Vaasan yliopisto
UNIVERSITY OF VAASA

Heikki Anttila

Herding Bias and Its Impact on Long-Term Fund Performance: A Human vs. AI Comparison

Evidence from the US

School of Accounting and Finance
Master's thesis in Finance
Master's Degree Programme in Finance

Vaasa 2025

UNIVERSITY OF VAASA
School of Accounting and Finance
Author: Heikki Anttila
Title of the thesis: Herding Bias and Its Impact on Long-Term Fund Performance: A Human vs. AI Comparison : Evidence from the US
Degree: Master of Science in Economics and Business Administration
Discipline: Finance
Supervisor: Veda Fatmy
Year: 2025 **Pages:** 92

ABSTRACT :
The growing role of artificial intelligence in asset management (AI) has raised questions on how it compares to human fund managers, especially considering behavioral biases and their effect on fund performance. Herding bias is a well-studied topic in financial literature, however, its implications in comparison to AI-managed funds are yet to be explored. The objective of this thesis is to examine the herding bias and its impact on the long-term fund performance of human-managed funds compared to AI-managed funds. The main focus of the paper is to study whether human-managed funds exhibit herding behavior and whether such behavior affects their performance relative to AI-managed funds. The comparison focuses on U.S.-based fund categories from 01.01.2019 to 24.09.2024.

The key method for detecting herding behavior among the funds during the whole sample period and the subperiods is the Cross-Sectional Absolute Deviation (CSAD) model, which estimates return dispersion relative to market movements. The empirical study uses daily fund-level returns on both human-managed and AI-managed funds. In addition to the whole sample period, the study examines four subperiods: the COVID-19 pandemic, the Russia-Ukraine war, the Silicon Valley Bank collapse, and the Israel-Gaza conflict. To compare performance between funds, mean return, cumulative return, and the Sharpe ratio are utilized. The two hypotheses are based on previous literature and address both the whole sample period and the subperiods.

The findings of this thesis do not provide statistically significant herding behavior among the human-managed fund categories during the whole sample period or the subperiods. Despite the absence of herding, the fund performance metrics reveal that AI-managed funds offer stable risk-adjusted returns during the sample period. However, human-managed fund categories Growth and Balanced offer superior returns and risk-adjusted returns during most of the periods. These results indicate that the performance differences are based more on the strategy and context than on herding behavior.

When considering the results of the thesis as a whole, the evidence of herding behavior remains inconsistent with previous literature. However, the findings are consistent with the Efficient Market Hypothesis, which states that markets portray all available information. The varying performance differences highlight the relevance of fund strategies and introduce the fact that AI funds' advantage lies in consistency. This thesis contributes to the limited body of research that directly compares behavioral biases and performance differences between human and AI-managed funds. The study highlights the importance of fund types, philosophies, and market conditions in forming outcomes. The results also pave the way for future research that utilizes updated measures for detecting herding and focuses on different markets and behavioral biases.

KEYWORDS: Behavioral Finance, Herding Behavior, Artificial Intelligence, Fund Management, Cross-Sectional Absolute Deviation.

TIIVISTELMÄ :
Tekoälyn kasvava rooli omaisuudenhoidossa on herättänyt kysymyksiä siitä, miten se vertautuu ihmisten hallinnoimiin rahastoihin, erityisesti käytöksellisten harhojen ja niiden vaikutuksien näkökulmasta. Laumakäyttäytyminen on laajalti tutkittu aihe rahoituskirjallisuudessa, mutta sen vaikutuksia verrattaessa tekoälyn hallinnoimiin rahastoihin ei vielä ole tutkittu. Tämän pro-gradu tutkielman tavoitteena on tutkia laumakäyttäytymisen esiintymistä ja sen vaikutusta ihmisjohtoisesti hallinnoitujen rahastojen pitkän aikavälin tuottoon verrattuna tekoälypohjaisiin rahastoihin. Tutkimuksen pääpaino on selvittää, esiintyykö ihmisjohtoisissa rahastoissa laumakäyttäytymistä ja heikentääkö tämä mahdollisesti niiden suhteellista tuottavuutta verrattuna AI-rahastoihin. Vertailun kohteena ovat Yhdysvalloissa toimivat rahastokategoriat ajanjaksolla 1.1.2019–24.9.2024.

Keskeisenä menetelmänä laumakäyttäytymisen tunnistamisessa käytetään Cross-Sectional Absolute Deviation (CSAD) -mallia, joka mittaa tuottojen hajontaa suhteessa markkinaliikkeisiin. Empiirisessä tutkimuksessa käytetään päivätason rahastotuottoja sekä ihmisen että tekoälyn hallinnoimista rahastoista. Koko otosjakson lisäksi tutkimuksessa tarkastellaan neljää osajaksoa: COVID-19-pandemiaa, Venäjä–Ukraina-sotaa, Silicon Valley Bankin romahdusta ja Israel–Gaza-konfliktia. Rahastojen tuottavuuden vertailussa käytetään keskimääräistä tuottoa, kumulatiivista tuottoa sekä Sharpen lukua. Tutkielman kaksi hypoteesia pohjautuvat aiempaan kirjallisuuteen ja käsittelevät sekä koko otosjaksoa että osajaksoja.

Tutkimuksen tulokset eivät osoita tilastollisesti merkittävää laumakäyttäytymistä ihmisjohtoisissa rahastoissa koko otosjakson tai osajaksojen aikana. Laumakäyttäytymisen puuttumisesta huolimatta tuottolukujen tarkastelu osoittaa, että tekoälyrahastot tarjoavat vakaampia riskikorjattuja tuottoja tarkastelujakson aikana. Kuitenkin ihmisjohtoiset Kasvu- ja Tasapainotettu-rahastot saivat parempia kokonaistuottoja ja riskikorjattuja tuottoja useimmissa tarkastelluissa jaksoissa. Tulokset viittaavat siihen, että tuottoerot perustuvat enemmänkin rahaston strategiaan ja markkinatilanteeseen kuin laumakäyttäytymiseen.

Tarkasteltaessa tutkielman tuloksia kokonaisuutena, laumakäyttäytymisen empiiriset todisteet ovat ristiriidassa aiemman kirjallisuuden kanssa. Tulokset ovat kuitenkin linjassa tehokkaiden markkinoiden hypoteesin kanssa, jonka mukaan markkinahinnat heijastavat kaikkea saatavilla olevaa informaatiota. Rahastojen vaihtelevat tuottoprofiilit korostavat strategioiden merkitystä ja osoittavat, että tekoälyrahastojen etu piilee johdonmukaisuudessa. Tutkielma täydentää harvalukuista tutkimuskenttää, joka vertailisi suoraan käytöksellisiä harhoja ja tuottoeroja ihmis- ja tekoälypohjaisten rahastojen välillä. Tämä tutkimus korostaa rahastotyyppien, sijoitusfilosofioiden ja markkinatilanteiden merkitystä lopputuloksiin. Tutkielma luo myös pohjaa jatkotutkimukselle, joka voisi hyödyntää kehittyneempiä metodeja laumakäyttäytymisen tunnistamiseksi sekä keskittyisi eri markkinoihin ja käytöksellisiin harhoihin.

AVAINSANAT: Behavioristinen Rahoitus, Laumakäyttäytyminen, Tekoäly, Rahastojen Hallinnointi, Cross-Sectional Absolute Deviation

[1] In the making of this thesis, artificial intelligence tools were utilized for enhancement purposes. Grammarly was employed to elevate the quality of writing. ChatGPT was used for consultancy and idea purposes.

Table of Contents

Figures

Tables

Abbreviations

EMH	Efficient Market Hypothesis
EUT	Efficient Utility Theory
MPT	Modern Portfolio Theory
CAPM	Capital Asset Pricing Model
CSSD	Cross-Sectional Standard Deviation
CSAD	Cross-Sectional Absolute Deviation
AI	Artificial Intelligence
ML	Machine Learning

1 Introduction

Behavioral finance rose as an approach after traditional finance could not explain certain trading behaviors through traditional economic theories (Barberis & Thaler, 2003). Behavioral biases or cognitive biases are central to behavioral finance, which incline humans to use shortcuts while making decisions (Jain et al., 2015). Behavioral biases have been recognized as critical factors influencing investor behavior and financial markets.

One of the most studied biases is herding behavior, where investors mimic the collective actions of other investors instead of relying on their analysis or information (Christie & Huang, 1995). Herding mentality often leads to inefficiencies in the market and can result in the creation of bubbles, mispricing of securities, and crashes. Herding is particularly present during periods of high volatility and uncertainty (Devenow & Welch, 1996). In these times, investors tend to follow others' trading behavior out of fear of missing out or concern about major losses. This behavior has been documented in human-managed funds where behavioral biases play a role.

As behavioral finance rose against traditional finance, now artificial intelligence (AI) is rising to battle the cognitive biases that the human brain possesses. With the rise of AI in finance and fund management, the question arises whether AI-powered funds, driven by algorithms and data rather, are less prone to human biases and can produce superior returns in the long term. AI's development in asset management can potentially reduce or even eliminate behavioral biases. AI-driven funds utilize machine learning and data-driven strategies, which are said to make decisions based on objective market indicators and prediction models (Kolanovic & Krishnamachari, 2017). In contrast to human managers, AI systems do not show fear, greed, or other emotional reactions that frequently result in irrational decisions (Hirshleifer, 2020). AI may outperform human-managed funds, especially during high volatility, since it can process large volumes of data and execute transactions quickly. However, the degree to which AI-powered funds outperform humans and whether they can completely disregard behavioral biases is yet to be answered.

The inhumane nature of AI does have some disadvantages in comparison with humans, which might give the edge to human-managed funds. Inaccurate data may cause AI systems to make unreasonable investment decisions (Barocas et al., 2023). Barocas continues that humans usually do not make these unreasonable choices and usually rely on moral significance among the used attributes. Additionally, using flawed training data while creating the algorithm can lead to poor decision-making (IBM, 2023).

The U.S. financial market provides a diverse environment for detecting these dynamics, given its liquidity, various market participants, and presence of human- and AI-managed funds. In recent years, the world of stocks has experienced multiple periods of significant volatility, including the COVID-19 pandemic, the Russia-Ukraine war, the Silicon Valley Bank collapse, and the Israel-Gaza war. Studying and potentially detecting herding during these periods offers valuable information through which the comparison between human- and AI-managed funds can be closely examined.

1.1 Purpose of the Study

This study primarily aims to examine the impact of herding behavior on the long-term performance of human-managed funds compared to AI-powered funds within the U.S. financial markets. More specifically, it focuses on periods of high market volatility from 2019-2024, including COVID-19, the Russia-Ukraine war, the Silicon Valley Bank collapse, and the Israel-Gaza conflict. The purpose of the study is to evaluate whether herding behavior is more prevalent among human fund managers and whether AI-powered funds can diminish emotional biases and deliver superior long-term performance.

Investors are increasingly debating whether AI in fund management can eliminate cognitive and emotional heuristics that traditionally have affected human fund managers (Kolanovic & Krishnamachari, 2017). According to Hirshleifer (2020), AI has the potential to process larger volumes of data and make quick decisions without being emotionally influenced. However, it is still unclear whether AI-driven funds are completely free from biases or if they show systematic behavior resembling herding, particularly in highly volatile market conditions.

This study attempts to analyze the levels of herding during turbulent markets and then compare the returns between human and AI-managed funds. The paper will explore whether avoiding trading in the same direction has produced better long-term returns and overall outcomes by utilizing metrics such as mean return, cumulative return, and Sharpe ratio. For detecting herding behavior, the Cross-Sectional Absolute Deviation (CSAD) model from seminal work by Chang et al. (2000) will be utilized.

1.2 Contribution to the Existing Literature

This thesis offers a new perspective to the existing literature by investigating whether herding behavior influences the performance of funds managed by humans compared to those managed by AI, which should be unaffected by such biases. Despite the growing popularity of AI in fund management, there is a scarcity of academic studies that directly compare its performance with that of human managers. Existing research on AI in finance typically centers around areas such as algorithmic trading, predictive modeling, or risk management, rather than providing a head-to-head performance comparison with human managers facing behavioral constraints (Chen & Ren, 2022; Grobys et al., 2022). By examining human-managed funds, which may be influenced by herding bias, alongside AI-managed funds that are anticipated to function solely on data-driven methods, this thesis delivers a comparative analysis that is currently absent in existing literature.

