum to 1
for i in [portfolio1_weights, portfolio2_weights, portfolio3_weights, portfolio4_weights, portfolio5_weights]:
    print(i.sum())

# printing the weights in a table

weights = pd.DataFrame([portfolio1_weights, portfolio2_weights, portfolio3_weights, portfolio4_weights, portfolio5_weights], inde
weights
```

```
1.0
1.0
1.0000000000000002
0.9999999999999999
1.0000000000000002
```

Out[46]:

	VTI	VEA	VWO	AGG	TIP	GLD	IYR
Portfolio 1	0.109	0.050	0.050	0.3375	0.3375	0.066	0.05
Portfolio 2	0.241	0.105	0.050	0.2425	0.2425	0.069	0.05
Portfolio 3	0.335	0.189	0.066	0.1450	0.1450	0.070	0.05

In [47]:
```
# constructing benchmark indexes starting on 100 according to the paper distributions putting into a dataframe
benchmark_index = pd.DataFrame()

for i in benchmark_tickers:
    benchmark_index[i] = benchmark_prices[i] / benchmark_prices[i].iloc[0] * 100

benchmark_index.head()
```

Out[47]:

Date	VTI	VEA	VWO	AGG	TIP	GLD	IYR
2016-01-19	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000
2016-01-29	99.989833	96.915560	99.675633	100.676751	101.220848	110.930343	99.249989
2016-02-29	106.600213	103.430355	112.163485	101.565199	102.908407	109.995327	108.138859
2016-03-31	107.803988	106.287805	113.492289	101.824609	103.123865	115.614778	107.601112
2016-04-29	109.673784	105.969329	109.820778	101.854189	102.459650	108.518000	109.976302

In [48]:
```
# calculating the portfolio benchmark returns and putting into a dataframe
benchmark_portfolios = pd.DataFrame()

for i in range(1,6):
    benchmark_portfolios[str(i)] = benchmark_index.dot(weights.iloc[i-1])

benchmark_portfolios.head()
```

Out[48]:

Date	1	2	3	4	5
2016-01-19	100.000000	100.000000	100.000000	100.000000	100.000000
2016-01-29	101.152793	100.834326	100.395002	100.049384	99.467618
2016-02-29	104.075592	104.740483	105.417487	105.998005	106.227305
2016-03-31	104.920380	105.873075	106.883841	107.865191	108.092194
2016-04-29	104.360871	105.581863	106.737674	107.710815	108.017253

Annex 3 – Statistical tests

Testing for tactic allocation/rebalancing efficiency on robo-advisors vs. pure hold strategies

Null hypothesis (H0): Robo-advisors are no better than pure hold strategies in terms of rebalancing efficiency. Translates into

$$H_0 : \mu_{robo} - \mu_{hold} = 0$$

where μ_{robo} correspond to the mean returns of robo-advisors and μ_{hold} correspond to the mean returns of pure hold strategies. Across 94 month observations.

Returs are defined as

$$r_t = \frac{p_t - p_{t-1}}{p_{t-1}}$$

where p_t is the price of the portfolio at time t.

Test is a two-tailed t-test with different significance levels

In [54]:
```
for i in range(1,6):
    portfolio_returns = ra_returns[str(i)]
    benchmarki_returns = benchmark_returns[str(i)]

    # Perform a paired t-test and add to a list of results
    t_stat, p_value = stats.ttest_rel(portfolio_returns, benchmarki_returns)

    # Display the results for each pair
    print(f'\nPortfolio {i} vs Benchmark:')
    print(f'Test Statistic: {t_stat}')
    print(f'P-value: {p_value}')



    # Check for significance at different alpha levels (e.g., 0.05, 0.01)
    alpha_levels = [0.05, 0.01]

    for alpha in alpha_levels:
        if p_value < alpha:
            print(f"At {alpha} significance level, reject the null hypothesis.")
        else:
            print(f"At {alpha} significance level, fail to reject the null hypothesis.")
```

Testing for differences in volatility between robo-advisors and pure hold strategies

Now we test for differences in volatility between robo-advisors and pure hold strategies, our null hypothesis assumes that the variance of the portfolio is equal to the variance of the benchmark. As alternative hypothesis we assume that the variance of the portfolio is higher than that of the benchmark

$$H_0 : \sigma^2_{robo} <= \sigma^2_{hold}$$
$$H_1 : \sigma^2_{robo} > \sigma^2_{hold}$$

In [59]:
```
import scipy.stats as stats
import numpy as np

def f_test(x, y, alternative='two-sided'):

    """
    Calculates the F-test.
    ----------------------------------------------
    param x: The first group of data
    param y: The second group of data
    param alternative: The alternative hypothesis, one of "two_sided" (default), "right" or "left"
    return: a tuple with the F statistic value and the p-value.
    """

    df1 = len(x) - 1
    df2 = len(y) - 1

    F = np.var(x) / np.var(y)

    if alternative == 'right':
        p_value = stats.f.sf(F, df1, df2)

    elif alternative == 'left':
        p_value = stats.f.cdf(F, df1, df2)

    else:
        p_value = stats.f.sf(F, df1, df2) * 2

    return F, p_value
```