While herding and related behavioral biases have been widely examined in human-managed funds (Lakonishok et al., 1992; Brown et al., 2014; Jiang & Verardo, 2018), no previous research has systematically evaluated the performance differences between human and AI fund management with a focus on herding. This research addresses a significant gap by analyzing how herding among human fund managers impacts their long-term performance when compared to AI-managed funds, which operate without emotional or psychological factors.

1.3 Structure of the Thesis

The structure of the study is the following. The first chapter presents the introduction for the study by outlining its purpose and contribution to the prevailing literature. The theoretical background is introduced in the second part of the thesis by explaining key theories from traditional finance, behavioral finance, and artificial intelligence in fund management. The third chapter is dedicated to the literature review, which includes previous relevant research and hypothesis development. This chapter establishes the framework upon which the research hypotheses are built. The fourth chapter outlines the methodology used in the empirical part of the study. It explains the models and formulas applied to measure herding activity and to calculate the performance metrics of human and AI-driven funds. In the fifth chapter, the data collection process and descriptive statistics of the dataset are presented. The sixth chapter presents the empirical results of the study. The results are discussed and evaluated with an emphasis on the research hypotheses. The seventh chapter provides a discussion about the prevailing limitations of the study and suggestions for future research. Lastly, the final chapter concludes the findings and explores their possible implications and overall contribution.

2 Theoretical Background

Commonly, finance has been divided into traditional and behavioral finance. Traditional finance aims to explain phenomena using rational means, while the new approach, behavioral finance, argues that some events can be better explained using irrational agents (Barberis & Thaler, 2003). According to Holtfort (2018), traditional finance assumes perfect market conditions, and behavioral finance contradicts this view by assuming that psychological factors affect investors' decision-making. The theoretical background part of the study is divided into three subsections. First, this thesis examines traditional finance. Then, light is shed on the evolution of finance to the recognition of behavioral finance. Lastly, the latest and most revolutionary area of finance, artificial intelligence, is introduced. This chapter provides the necessary theories and hypotheses to understand the topic of the study better.

2.1 Traditional Finance

Traditional finance, often recognized as standard finance, is based on core theories and principles (Kumar and Goyal, 2015). These include the arbitrage principles developed by Miller and Modigliani, Markowitz's portfolio theory, the Capital Asset Pricing Model (CAPM) proposed by Sharpe, Lintner, and Black, and the option-pricing model of Black, Scholes, and Merton. According to Kumar and Goyal, at the core of the aforementioned is the Efficient Market Hypothesis (EMH). The EMH relies on the assumption that the asset prices incorporate all available information. Additionally, the EMH also suggests that market participants act rationally and have access to accurate information. This prevents asset mispricing and opportunities for arbitrage. In addition to the Efficient Market Hypothesis, the other core principle in traditional finance is the Expected Utility Theory (EUT). Next, the two mentioned theories are examined in more depth. The Modern Portfolio Theory by Markowitz is also introduced to frame the fund management aspect of the thesis.

2.1.1 Efficient Market Hypothesis

Efficiency is a key principle in finance. For many years, scholars and economists have examined its relevance in capital markets, leading to the Efficient Market Hypothesis (EMH) becoming a central topic in financial research (Ţiţan, 2015). The study by Ţiţan indicates that the EMH has sparked discussion, with many scholars either supporting it or questioning its legitimacy. It is essential to comprehend the roots of this idea and the development of research on market efficiency, especially in recent years, to understand the current debates and varying viewpoints on the EMH.

The Efficient Market Hypothesis aligns with the Random Walk Theory (RWT) (Malkiel, 2003). As explained by Malkiel, the RWT describes a sequence of prices where all future prices deviate from previous prices randomly. The reasoning for the RWT is that if information flows freely and is instantly shown in stock prices. THerefore the stock price of tomorrow will only show tomorrow’s information and will not correlate with today’s price changes. However, news is unpredictable. Price changes must also appear random. Malkiel states that this implies prices to fully portray all available information. This lets even uninformed investors purchase a diversified portfolio at current market prices and obtain the same rates of return as financial experts.

The generalized version of the Efficient Market Hypothesis was first introduced in 1970 by Eugene Fama. In his research, Fama clarifies that the primary function of the capital market is to distribute ownership of the economy's capital assets. Ideally, this market would operate in a way where prices accurately signal resource allocation; that is, firms can make informed decisions regarding production and investment, while investors can choose from securities that represent ownership of these companies' activities under the assumption that security prices at any given moment "*fully portray*" all available information. A market characterized by prices that consistently "*fully portray*" the available information is considered "*efficient*."

According to Fama (1970), the EMH divides asset prices into three subsections. The first category, weak form tests, evaluates whether prices solely depend on past price information. Following that, semi-strong form tests examine how effectively prices reflect publicly accessible information, like earnings reports or stock splits. Finally, strong form tests investigate whether specific investors or groups possess exclusive access to vital information that may affect pricing. According to the author, the results suggest that, with a few notable exceptions, the efficient markets hypothesis largely stands up to empirical examination.

In her study, Ţiţan (2015) discusses various research examining the three forms of the Efficient Market Hypothesis. Most of this research does not support the semi-strong and strong forms of the EMH, as financial data fails to validate these theories. Opinions on the weak form of the EMH, which includes the random walk theory, are mixed. Some studies within the weak form suggest that abnormal returns result primarily from random chance, with overreactions and underreactions occurring at approximately equal probabilities, providing support for the weak form of the EMH.

A commonly observed pattern in financial data is that anomalies often diminish or disappear as analytical models improve (Ţiţan, 2015). This suggests that these anomalies may stem from the methodologies used. Ţiţan emphasizes that most research in this field employs event studies; some of these studies analyze the immediate price response to announcements, arguing that financial assets quickly adjust to new information, thus supporting the idea of market efficiency. However, other studies take a longer-term perspective, noting a gradual adjustment of prices to new information. This challenges the Efficient Market Hypothesis (EMH) by indicating potential inefficiencies over medium- and long-term periods.

As noted by Ţiţan (2015) in the first paragraph of this subsection, the EMH has faced both support and criticism. Critics argue that certain market phenomena, such as price anomalies and behavioral biases, challenge the notion that markets incorporate all available information efficiently. Studies conducted by Fama and French (1988) and Poterba and Summers (1988) found evidence of mean reversion in stock returns. These findings indicate that returns can deviate from efficiency over the long term due to overreactions and subsequent corrections. Behavioral finance researchers DeBondt and Thaler (1995) and other have connected these patterns to psychological factors. Such factors include investor overconfidence and sentiment cycles, which can lead to temporary mispricings. Moreover, the concept of limits to arbitrage, where rational investors are unable to fully correct mispricings caused by irrational behavior, challenges the EMH. This concept suggests that irrationality can have lasting effects on market prices (Malkiel, 2003; Schwert, 2001).

2.1.2 Expected Utility Theory

The Expected Utility Theory (EUT) is a fundamental framework for decision-making under uncertainty (Fishburn, 1981). Originally formalized by Von Neumann and Morgenstern in 1944, this theory offers insights into how to make rational choices when the outcomes of our actions are uncertain (Briggs, 2014). Its core principle is to select the action that yields the highest expected utility. As noted by Ritter (2003), the EUT is viewed as normative rather than descriptive, highlighting that it places greater emphasis on the level of wealth itself rather than on variations in that wealth. In his research, Briggs also treats the EUT as how the decisions should be made rather than how they are done, of which the latter represents how the EUT is used in classical economics.

According to Briggs' research, the expected utility of a particular action is the average of the utilities of its possible outcomes, weighted by their probabilities. In this context, the utility of each outcome indicates the degree to which that outcome is favored compared to other alternatives. Moreover, the utility of each outcome is modified by the probability that the action will lead to that specific result, states Briggs. In the study, Briggs simplifies the EUT using an example; suppose you are going for a walk, and you are wondering whether to bring your umbrella on a sunny day. You would rather not carry it for nothing, but it would be better to have it, in case of rain.

Briggs continues that the abovementioned scenario can be formalized using three types of elements. First, the outcomes, meaning things that are directly preferred or not. There are three in the problem. Staying dry and not carrying an umbrella, staying dry but burdened with the umbrella, or getting wet. Next, the states, which are the factors beyond your control that affect the decision's outcome. Here, the states are rain or no rain. Lastly, the acts, indicating things that the decision-maker prefers and can do. In this case, the acts are carrying the umbrella or leaving it at home. According to the example provided in Briggs' study, the EUT helps rank these choices on the choice worthiness: the more expected utility you gain, the more reasonable it is to select that option.

Similar to the Efficient Market Hypothesis, the Expected Utility Theory also faces views both for and against. The EUT faces criticism mainly from two perspectives. First, the EUT is considered irrational (Malkiel, 2003; Briggs, 2014). Secondly, according to Briggs, some critics claim it to be impossible.

As Briggs (2014) mentioned, multiple authors have provided evidence that the EUT appears to offer incorrect guidance. Some examples suggest that rational preferences deviate from the EUT, implying that maximized expected utility might not be essential for rational behavior. Briggs also provides cases where the EUT allows irrational preferences, indicating that maximizing expected utility might not be sufficient for rationality. However, Malkiel (2003) contradicts the criticism of the EUT being irrational by stating that even if the market participants act irrationally, the market can remain efficient. The author emphasizes that efficiency can persist despite stock prices sometimes showing more volatility than what fundamentals like dividends and earnings justify.

As stated, the EUT has also received objections on the fact that it is impossible. In his study, Feldman (2006) notes that utilitarians are drawn to the notion that an action is morally right if it results in the most favorable outcome. However, the author states that critics have been arguing that in numerous instances, the agents are unable to identify which of the options would produce the best result. Therefore, the traditional principle cannot be relied on to guide our decisions. According to Briggs (2014), similar points have been made by Smith (2010) and March and Simon (1958). Furthermore, McGee (1991) argues that it is mathematically impossible to maximize expected utility, even with a perfect computer equipped with infinite memory. McGee explains that to maximize expected utility, a rational agent should accept any wager based on a true arithmetic statement while refusing wagers related to false statements in arithmetic. However, since the set of all true arithmetic statements is not recursively enumerable, no Turing machine can determine the truth or falsity of all such arithmetic statements.

2.1.3 Modern Portfolio Theory

Modern Portfolio Theory (MPT) was pioneered by Harry Markowitz in 1952. It is regarded as one of the most compelling works of traditional finance. The paper by Markowitz (1952) revolutionized the investment process and finance by introducing a quantitative framework for portfolio building that maximizes expected return for a given level of risk. The MPT relies on the rules of diversification and efficient frontier optimization, allowing investors to make decisions based on statistical measures of risk and return (Markowitz, 1952). At first, MPT attracted minimal attention, but over time, the financial community fully embraced the concept (Fabozzi et al., 2002). Now, financial models derived from those foundational ideas are continuously being updated to include all the new insights generated from that groundbreaking research.

In the center of Modern Portfolio Theory lies Markowitz's Portfolio Selection Model, focusing on diversification as a means to reduce risk. According to Fabozzi et al. (2002), MPT measured the idea of diversification by introducing the statistical concept of covariance or correlation. Essentially, this principle suggests that investing all your funds in assets that are likely to fail simultaneously. This means that their returns are closely related, regardless of how low the probability is that any individual investment will fail. Fabozzi et al. point out that this is because if one particular investment fails, it is highly probable that its strong correlation with the other investments will also lead to those investments failing. Eventually resulting in the collapse of the entire portfolio.

The paper by Markowitz proposes that investors can optimize portfolios by balancing the trade-off between risk and return or mean-variance to construct an efficient frontier of optimal portfolios (Markowitz, 1952; Fabozzi et al., 2002). Fabozzi et al. (2002) noted that this frontier is efficient because each point on it represents a portfolio that achieves the highest expected return for a given level of risk or the lowest risk for a specific level of expected return. The portfolios located on this frontier establish the set of efficient portfolios.

Expanding on Markowitz's research, Sharpe (1964), Lintner (1965), and Mossin (1966) developed the Capital Asset Pricing Model (CAPM), which builds upon Modern Portfolio Theory to quantify the link between systematic risk and expected returns (Fama & French, 2004). The CAPM operates under the premise that investors maintain a diversified portfolio to eliminate unsystematic risk, indicating that only systematic risk (market risk) should affect asset prices. The model's formula forecasts an asset's expected return based on the risk-free rate, the asset's beta (which measures its sensitivity to the market), and the market risk premium (Fabozzi et al., 2002; Sharpe, 1964).

The CAPM strengthened the MPT concept of the risk-return trade-off, highlighting that investors should receive compensation solely for assuming systematic risk since unsystematic risk can be mitigated through diversification in an efficient portfolio (Fama & French, 2004). Sharpe (1964) notes that the CAPM serves as a standard for assessing asset performance and reinforces the principle that assets with higher risk (indicated by beta) are expected to provide greater returns over time.

Despite its widespread adoption, Modern Portfolio Theory has faced criticism, largely regarding its assumptions about behavioral aspects and market conditions. A major criticism is that MPT depends on past correlations and returns to predict future performance, which might not represent actual market behavior (Jagannathan & Ma, 2003). The authors Jagannathan and Ma (2003) contend that applying specific limitations on portfolio weights can improve diversification and decrease risk, which questions MPT's dependence on optimization without constraints.

DeMiguel et al. (2009) also studied an optimally diversified portfolio against the "*naïve*" equally weighted portfolio (1/N strategy) and found that the sample-based mean-variance portfolio performed comparably or even worse. According to the authors, MPT-optimized portfolios may lead to errors when applied to real-world data, making them less effective than the 1/N strategy.

Furthermore, MPT has also been questioned by behavioral economists, arguing that investors often behave irrationally and might not optimize the risk-return relationship in the way MPT assumes. Research in behavioral finance suggests that cognitive biases, such as overconfidence and loss aversion, can impact investment decisions, leading to deviations from MPT's predictions (Malkiel, 2003). Despite receiving criticism from various perspectives, MPT has significantly influenced the portfolio management industry. Following the traditional finance theories, this study will next present the theoretical framework for the behavioral finance component.

2.2 Behavioral Finance

The conventional structure of finance is attractively simple, and it would be gratifying if its forecasts were validated by the data (Barberis & Thaler, 2003). After extensive research, it became regrettably evident that fundamental truths regarding the overall stock market, the variation of average returns, and excessive market volatility are not easily interpreted within this framework (Shiller, 2003; Barberis & Thaler, 2003). This suggests that psychological and emotional factors play a major role in the financial market.

During the 1980s, the field of behavioral finance emerged, integrating behavioral and psychological elements into the processes of economic and financial decision-making (Kumar & Goyal, 2015). This discipline questions the efficient market hypothesis and aids in understanding the reasons behind the specific behaviors of investors when investing in financial assets. According to Barberis & Thaler (2003), behavioral finance represents a new perspective on financial markets that has developed as a reaction to the challenges encountered by the conventional paradigm. It suggests that certain financial events can be more effectively interpreted using models where some agents are not entirely rational. To be precise, it investigates the implications of loosening one or both of the two principles that form the basis of individual rationality.

The authors Barberis and Thaler (2003) state that behavioral finance consists of two areas: limits to arbitrage and psychology. Limits to arbitrage posit that rational investors may struggle to correct the fluctuations caused by less rational investors. The psychological building block of behavioral finance, on the other hand, captures the various types of deviations from complete rationality that are anticipated to be encountered.

A key factor contributing to the fast acknowledgment of behavioral finance is the evolution of the prospect theory. Kahneman and Tversky (1979) introduced the prospect theory, which serves as an alternative to Expected Utility Theory in understanding decision-making in uncertain situations (Kumar & Goyal, 2015). In their paper, Kahneman and Tversky oppose the EUT for being utilized as a descriptive model, even though it has been welcomed as a normative theory. Therefore, the model presumed that all rational individuals would prefer to follow the theory's axioms and that, most of the time, the majority of people generally do so. The authors describe various instances where the preferences of individuals contradict the assumptions of the Expected Utility Theory. For example, the paper illustrates that individuals tend to put weight on outcomes that are regarded as foolproof compared to solely probable. In this instance, the preferences were examined only between positive probabilities. Additionally, to support their claim, Kahneman and Tversky also portray that the EUT is similarly violated when the probabilities are switched to negative counterparts.

The research conducted by Kahneman and Tversky has led to greater acceptance of the cognitive aspects of behavioral finance. This has resulted in the introduction of various behavioral biases, with herding behavior being the primary focus of this thesis. A few other common behavioral biases include overconfidence, mental accounting, disposition effect, and heuristics (Ritter, 2003). In addition to behavioral biases, agency theory addresses the most favorable form of contract to handle relationships. In agency theory, one ‘principal’ (e.g., investor) delegates responsibility to another ‘agent’ (e.g., fund manager) (De Camargo Fiorini et al., 2018). While behavioral biases explain cognitive actions that impact decision-making, agency theory provides an additional explanation based on incentive structures. This relationship in the fund management context may lead to biased behavior, such as herding. Although agency theory is not behavioral, it can create similar irrational outcomes and is relevant when comparing human-managed funds to AI alternatives. Next, the main topic of herding will be further explored.

2.2.1 Herding in Financial Markets

The concept of herding is observed in a variety of fields, ranging from neurology and zoology to sociology, psychology, economics, and finance. In the areas of economics and finance, herding or herd behavior typically refers to the tendency of economic agents to copy one another's actions and/or make decisions influenced by the actions of others

(Spyrou, 2013). In the fields of finance and economics, herding behavior has been largely examined and documented in various market conditions (Alexakis et al., 2023). According to the authors Alexakis et al. (2023), herding is a fairly typical behavioral bias that involves trading actions that are correlated and driven by imitation, regardless of individual insights, opinions, or evaluations.

The context of herding behavior dates back to 1936 when Keynes first rationalized the decision-making process through psychological aspects (Bekiros et al., 2017). According to the paper by Bekiros et al. (2017), Keynes outlines herd behavior as an act mimicking “animal spirits” or “beauty contests.” The work by Keynes emphasizes that when facing uncertainty or asymmetric information, individuals tend to choose assets with high short-term market values instead of those with solid fundamentals. Additionally, the theory of “animal spirits” suggests that during uncertain times, fear, and panic, people are subject to their instincts rather than reason, leading to irrational behavior. Moreover, under uncertainty, herding potentially creates irrational optimism that may evolve into a bubble in the market. Thus, it can be stated that herd activity enables the growth of volatile markets.

There are various studies conducted on the topic of herding. In each of the studies, an own definition is provided. For instance, herding can refer to a group of investors who are buying or selling in the same direction at the same time (Nofsinger & Sias, 1999). Avery and Zemsky (1998) note that it can also be market participants who disregard their previous analysis and trade by mimicking the previous trade’s trend. There may also be mutual imitation or significant consensus among analyst forecasts (Welch, 2000; DeBondt & Forbes, 1999). Moreover, herding can show in exhibiting a certain level of correlated behavior (Hwang & Salmon, 2004). Sias (2004) notes that a group of investors following one another into or out of the same securities can also be considered as herd behavior. According to the studies mentioned above, the definition of herding remains mostly the same, based on the main focus of the study.

In addition to conventional herding, recent empirical research has shown instances of reverse herding (Bekiros et al., 2017). In their paper, Bekiros et al. (2017) detail that in reverse herding, investors behave contrary to the prevailing market consensus. According to the authors, this results in an unusually high degree of variation in cross-sectional returns. In the mentioned scenario, market participants may have overlooked or undervalued their own insights and information in favor of distinct price movement signals coming from the market. This subsequently aligns their beliefs with a prevalent "dominant view" (a specific group of assets), resulting in significant herding behavior in and out of positions. The authors Bekiros et al. highlight that this pattern suggests price rises (falls) occur in an "excessive manner," leading to a systematic increase in the dispersion of market returns beyond what would be considered rational pricing.

As stated, herding behavior has implications in a variety of fields. In a more recent study, Alexakis et al. (2023) highlight that herding behavior significantly impacts asset pricing, market efficiency, portfolio diversification, and overall market stability in the financial markets. According to Chiang and Zheng (2010), asset prices can deviate from their fundamental values due to imitative trading activities. This leads to a breakdown in market efficiency. Furthermore, this type of herding can lead to inadequately diversified portfolios, increasing exposure to difficult-to-hedge risks. Consequently, market participants must recognize such correlated trading behaviors to modify their asset allocation strategies accordingly. Alexakis et al. (2023) affirm that this herding tendency is often amplified during crises, potentially causing cross-market herding and a contagion effect.

The behavior of imitating others and trading in the same direction might be perceived as rational on an individual level (Hwang & Salmon, 2004). However, such behavior might not necessarily result in efficient market outcomes, as stated earlier. The study conducted by Bekiros et al. (2017) finds that herd behavior is often heightened during extreme market situations. The authors observe that during periods of significant volatility, herding is detected at the start and turns to unimportant closer to the end of the crisis. Similarly, in their study, Chiang and Zheng (2010) reinforce that a crisis initiates herding behavior in the country where it originates, leading to a contagion effect that extends the crisis to adjacent nations. It can be stated that herding behavior is largely related to uncertainty in the market but not the root cause.

2.2.2 Dimensions of Herding Behavior

In their study, Bikhchandani and Sharma (2000) classify herding into two distinct types in the financial markets, depending on the way investors respond to new information. *Spurious herding* happens when groups facing similar decision-making issues and information are inclined to arrive at similar decisions. *Intentional herding*, on the other hand, arises from a clear intention among investors to imitate the behaviors of their peers. The authors Bikhchandani and Sharma state that spurious herding represents an efficient outcome, while intentional herding may not yield the same efficiency. However, it is important to note that empirically differentiating between spurious herding and intentional herding is often more challenging than it seems. The differentiating might even be unattainable, as a variety of factors can influence an investment decision.

Spurious herding, often referred to as unintentional herding, takes place when investors independently arrive at similar trading choices (Indārs et al., 2019). These choices are influenced by common information or external circumstances without directly mimicking others' behavior. According to Indārs et al. (2019), this type of herding emerges from "homogenous trade decisions in line with company fundamentals", where investors respond comparably to the same information set, such as earnings reports or macroeconomic indicators. In these instances, herding is fueled by fundamental factors and the decisions are based on objective and rational information. Nonetheless, spurious herding can also arise from information inaccuracies, behavioral biases, and typical trading patterns that lead investors to behave similarly. This can happen even when their decisions are derived from misleading or incomplete data (Indārs et al., 2019). This non-fundamental variant of spurious herding highlights how cognitive biases may lead investors to interpret information. Similarly, this results in synchronized market actions that are not directly founded on fundamentals.

Intentional herding, on the other hand, refers to a deliberate choice made by investors to copy the behavior of other market participants. This phenomenon is marked by a "strong willingness of investors to replicate the actions of others" (Indārs et al., 2019). Intentional herding behavior could be further divided into either *rational* or *irrational behavior* among economic actors (Wang et al., 2021). The study by Indārs et al. (2019) notes that investors are regarded as engaging in rational herding when they base their imitation of investment choices on fundamental information. This rational dimension of intentional herding is driven by informational, compensational, or reputational motivations. Investors believe that imitating informed traders will yield favorable results (Indārs et al., 2019). Rational herding contributes to the incorporation of new information into prices, bringing them closer to their fundamental values (Wang et al., 2021). Conversely, intentional herding can also take on an irrational form when investors replicate decisions based on non-fundamental elements, such as noise or speculative trends. This happens without considering the true value of assets. Indārs et al. (2019) note that this version of herding can result in "erroneous investment decisions being copied." Irrational herding can also lead to price deviations from fundamental values, causing increased volatility and reducing market efficiency. In the worst case, possibly leading to the creation of asset bubbles (Wang et al., 2021; Indārs et al., 2019).

2.2.3 Drivers of Herding Behavior

The motivations for herd behavior can vary widely (Spyrou, 2013). As indicated earlier, market players might draw conclusions based on the actions of earlier participants, or investors may respond to the emergence of fundamental information. Also, analysts might follow the crowd to safeguard their reputation, and institutional investors may conform for reasons tied to compensation. Some investors might just act irrationally, and herd behavior can emerge due to psychological or social norms. As stated in the chapter on dimensions of herding, intentional herding includes *rational* and *irrational herding behavior*. Rational herding stems from inadequate information, reputational concerns, and the structure of compensation. In turn, irrational herding is driven by psychological factors, such as behavioral biases. Spurious or unintentional herding, conversely, is driven by characteristics and relative homogeneity (Holmes et al., 2013).

One of the primary factors driving rational herding is informational cascades. As explained by Bikhchandani et al. (1992), an informational cascade happens when it becomes advantageous for a person, having observed the choices of those before him, to mimic the behavior of the previous individual without considering their private information. Devenow and Welch (1996) enhance this explanation with an illustration: An investor who possesses the most negative private information might still be influenced to buy if they observe that three other investors have already made purchases (the knowledge of these three transactions may outweigh their negative private information). However, afterward, all following investors will lack any additional positive information and will behave similarly, even though everyone recognizes that these purchases (or future ones) provide no informative value. This model can account for widespread herding (clumping) based on an erroneous decision, and low consensus (when surveyed). It can also lead to vulnerability (where a small amount of public information can overturn longstanding trends since cascades can form from very little publicly shared data), and a strong reliance on initial conditions (specifically, the purchase choices of the first few investors).

In addition to informational cascades, rational herding can be driven by the reputational concerns of the investor (Bikhchandani & Sharma, 2000). According to Bikhchandani and Sharma (2000), reputational concerns or career concerns stem from doubts regarding a specific manager's skills or abilities. The fundamental concept, originally introduced by Scharfstein and Stein, is that if both an investment manager and the employer are unsure of the manager's capability to select the right stocks, clinging to the actions of other investment professionals maintains the uncertainty about the manager's capacity to handle the portfolio. This situation works favorably for the manager, and if other investment professionals find themselves in a comparable position, herding behavior is likely to take place.

Furthermore, Bikhchandani and Sharma (2000) address the third driver of rational herding, compensation-based herding. If the earnings of an investment manager rely on their performance relative to that of their competitors, this distorts the manager's motivations, resulting in a portfolio that is ultimately inefficient. The addressed situation might lead to herding behavior. The authors Maug and Naik (1995) examine compensation-based herding utilizing an example: an investor (the agent) who is risk-averse and whose remuneration is tied to their performance in comparison to a benchmark, which might be the returns of other investors or a market index. Both the agent and the benchmark possess limited private information regarding stock returns. The benchmark investor makes the first move, and the agent, upon observing these actions, has a motivation to imitate. According to Maug and Naik, this leads to them modifying their portfolio to more closely match that of the benchmark. Furthermore, the structure of the agent's compensation incentivizes them to replicate the benchmark's portfolio instead of solely basing their trading decisions on their account. Maug and Naik (1995) clarify that the compensation imposes penalties for underperformance against the benchmark.

Informational cascades, reasons related to reputation, and herding based on compensation indicate that herding is conducted with intention (Holmes et al., 2013). Contrarywise, herding might branch from relative homogeneity among investment professionals (for instance, similar educational and social backgrounds). This could lead them to interpret the same information signals similarly. Likewise, characteristic herding includes institutions being drawn to investments that possess specific characteristics, such as high historical returns (for example, momentum trading). According to Holmes et al., the arguments regarding relative homogeneity and characteristics imply that herding may occur without intent. This leads to a thought-provoking and applicable question arising about whether herding behavior results from a deliberate choice to follow or if it happens unintentionally.

2.3 Artificial Intelligence in Finance

The landscape of asset management is constantly changing, driven by advancements in technology and investors' changing preferences (Stier, 2022; Bartram et al., 2020). In the article by Deloitte, Stier states that traditional methods of differentiation in investment management are becoming more standardized. This is when artificial intelligence (AI) offers fresh opportunities that go beyond merely lowering costs and improving operational efficiency.

According to Bartram et al. (2020), AI has enhanced portfolio management, trading, and risk management practices. The evolution has been achieved by boosting efficiency, accuracy, and compliance. The authors Bartram, Branke, and Motahari specify that AI methodologies assist in portfolio construction by providing more accurate forecasts of risk and returns while having more sophisticated limitations. According to the three authors, trading algorithms leverage AI to create innovative trading signals and execute trades with reduced transaction expenses. Moreover, Bartram et al. continue that AI also enhances risk modeling and forecasting by deriving insights from new data sources. Ultimately, the success of robo-advisors is largely attributed to AI techniques. However, Bartram et al. emphasize that the application of AI also introduces new risks and challenges generated from model opacity, complexity, and dependence on data integrity.

To begin the chapter about artificial intelligence, an overview of AI is presented to provide a foundation for the finance context. From there, the study moves on to examine AI's applications in the decision-making of investment as well as its biases and limitations to support the viewpoint of this thesis.

2.3.1 Overview of Artificial Intelligence

To thoroughly grasp the advantages and limitations of AI in fund management, it is crucial to delve into the mechanics and framework of AI. By investigating the core algorithms and decision-making frameworks employed by AI systems, it is possible to assess the dependability and efficiency of AI-driven strategies in fund management. Gaining insight into the mechanics of AI also allows for the tackling of issues related to transparency, interpretability, and ethical considerations linked to the application of AI in finance.

The first idea for artificial intelligence dates back to 1956, when a team of computer scientists suggested that computers could be programmed to reason as well as think (Choi et al., 2020). According to Choi et al. (2020), this suggests that every part of learning or any other trait of intelligence could theoretically be described in such detail that a machine could be developed to replicate it. This idea was referred to as “artificial intelligence”. Artificial intelligence can be defined as a focus on creating machines that exhibit intelligent behavior (Stone et al., 2022). According to the authors Stone et al. (2022), intelligence refers to the ability that allows an entity to operate effectively and with anticipation in its surroundings. The study refers to AI as a science and a combination of computational technologies. These areas are encouraged by the ways humans utilize their physical bodies and nervous systems to perceive, learn, reason, and act. However, Stone et al. emphasize that even though AI draws inspiration from human nature, its operation differs from it. Although advancements in AI have been uneven and difficult to forecast, considerable progress has been made since the field was established sixty years ago.

In general, AI can be categorized into two types: deductive and generative (Arora et al., 2023). Deductive AI refers to computer systems that evaluate extensive datasets to identify patterns and draw conclusions. On the other hand, in their recent study, Arora et al. mention that generative AI learns from current data to create new material. From these two types, generative AI has gathered a lot more attention in the past couple of years. As generative AI continues to evolve, speculation around its potential for self-design and iterative algorithm improvement has gained traction, raising the prospect of artificial general intelligence (AGI) outpacing human intelligence and influencing the future organization of work. Arora et al. (2023) highlight that these concepts have traditionally belonged to the realm of science fiction. However, the capacity of large language models to create computer code that exceeds the skills of many data scientists has heightened both enthusiasm and apprehension regarding AGI.

Choi et al. (2020) describe that AI is part of data science and includes both traditional programming and machine learning (ML). Machine learning consists of various models and techniques, which include deep learning (DL) and artificial neural networks (ANN). This division is portrayed in the figure below:

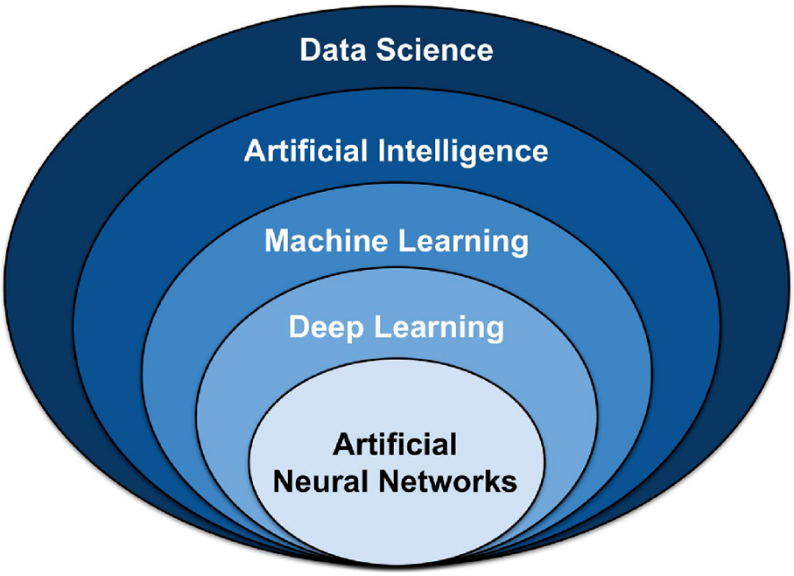


Figure 1. Dimensions of Select Data Techniques (Choi et al., 2020).

In the field of Machine Learning (ML), a computer receives a set of inputs (variables and datasets) along with an output that results from those input variables (Kolanovic & Krishnamachari, 2017). The machine then identifies or 'learns' a relationship that connects the input to the output. Ultimately, Kolanovic and Krishnamachari (2017) state that the effectiveness of this learning process is evaluated 'out of sample'. This assesses its capability to acquire valuable insights into the relationships among variables and forecast results in previously unseen scenarios. ML can further be categorized into supervised learning, unsupervised learning, and reinforcement learning (Lotfi & Bouhadi, 2021).

In the first category, Supervised Learning (SL), the aim is to find a rule or an 'equation' that could be used to forecast a variable. For example, the idea might be to identify a momentum indicator that can most effectively forecast future market performance. Kolanovic and Krishnamachari (2017) mention that this can be achieved by utilizing sophisticated regression models to evaluate which model demonstrates greater predictive capability and holds the most resilience to changes in the regime. Furthermore, in Unsupervised Learning (UL), the focus is on revealing the construct of data. For reference, market returns could be gathered to distinguish the main market drivers. Kolanovic and Krishnamachari explain the matter further by providing an example: A thriving model might discover that, at a certain moment, the market is influenced by factors such as momentum, energy prices, the value of the USD, and an emerging factor that could be associated with liquidity. Lastly, according to Latfi and Bouhadi (2021), Reinforcement Learning (RL) enables agents to acquire knowledge on how to act within an environment filled with error. To put it simply, the algorithm analyzes the outcomes of its actions and learns from the mistakes made when undesirable results occur. This concept is referred to as the reward principle. The reward principle seeks the optimal actions to maximize the rewards. Latfi and Bouhadi state that this learning approach is fundamentally different from classification or planning, as it operates in an unknown and potentially changing environment, and it is achieved without any supervision.

Deep Learning (DL) is a part of Machine Learning, as illustrated in Figure 1 above. As described by Kolanovic and Krishnamachari (2017), deep learning is a method of ML that processes data through several layers of learning, hence the term 'deep'. It typically begins by understanding simpler concepts and then integrates these to grasp more complex ideas and abstract concepts. It is often said that automation's objective is to carry out tasks that are simple to outline but tedious to execute for humans. Alternatively, the purpose of DL AI systems is to tackle tasks that are challenging for humans to specify yet straightforward to perform. The authors Kolanovic and Krishnamachari state that DL essentially mirrors the way humans acquire knowledge. This represents a true effort to artificially replicate the intelligence of humans. However, in the context of finance, Dixon and Halperin (2019) state that in areas other than natural language processing or text mining, DL is often not essential for most applications in finance. It rather serves as a helpful convenience.

The last segment of Figure 1, Artificial Neural Networks (ANN) are machine learning algorithms (Choi et al., 2020). According to Chen et al. (2019), ANNs are based on the functionality and structure of biological neural networks that can draw knowledge from intricate or inaccurate data. The authors further clarify that within the climate of wireless communications, ANNs can be utilized to forecast and explore networks as well as the behavior of users. Thus, it provides user data for unraveling various wireless networking issues. For instance, ANNs can solve problems related to cell association, allocation of computational resources, spectrum management, and replacement of sealed content. Furthermore, recent advancements in the smart mobile applications industry have considerably accelerated the level of interaction with mobile systems for human users. Chen et al. inform that an educated ANN can be categorized as a "professional" in operating with human-related information. Thus, employing ANNs to gather insights from the user's surroundings can enable a wireless network to anticipate users' future actions. As a result, this can formulate an optimal strategy to enhance the overall quality of service and reliability. Lastly, Chen et al. point out that there is a diverse set of ANNs. Every kind of ANN is according to the paper suitable for a specific learning task. The authors mention Modular Neural Networks, Recurrent Neural Networks, Generative Adversarial Networks, Deep Neural Networks, Spiking Neural Networks, Feedforward Neural Networks, and finally Physical Neural Networks.

2.3.2 Artificial Intelligence's Applications in Fund Management

Artificial intelligence in the field of finance has been a topic of interest in research for decades (Cao, 2021). For instance, financial markets, the banking industry, the insurance industry, risk management, regulation, and trading have evolved to the next generation of Financial Technology (FinTech). According to the study by Cao, FinTech has made smart digital currencies, lending, asset and wealth management, and accounting possible. In addition to FinTech, economics and finance (EcoFin) are also being linked with AI at a growing pace. Among the sectors impacted by FinTech, asset management is arguably the most significantly affected and is anticipated to experience the greatest number of job reductions in the near future (Bartram et al., 2020). Many asset management firms are currently employing AI and statistical models to operate trading and investment platforms. The growing reliance on AI for a variety of tasks within asset management necessitates a more thorough analysis of the different techniques and applications. Additionally, it demands the associated opportunities and challenges they present to the industry.

As outlined in the overview section, Artificial intelligence predominantly focuses on machine learning. Machine learning currently stands as the most widely used method in the field (Bartram et al., 2020). As stated by Bartram et al. (2020), there is a significant number of applications for ML. Additionally, most ML techniques in asset management and finance primarily depend on a few key methods. These encompass artificial neural networks, cluster analysis, decision trees, random forests, evolutionary algorithms, least absolute shrinkage and selection operator (LASSO), support vector machines, and natural language processing (NLP). Following in Figure 2, the key characteristics of these methods are:

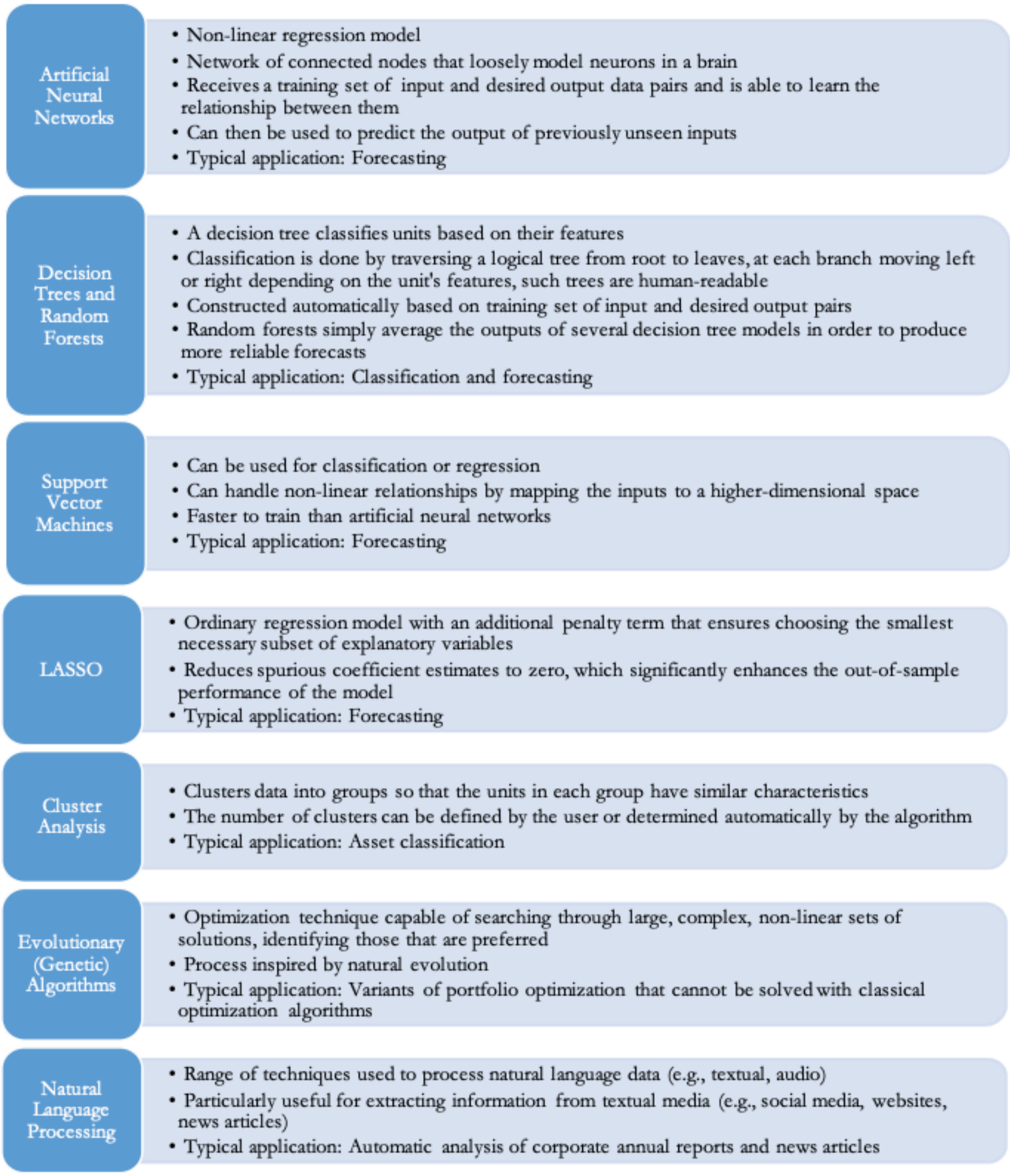


Figure 2. Main AI Methods in Asset Management (Bartram et al., 2020)

As outlined by Bartram, Branke, and Motahari (2020), the area of asset management includes three main elements in which AI has an impact. The elements are portfolio management, trading, and risk management, all of which play a crucial role when it comes to fund management. In portfolio management, AI plays a pivotal role in generating alpha and managing sigma. It also transforms portfolio optimization. In the area of trading, AI applies to algorithmic trading, transaction cost analysis, and trade execution. Lastly, in portfolio risk management, Bartram et al. state that AI contributes to the contexts of market and credit risk.

In portfolio management, AI methods can be utilized to conduct advanced fundamental analysis and to enhance optimal asset allocations (Bartram et al., 2020). Considering the various difficulties faced by traditional portfolio optimization techniques, AI methods frequently yield improved estimations of both returns and covariances. These can then be applied within classic portfolio optimization models. AI applications can predict expected returns via LASSO, neural networks, and support vector machines. Also, using neural networks and support vector machines, AI can estimate variances. Additionally, Bartram et al. point out that the traditional covariance matrix can be substituted with a tree structure utilizing hierarchical clustering. Furthermore, AI can be directly used for making asset allocation decisions to build portfolios that more accurately achieve performance objectives. Artificial intelligence employs genetic algorithms to address optimization challenges within intricate constraints. Finally, neural networks are capable of directly generating optimal portfolios or those that, for instance, replicate an index.

AI technologies are increasingly applied in trading (Bhuyan & Singh, 2022). Due to the rising speed and complexity of transactions, AI methods are becoming essential in the trading arena. As stated earlier, AI has implications in algorithmic trading, transaction cost analysis, and trade execution. One of the most attractive aspects of AI is its ability to process large amounts of data and generate trading signals. As a result of these signals, a new field known as algorithmic trading has developed. According to Bhuyan and Singh, algorithmic trading can be programmed to carry out trades automatically. Additionally, AI techniques can further reduce transaction costs by automatically evaluating the market and identifying the optimal timing, size, and placement for trades. In trade execution, AI systems consider market dynamics, liquidity limitations, and execution risks to guarantee that trades are executed effectively (Bartram et al., 2020). Through continuous learning from market feedback, AI systems can adjust their execution strategies to optimize cost efficiency and sustain a competitive edge.

AI's contributions to portfolio risk management are transformative, particularly in its ability to model and forecast risks more precisely (Bartram et al., 2020). In the area of market risk, AI systems analyze complex datasets to predict market volatility and assess macroeconomic trends. According to Aziz and Dowling (2018), ML is especially applicable in market model stress testing to distinguish either accidental or developing risks in trade behavior. Aziz and Dowling remark that due to insufficiencies in conventional credit risk management techniques, there is a growing interest in the application of AI and ML methods. Bartram et al. (2020) explain that AI provides valuable resources for assessing the financial stability of counterparties and forecasting the likelihood of defaults. AI models deliver detailed insights into credit exposures by examining past data, financial reports, and even unstructured information like news articles.

2.3.3 Artificial Intelligence's Limitations and Biases

Artificial Intelligence has significantly shaped the financial sector by creating new possibilities and offering advancements in efficiency, risk management, and customer service. However, the integration of AI does not come without challenges, especially concerning the limitations of AI and biases that can impact its decision-making processes. The implementation of AI also poses risks in the frontiers of ethicality, fairness, and technicality.

According to an article by IBM (2023), artificial intelligence bias, often known as machine learning bias or algorithmic bias, pertains to AI systems that yield biased outcomes. This mirrors and continues existing human biases in society, including both historical and contemporary social inequalities. Bias may arise from the original training data, the algorithm itself, or the predictions generated by the algorithm. In training data bias, AI systems develop decision-making capabilities based on the training data they receive. Thus, if the data is flawed to start with, the bias presents itself in the decision made by the AI system.

The article by IBM explains that the algorithmic bias stems from the usage of flawed training data. This may lead to algorithms that continuously generate mistakes and unjust results or even exacerbate the biases present in the inaccurate data. The article clarifies that algorithmic bias can also stem from programming mistakes. In this scenario, a developer might disproportionately weigh certain factors in the algorithm's decision-making due to their own conscious or subconscious biases. For instance, variables like income or vocabulary could be utilized by the algorithm, unintentionally leading to discrimination against individuals of a particular race or gender.

The article also informs that an AI bias can arise from human errors. For example, when people handle information and make decisions based on it, they are unavoidably affected by their personal experiences and preferences. Therefore, these biases might be built into the AI systems via the selection process or the weight of data. Similarly to behavioral finance, this is referred to as a cognitive bias. The IBM article visualizes that this cognitive bias may cause favoring of certain geographic areas, for example, while gathering datasets.

Human decision-makers rarely prioritize maximizing predictive accuracy above all else. They often consider whether the attributes used for predictions have moral significance (Barocas et al., 2023). This is one reason to approach comparisons that suggest the superiority of statistical decision-making with caution. As mentioned by Barocas et al. (2023), humans are also less likely to make unreasonable choices. However, such occurrences could arise in automated decision-making, possibly due to inaccurate data. These differences between human and automated decision-making highlight why machine learning-based decision-making systems may be unjust.

3 Literature Review

In this section of the research, the thesis provides a thorough summary of relevant previous studies. It offers a comprehensive literature review that plays a crucial role in shaping the hypothesis. This review will identify gaps and limitations in the existing literature and illuminate areas where further investigation is needed. This paper delves into studies focusing on herding behavior. It explores how collective actions influence individual decision-making, alongside research related to the advancements and implications of artificial intelligence. Moreover, the analysis will extend to studies on fund management and the decision-making processes involved. This ensures a well-rounded perspective on the overarching themes presented in the thesis. Through this detailed examination, this thesis aims to lay a solid foundation for the development of the hypotheses.

3.1 Overview of Herding Behavior in Financial Markets

As the theoretical background section already insinuated, herding behavior has gathered a lot of attention from finance researchers and other fields of science. Even though herding in the financial markets is a widely discussed topic among academics, the empirical evidence is surprisingly scarce (Welch, 2000). In his study on an overview of herding-related research, Spyrou (2013), in a similar way, states that there are many issues when delving deeper into evidence and limitations of herding behavior. As previously discussed, the theory of herding is categorized into models that suppose rational or close to rational behavior and models that suppose irrational agents. Spyrou continues that this literature gap between rational and non-rational models should be narrowed by utilizing models that interact between sources of herding. Meanwhile, various models provide implications that are hard to process empirically with current databases. Secondly, Spyrou remarks that in addition to the difficulties in the models of herding, the empirical evidence tends to be inaccurate. For instance, although numerous significant papers identify little evidence of herding among institutional investors, other research presents conflicting results. Similarly, while several studies report findings that align with analyst herding for various reasons, more recent research suggests that analysts tend to be "*anti-herd*." Lastly, Spyrou states in his study that the primary empirical methods used to assess herding possess limitations that might prevent economists from completely grasping the herding process.

However, despite the conflicting results considering herding research, various seminal papers have created a foundation for this area. One of these is the paper by Bikhchandani and Sharma (2000) that has been addressed previously in this study. The authors distinguish a division between "spurious herding" and "intentional herding." In addition to Bikhchandani and Sharma (2000), other important works examining the root causes of herding include papers by Banerjee (1992), Hirshleifer and Teoh (2003), and Avery and Zemsky (1998), to name a few.

Some other influential studies on herding are conducted by Lakonishok et al. (1992), Christie and Huang (1995), and Chang et al. (2000). These three provide methods for measuring herding behavior in the financial markets. First, Lakonishok et al. (1992) created the LSV method. Next, Christie and Huang (1995) developed the Cross-Sectional Standard Deviation (CSSD) method a few years later. Lastly, Chang et al. (2000) enhanced the CSSD method by taking the Cross-Sectional Absolute Deviations of returns at the millennium's break. In their groundbreaking study, Christie and Huang (1995) investigate whether returns on equity suggest the prevalence of investor herding behavior during market volatility. To capture herd activity, the authors predict the cross-sectional standard deviation (CSSD) of returns. Contrary to rational asset pricing models predicting increasing dispersions, the CSSD model assumes dispersions to be rather low. They discover no consistency with herding behavior in daily or monthly returns during major price deviations. According to Christie and Huang, the expectancy of herding is the highest during significant down-market swings. However, the extent of the rise in the dispersion of actual returns corresponds to the rise in the variability of predicted returns derived from a rational asset pricing model.

In their study, Chang et al. (2000) investigate the herding behavior of investors within varying international markets (i.e., Japan, South Korea, Hong Kong, the US, and Taiwan). While they detect no presence of herding in Hong Kong or the US, they do find robust evidence from the emerging markets of South Korea and Taiwan. However, the main contribution of the study by Chang et al. (2000) is the invention of the Cross-Sectional Absolute Deviation model. Further continuing the work of Chang et al. (2000), Chiang and Zheng (2010) propose an enhanced model to detect herding behavior. In comparison, their model takes asymmetric investor behavior into account. Using their method, Chiang and Zheng investigate herding in global markets. They detect herding in both up and down markets in advanced and Asian markets. However, the US market does not portray herding during the study period. Evidence of herding behavior is documented by Chiang and Zheng solely during the period of the financial crisis. Similarly, authors BenSaïda et al. (2015) do not find evidence of herd activity in the US market, even though the study period ranges from 2000 to 2014.

As the previous literature shows, herding behavior varies significantly based on market conditions, geographic locations, and methodologies used. Key studies, like those by Christie and Huang (1995) and Chang et al. (2000), indicate that herding is more prevalent in emerging markets than in developed markets like the US. The maturity of the market and investor behavior play essential roles in how herding manifests. While some research links herding to market volatility, others, like BenSaïda et al. (2015), find its absence in the US market. Such inconsistencies highlight the influence of data periods, model assumptions, and unique market dynamics. This suggests that herding is a complex phenomenon shaped by specific contexts and a blend of rational and irrational factors.

3.2 Herding Behavior in Volatile Market Conditions

Researchers have shown significant interest in the US market, particularly regarding herding during various bubble and crisis periods (Alexakis et al., 2023). As noted earlier, herding behavior is most common during market turbulence. Nonetheless, Alexakis et al. (2023) state that the empirical findings are ambiguous and vary primarily based on the examined period and the methodology used.

In their study, Bekiros et al. (2017) examine herd behavior under uncertain market conditions and investigate whether it impacts volatility. Utilizing a modified version of the Cross-Sectional Absolute Deviation model, the authors observe signs that herding behavior tends to intensify during extreme circumstances. Bekiros et al. state that at the onset of a crisis, herding behavior is noted, but it becomes negligible as the crisis progresses. According to their observations, the herding tendencies in the US market display dynamic trading patterns that vary over time. These tendencies can be linked to factors such as overconfidence or a pronounced “flight to quality,” particularly evident after the global financial crisis. Additionally, implied volatility shows asymmetric trends and significantly influences irrational behavior.

In a more recent study, Alexakis et al. (2023) examine herding activity during the COVID-19 pandemic. Also, utilizing the CSAD method, the authors investigate the volume of trading, herding dynamics, and events to detect herding under market stress. Similarly to Bekiros et al., the authors find evidence indicating that investors portray herding activity during significant periods of the crisis. The outbreak of the COVID-19 pandemic instigated fear among investors and created overall uncertainty in the markets, making herding behavior more prevalent. Post-pandemic, there is a plethora of research on the effect of herding in financial markets during COVID-19. In a similar way to Alexakis et al., Ferreruela and Mallor (2021) show herding behavior on days with high volatility during the pandemic sub-period in both Spain and Portugal. Exploring the major Asian stock markets, Jiang et al. (2022) also discover evidence of herding behavior during the pandemic. The authors detect a clear rise in the magnitude of herding around the crash of the 2020 spring.

In their research paper, Belhoula and Naoui (2011) investigate herd behavior and positive feedback trading in the US market during times of significant volatility. The pair finds evidence of both positive feedback trading and herding behavior. Galariotis et al. (2015) also find evidence that indicates herding behavior among US investors due to non-fundamentals and fundamentals during various market crises. The authors Galiatoris et al. also document herding spill-over impacts from the US market to the UK in times of financial crises. In a later study, Galiatoris, Krokida, and Spyrou (2016) find further evidence of herd mentality regarding high liquidity stocks in the US from 2000 to 2015, including multiple shorter periods. The trio states that, particularly during crisis and post-crisis periods, the variance in the average liquidity of the equity market is influenced by the clustering of returns.

The studies above indicate that herding behavior becomes more pronounced during periods of market instability, particularly at the beginning of crises, as seen during the global financial crisis and the COVID-19 pandemic. Nevertheless, herding behavior typically lessens as markets regain stability over time (Bekiros et al., 2017; Alexakis et al., 2023). Volatility acts as a major factor influencing herding, with fear and uncertainty heightening irrational decision-making. Additionally, cross-market spillovers, such as those observed between the US and the UK during crises (Galariotis et al., 2015), further illustrate the interconnected nature of herding during chaotic periods, emphasizing its considerable effect on market dynamics.

3.3 Herding and Fund Management

Herding behavior is widely studied in the financial markets from diverse perspectives. Herding has also been extensively researched from a fund management and performance perspective, which aligns with this thesis topic. In their influential 1992 research, Lakonishok et al. studied tax-exempt funds to detect herd behavior and positive feedback trading. Their paper revealed that pension fund managers tend not to participate in positive feedback trading or herd activity. However, Lakonishok et al. did discover herd behavior in smaller stocks, although no impact on stock price movement was found.

Herding behavior among mutual funds has also been studied through analyst recommendations and its impact on stock prices. The research by Brown, Wei, and Wermers (2014) indicates that mutual funds tend to "herd" by making similar trades in response to analyst upgrades that are widely supported. Additionally, they collectively withdraw from stocks that receive broad consensus downgrades from analysts. As stated by Brown et al., the impact of changes in analyst recommendations on fund herding is more pronounced in cases of downgrades and among managers who have heightened career concerns. According to Brown et al., changes in analyst recommendations prompt herding behavior among career-focused fund managers, resulting in price instability as mutual fund ownership of stocks rises.

Continuing with the review of fund managers' herding behavior, Wylie (2005) similarly documents herding activity among mutual fund managers in the U.K. The author notes that the observed herding behavior reflects a rise in the number of managers trading a specific stock over time. This increase is more pronounced for both the smallest and largest stocks. Wylie points out that the documented herding is similarly found among studies of U.S.-based pension and fund managers. According to the study, herding is more pronounced at the stock level rather than at the industry level. The study by Wylie indicates that herding behavior among fund managers does not necessarily vary depending on the geographical location. Moreover, the study notes that the investment management industry in the U.K. is comparable to that in the U.S.

In a more recent study, Jiang and Verardo (2018) investigate mutual funds and the possible skill behind herding behavior. The study reveals an inverse relationship between herding behavior and skill within the mutual fund sector. Jiang and Verardo observe that fund managers tend to mimic the trading activities of institutional investors. The authors indicate that funds exhibiting herding behaviors outperform their antiherding counterparts by more than 2% annually. Variations in skill are the reason behind this performance disparity. Antiherding funds excel in making investment choices, even for stocks that institutions do not frequently trade, and they can foresee the actions of the crowd. Additionally, the performance difference between herding and antiherding funds is enduring, more pronounced when skill holds greater value, and is larger among managers who have heightened career concerns.

The literature suggests that herding behavior in fund management can have positive and negative effects. Its influence on fund performance is significantly dependent on factors like managerial expertise, prevailing market conditions, and outside influences. These results highlight the necessity of delving deeper into the consequences of herding, especially when comparing human-managed funds with those driven by AI. Next, this thesis delves deeper into the use of AI in fund management and its performance compared to human-managed funds.

3.4 Human vs. Artificial Intelligence in Fund Management

The comparison between human- and AI-managed funds has raised questions in recent years' literature. AI was introduced to fund management in 2017 when the AIEQ-named fund was founded (Chen & Ren, 2022). The fund raised over 70 million USD in a few weeks due to its popularity. This was the first step of AI's inclusion in the asset management industry. From then on, the amount of AI-powered funds has grown rapidly.

In their paper on the performance of AI-powered mutual funds, Chen and Ren (2022) compare the advantages and disadvantages between human- and AI-powered funds. According to the authors, the benefits of AI in fund management are well established, emphasizing its advantages over human managers. AI can quickly and efficiently process large amounts of data, facilitating advanced predictive modeling and decision-making, as noted by Krauss et al. (2017) and Adcock & Gradojevic (2019). Unlike humans, AI operates without the limitations of cognitive biases, optimizing decision-making through data learning (Bazley et al., 2020; Linnainmaa et al., 2021; D'Acunto et al., 2019). The decline in the performance of human-managed funds and fewer skilled managers has increased interest in the potential of AI technologies (Barras et al., 2010; Ratanabanchuen & Saengchote, 2020; Chen & Ren, 2022).

However, Chen and Ren (2022) argue that AI funds face challenges. Particularly, challenges in questioning whether they genuinely outperform traditional financial models in predicting stock returns. While machine learning models can identify useful predictive signals, their additional predictive strength compared to traditional methods is often limited (Gu et al., 2020). Furthermore, the high trading frequency associated with AI portfolios raises concerns about transaction costs and net returns. Research by Carhart (1997) indicates that actively managed funds often underperform after accounting for these costs, prompting the need to evaluate whether AI funds achieve an optimal balance between returns and turnover. These factors reveal the potential and limitations of AI in fund management, highlighting the need for further investigation into its performance across various market conditions.

Grobys, Kolari, and Niang (2022) study the confrontation between artificial intelligence and human involvement in hedge fund management. The trio employs partially hand-collected data and forms sample hedge funds into different categories based on the level of automation. The results of the paper state that the hedge funds with the least amount of human involvement perform best. Additionally, the authors observe that a zero-cost strategy contrasting man with machine, where a long position is taken that utilizes the most automation and a short position where human involvement is the highest, produces a notably significant spread of at least 50 basis points each month. Grobys et al. conclude that the degree of automation is a crucial factor in the profitability of the hedge fund sector.

In a slightly more recent study, Cao et al. (2024) find conflicting evidence between AI and humans in stock picking. The authors state that an AI analyst designed to process corporate disclosures, industry trends, and macroeconomic data outperforms most analysts in predicting stock returns. However, Cao et al. emphasize that humans excel in scenarios where institutional knowledge is critical, such as with intangible assets and financial difficulties. AI tends to excel when dealing with transparent yet large volumes of information. Human input offers considerable added value in a combined AI and human approach, which also significantly minimizes extreme errors. When “alternative data” becomes available, human analysts can catch up to machines if their organizations invest in AI capabilities. Recorded relationships between machines and humans demonstrate how people can leverage their strengths to better adapt to the increasing growing abilities of AI.

Harvey et al. (2017) examine and compare the performance of discretionary versus systematic hedge funds. Systematic funds implement strategies based on rules, with minimal or no daily human involvement. From 1996 to 2014, the performance of both systematic and discretionary managers appears similar after accounting for volatility and factor exposures. Similarly, Abis (2020) investigates the discrepancies in performance between quantitative and discretionary funds. Abis remarks that quantitative funds tend to hold more stocks, focus on stock selection, and participate in more crowded trades. On the other hand, discretionary funds invest in less widely known stocks, alternate between picking and timing, and tend to outperform quantitative funds during economic downturns.

According to the earlier studies mentioned, the comparison between funds managed by AI and those managed by humans has become a more pertinent topic in financial research, especially as AI-managed funds have expanded rapidly since their launch in 2017. AI's capability to analyze large volumes of data quickly and remove cognitive biases provides it with a competitive advantage in predictive modeling and decision-making, which fuels interest in its potential to surpass human managers. Nevertheless, there are ongoing concerns about AI's actual predictive capabilities compared to traditional models, its dependence on historical data, and how high-frequency trading might affect net returns. Recent research presents mixed findings on whether AI is superior. Hedge funds that are most automated generally perform better than those with significant human oversight, indicating that automation is a key factor in profitability. On the other hand, AI analysts excel over human analysts in stock selection that involves heavy data analysis, yet human insight remains crucial for assessing intangible assets and financial risks. Likewise, an analysis of systematic versus discretionary hedge funds indicates scattered evidence. While AI-driven quantitative funds gain from scalability and stock picking, human-managed funds have an edge in handling economic downturns. These insights emphasize both the advantages and limitations of AI and human fund management, suggesting that a combined approach may provide the most efficient strategy for optimizing performance.

3.5 Hypothesis Development

As discussed before, herding behavior is a well-researched topic in the financial markets in varying contexts and conditions. However, as previous literature has proven, the evidence on herding behavior is inconclusive. There are multiple potential reasons for this. There could be several reasons for these fragmented findings, considering herd activity. According to Spyrou (2013), the models used to detect herding are allocated into two classes: models assuming rational agents and models assuming non-rational agents. There is yet one that considers both. Secondly, Spyrou states that the evidence of herding behavior among institutional investors is scattered. Some studies find no evidence, and then some studies find consistent evidence. This stems from the reasons behind herding, whether it is spurious or intentional. Lastly, Spyrou mentions the limitations of empirical methods. The author questions the ability of economists to not completely comprehend the procedure of herding behavior.

Although research into herding behavior is increasing, a significant gap persists regarding its effects on fund performance, specifically when comparing human-managed to AI-managed funds. Most existing studies have concentrated on conventional fund management frameworks, leaving the exploration of herding tendencies in AI-driven funds, which should operate without behavioral biases, largely unaddressed. To fill this gap, this thesis leverages established herding detection methods to maintain empirical consistency and allow for comparison with previous research. By employing these methodologies on both human- and AI-managed funds, this study aims to uncover fresh insights regarding the performance consequences of herding in fund management, especially during periods of market volatility.

The first hypothesis is based on the studies by Jiang and Verardo (2018), Brown et al. (2014), and Chen and Ren (2022). Jiang and Verardo find that fund managers who herd tend to underperform their antiherding peers. This indicates that herd-driven decisions often result in suboptimal long-term returns. This supports the idea that human-managed funds, affected by biases like herding, may lag behind AI-managed funds, which are free from such influences. Furthermore, the research by Brown, Wei, and Wermers (2014) shows that fund managers often follow analyst recommendations, especially during downgrades. This type of herding behavior can lead to price fluctuations and inefficiencies, suggesting it contributes to weaker long-term fund performance. Chen and Ren (2022) provide evidence that AI-managed funds outperform human-managed ones by efficiently processing large amounts of data and avoiding biases like herding. This indicates that AI funds may achieve better long-term performance. Therefore, according to these research findings, the first hypothesis is as follows:

H1: Herding behavior negatively impacts the long-term performance of human-managed funds compared to AI-managed funds.

As noted, herding behavior tends to be most prevalent during turbulent market conditions. During financial crises and the COVID-19 pandemic, herding intensifies during periods of high market volatility (Bekiros et al., 2017; Alexakis et al., 2023; Ferreruela and Mallor, 2021; Jiang et al., 2022). This indicates that market stress intensifies herding activity, resulting in inefficiencies in human-managed funds. Chang et al. (2000) and Chiang and Zheng (2010) also document herding in global markets, with evidence suggesting that herding is particularly strong in emerging markets and during downturns. Grobys et al. (2022) remark that hedge funds with the least human involvement tend to outperform during periods of volatility. This implies that AI-managed funds might be more efficient in turbulent market conditions compared to human peers. Backed by these findings, the second and final hypothesis is as follows:

H2: Herding behavior is more prevalent during times of significant market volatility, leading to a greater performance divergence between human-managed and AI-managed funds.

4 Methodology

Next, an overview of the methodology used to produce this thesis' empirical results will be provided. The methodology consists of methods for measuring herding behavior and methods for calculating returns to compare the differences between human- and AI-managed funds.

4.1 Measures of Herding Behavior

The Cross-Sectional Standard Deviation (CSSD) model by Christie and Huang (1995) can be considered the first relevant way to measure herding behavior across the market. Later, many varying models have been developed for different types of data and market conditions. To study market-wide herding, the authors Christie and Huang stress the subject by utilizing the following equation:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}\left(R_{i,t}-R_{m,t}\right)^2}{N-1}}, \tag{1}$$

Where $R_{i,t}$ represents the stock return observed for a firm i at time t, and $R_{m,t}$ denotes the cross-sectional average of the N returns in the overall market portfolio at time t.

The above model acts as a foundation for the later-developed model by Chang et al. (2000). The Cross-Sectional Absolute Deviation (CSAD) model by Chang et al. suits better for the purposes of this thesis. In their research, the authors expand the work of Christie and Huang by introducing a novel and more effective method for detecting herding by analyzing equity return behavior. With a non-linear regression model, the authors explore the relationship between equity return dispersions, as indicated by the Cross-Sectional Absolute Deviation of returns, and the overall market return. In cases of strong or moderate herding, Chang et al. anticipate that return dispersions will diminish (or rise at a declining rate) as the market return increases. Based on their analysis, Chang et al. first produce an equation for the expected Cross-Sectional Absolute Deviation of returns, which is as follows:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right|, \tag{2}$$

Where the coefficients $R_{i,t}$, $R_{m,t}$ and N represent the same as in the CSSD model in the equation (1).

Further continuing the work of Chang et al. (2000), Chiang and Zheng (2010) propose a new model for detecting herding activity in the market. The model varies from the original CSAD model by involving a $R_{m,t}$ term on the right side. This enhancement addresses the asymmetric behavior of investors in various market conditions. The modified CSAD equation by Chiang and Zheng is as follows:

$$CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2\left|R_{m,t}\right| + \gamma_3 R_{m,t}^2 + \varepsilon_t, \tag{3}$$

Where $CSAD_t$ denotes the Cross-Sectional Absolute Deviation at time t. γ_0 is the intercept term, γ_1 represents the linear relationship between the market return $R_{m,t}$ and return dispersion. γ_2 captures the effect of the absolute market return $\left|R_{m,t}\right|$, and γ_3 measures potential non-linear effects through the squared market return $R_{m,t}^2$. Commonly, a significant negative γ_3 is interpreted as evidence of herding behavior. Lastly, the term ε_t is the error term at time t. The equation above is used to calculate the regressions for every fund and timeframe in MatLab.

The following equation is utilized to effectively calculate the daily returns for the CSAD model:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right), \tag{4}$$

Where R_t represents the change in the fund's closing price from time $t-1$ to time t, $\ln$ denotes the natural logarithm, P_t signifies the fund's closing price at time t, and P_{t-1} refers to the closing price of the fund one day before time t.

4.2 Fund Performance Metrics

If herding behavior is detected during any sample period, the fund performance metrics are calculated to spot performance differences between human- and AI-managed funds. To assess whether herding behavior has impacted performance, this thesis utilizes three different performance metrics. To acquire a comprehensive outlook, the mean return, the cumulative return, and the Sharpe ratio are calculated. Mean return addresses the raw return comparison between human-managed and AI-powered funds. Since it does not consider the cumulation of returns, cumulative returns are also calculated. Herding behavior commonly increases risk without proportionally increasing returns, therefore Sharpe ratio is also considered. Firstly, the formula for mean return is as follows:

$$Mean\ Return = \frac{1}{T}\sum_{t=1}^{T} R_t, \tag{5}$$

Where R_t is the daily return at time t and T is the total number of periods.

Next, to assess the cumulation of returns during periods of herding, the formula goes:

$$Cumulative\ Return = \left(\prod_{t=1}^{T}(1+R_t)\right) - 1, \tag{6}$$

Where R_t, t, and T have the same meaning as in the equation (5).

Finally, for the risk-adjusted performance, the Sharpe ratio is shaped as follows:

$$Sharpe\ Ratio = \frac{\bar{R} - R_f}{\sigma}, \tag{7}$$

Where $\bar{R}$ addresses the mean return of the portfolio. R_f is the risk-free rate, and this thesis utilizes the 3-month U.S. Treasury (when divided to daily ≈ 0,01 %). Lastly, σ denotes the standard deviation of the returns.

5 Data

This section of the thesis presents the relevant data utilized to provide empirical results for the study. The following sections illustrate all the essential specifications for the data, as well as the descriptive statistics. It also includes the collection methods and provides information on the utilized funds and the timeframe of the analysis. Furthermore, some additional graphs are provided for a comprehensive outlook.

5.1 Data Collection

The quantitative data for this thesis has been collected from the Refinitiv DataStream. The data is composed of US-based human-managed funds and AI-powered funds. The human-managed funds are categorized into different categories based on the investing style. The categories are growth, value, value-added, balanced, and income funds. These five fund categories give a balanced outlook on the U.S. fund management industry. The full list of the used funds is found in Appendix 1.

The timeframe for the thesis data is from 01.01.2019 to 26.09.2024. The study utilizes daily fund returns to detect herding and calculate performance metrics. All daily fund returns are presented in local currency, specifically the US dollar. However, since herding behavior is most prevalent during market volatility, in addition to the full sample period, a few notable turbulent occasions are examined separately. As stated in the introduction, these periods include COVID-19, the Russia-Ukraine war, the Silicon Valley Bank (SVB) collapse, and the Israel-Gaza conflict. For COVID-19, the period is from 01.02.2020 to 30.06.2020. Second, the Russia-Ukraine conflict is analyzed from 01.02.2022 to 29.07.2022. Third, the SVB collapse dates are from 01.03.2023 to 28.04.2023. Lastly, the Israel-Gaza war period is from 01.09.2023 to 30.11.2023. Herding behavior is tested for the entire sample as well as separately for each subperiod.

5.2 Descriptive Statistics

This section provides a comprehensive overview of the descriptive statistics for the funds featured in the study and establishes a foundational understanding of the data's attributes. Descriptive statistics include the summarization of key characteristics of the dataset and offer insights into the overall behavior of both human- and AI-managed funds. This analysis includes the computation of essential metrics such as the mean, standard deviation, skewness, and kurtosis of fund returns, which are vital for evaluating the performance and risk profiles of the examined funds. By exploring these statistics, this thesis aims to identify patterns and trends that will be further investigated later, especially concerning the performance effects of herding behavior among different types of funds. The following section outlines the descriptive statistics for the sample period spanning from 2019 to 2024:

Table 1. Descriptive Statistics of Cross-Sectional Absolute Deviations

Fund Type	AI	Growth	Value	Value-Added	Balanced	Income	S&P500
	CSAD	CSAD	CSAD	CSAD	CSAD	CSAD	Rm
Mean	0,0114	0,0092	0,0104	0,0102	0,0074	0,0088	0,0006
Median	0,0080	0,0068	0,0073	0,0070	0,0051	0,0060	0,0007
Std. Dev.	0,0124	0,0096	0,0122	0,0118	0,0088	0,0103	0,0126
Kurtosis	44,2269	43,9355	48,3486	54,6029	43,6593	40,0570	14,4988
Skewness	5,0889	4,9076	5,4387	5,6469	5,1161	4,8697	-0,5457
Minimum	0,0001	0,0002	0,0002	0,0003	0,0003	0,0002	-0,1198
Maximum	0,1688	0,1360	0,1672	0,1734	0,1176	0,1308	0,0938
Observations	1497	1497	1497	1497	1497	1497	1497

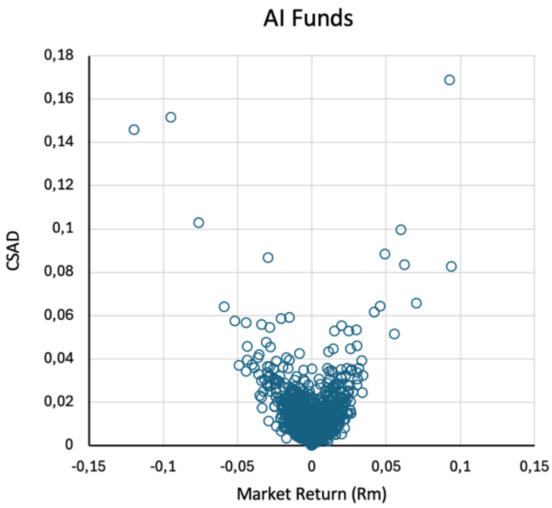
This table represents the descriptive statistics of daily cross-sectional absolute deviations and daily market index returns (Rm) for the S&P500 stock index.

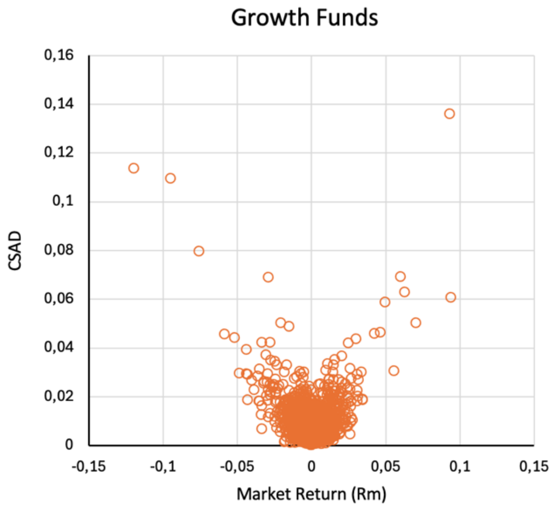
Based on the descriptive statistics in Table 1 above, AI funds exhibit the highest average CSAD (0,0114) among different fund categories, reflecting the most significant variation in returns. This implies that funds managed by AI might demonstrate reduced herding behavior compared to other fund types. In contrast, balanced funds display the lowest average CSAD of 0,0074, suggesting they might have the most pronounced herding tendency among all fund categories. Similarly to the mean CSAD, AI funds show the most significant standard deviation (0,0124), indicating a higher level of variability in their dispersion when compared to other types of funds. This supports the notion that AI funds might exhibit less reliable herding tendencies. Conversely, balanced funds, which have the lowest standard deviation of 0,0051, portray the steadiest dispersion. This potentially indicates a more uniform herding pattern. All fund types exhibit extreme kurtosis, with values far exceeding the typical threshold of 3 for a normal distribution. This shows the presence of fat tails, suggesting frequent occurrences of extreme values in dispersion. Value-added funds have the highest kurtosis of 54,6029, showing the most substantial presence of extreme outliers in dispersion, while Balanced funds have the lowest kurtosis (43,6593) among fund types.

The descriptive statistics table also reveals the minimum and maximum values of the funds. The minimum CSAD values occurred between the 19th of April 2019 and the 22nd of January 2020. This period had relatively stable market conditions, characterized by low volatility and high investor confidence, with little to no macroeconomic disruption. For instance, December 2019 had the minimum values of growth, value, value-added, and income funds. During this month, the U.S. and China announced their “Phase One” trade deal, resulting in optimism in the market (USTR, 2020). These calm conditions may have contributed to aligned expectations and reduced return dispersion, resulting in lower CSAD values.

The descriptive statistics indicate that the highest CSAD values for all types of funds were recorded on the 13th of March 2020, aligning with the peak of the COVID-19 market turmoil. This timeframe followed "Black Thursday" (March 12), when the S&P 500 faced one of its most significant one-day declines since 1987 (Tappe, 2020), succeeded by a similarly sharp recovery the following day. The intense volatility and uncertainty in global financial markets during this period triggered widespread investor panic, varied trading behavior, and increased returns dispersion, all of which are reflected in the CSAD metric. This observation aligns with existing research suggesting that herding behavior becomes more pronounced during times of market distress and crises (Bekiros et al., 2017; Alexakis et al., 2023).

Interestingly, the funds managed by AI displayed the minimum (0,0001 on April 19, 2019) and maximum (0,1688 on March 13, 2020) CSAD values across all fund types. This might indicate the highly reactive and data-driven characteristics of AI algorithms, which can heighten both convergence and divergence based on market conditions. In stable market phases, AI systems may interpret similar signals and produce comparable outputs, resulting in minimal dispersion among AI-driven strategies. In contrast, during periods of severe market stress, these algorithms may quickly react in a divergent manner to spikes in volatility or nonlinear trends. This further increases dispersion beyond what is observed in human-managed funds. Moreover, illustrating the capabilities and sensitivity of AI in fluctuating environments, and highlighting its distinct behavior compared to conventional fund management.





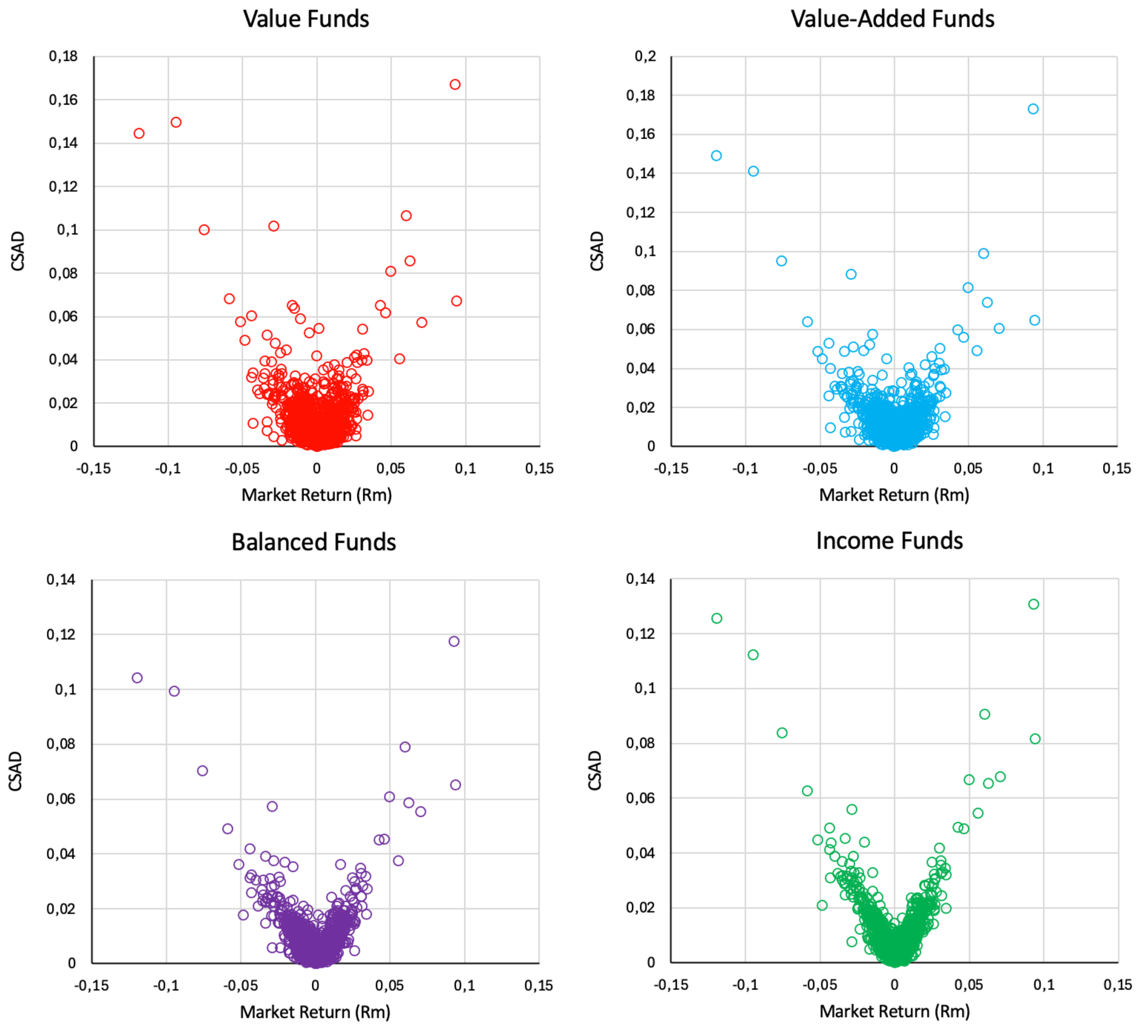


Figure 3. Relationship between fund CSADs and Market Return (Rm)

In Figure 3 above, the scatter plots reveal different herding behaviors associated with various fund types when plotting CSAD against market returns. This Figure indicates that Income and Balanced funds demonstrate the most substantial signs of herding, marked by closely grouped, concave shapes that indicate investor alignment during both extreme and ordinary market conditions. Value-added and Value funds also have signs of herding, especially in times of market distress, but with greater dispersion during downturns. Contrarywise, Growth funds exhibit a more scattered pattern with increased variance, suggesting a focus on specific strategies rather than joint movement. AI-managed funds, while displaying certain herding traits at extreme returns, show a broader distribution during moderate market fluctuations, likely reflecting a range of algorithmic reactions. In summary, the visual analysis reinforces the idea that herding will be more evident in traditional, lower-risk fund categories. In contrast, AI and growth-focused funds operate with greater individual variation.

6 Empirical Results

The empirical results chapter addresses the hypotheses outlined in Section 3.7. It is organized around the two key hypotheses, with each section dedicated to the analysis of the results derived from the regression models discussed earlier. The findings are thoroughly examined and compared to provide insights into the relationships between the variables under study.

6.1 Herding Behavior During the Whole Sample Period

As shown in the descriptive statistics in Table 1, the mean values for CSAD suggest that AI funds are least likely to portray herding in comparison with human-managed funds. Similarly, in Figure 3, the scatter plots insinuate that herding might be detected in balanced and income funds. This first section tests and covers the results of the first hypothesis:

H1: Herding behavior negatively impacts the long-term performance of human-managed funds compared to AI-managed funds.

This and the later hypothesis are addressed by using the equation (3). After the regressions are computed, the fund performance metrics, equations (5), (6), and (7), are calculated. The results of these equations are used to compare the performance differences between AI- and human-managed funds if herding behavior is detected. In case herding is not detected during the tested period, the performance metrics are still calculated and compared to provide context. The key coefficient to concentrate on is y_3. A negative and statistically significant y_3 is interpreted as evidence of herding behavior, a signal that investor decisions are clustered. In contrast, a positive y_3 indicates the absence of herding behavior. The R^2 coefficient signifies the proportion of the variance in the dependent variable (CSAD) that is explained by the independent variable (market returns). The regression results for the whole sample period and therefore H1 are presented in Table 2 below.

Table 2. Regression results of herding behavior during the entire sample period

Full Sample Period

	y_0		y_1		y_2		y_3		R^2
AI Funds	0,004	***	-0,011		0,749	***	5,468	***	0,698
	(16,266)		(-0,798)		(22,668)		(10,975)		
All Human Funds	0,003	***	0,000		0,613	***	4,935	***	0,736
	(16,088)		(-0,033)		(24,130)		(12,894)		
Growth	0,005	***	-0,018		0,460	***	5,100	***	0,604
	(19,487)		(-1,487)		(15,784)		(11,622)		
Value	0,005	***	-0,011		0,572	***	6,907	***	0,614
	(15,503)		(-0,695)		(15,590)		(12,489)		
Value-Added	0,004	***	-0,001		0,616	***	6,384	***	0,671
	(15,471)		(-0,091)		(18,816)		(12,946)		
Balanced	0,002	***	0,012		0,631	***	3,092	***	0,798
	(11,522)		(1,434)		(33,100)		(10,767)		
Income	0,002	***	0,015	**	0,846	***	2,587	***	0,875
	(10,401)		(1,938)		(48,116)		(9,757)		

The table shows the regression results for the equation (3). Statistically significant and negative coefficient y_3 represents herding activity. The t-statistics are parenthesized below the coefficients.

* The coefficient is significant on a 10 % level
** The coefficient is significant on a 5 % level
*** The coefficient is significant on a 1 % level

In the full sample period (01.01.2019-26.09.2024) regression results above, all fund categories, including both AI and human-managed funds, display a positive and significant y_3, indicating no formal herding behavior. However, it is notable that the value of y_3 varies across fund types. The AI funds category shows a y_3 of 5,468, which is higher than the average y_3 for all human-managed funds (4,935) and higher than Growth (5,100), Balanced (3,092), and Income (2,587) funds. Only Value (6,907) and Value-Added (6,384) show a greater coefficient y_3 than AI. These results imply that AI-managed funds tend to react less coordinately to market shifts than human-managed categories.

The high y_3 coefficients of Value and Value-Added funds suggest that return dispersion within these categories increases more sharply during extreme market conditions. This might reflect the distinct and fundamental philosophy of value investing. In contrast, Balanced and Income funds exhibit the lowest y_3 coefficients, which may stem from their more conservative nature of investing. The lower return dispersion in these fund types implies more synchronized behavior among managers, possibly due to similar risk-averse investment styles.

Although herding behavior was absent during the whole sample period, it provides context to the literature. Similarly to these findings, the studies by Chang et al. (2000) and BenSaïda et al. (2015) also found no evidence of herding in the U.S. market. Additionally, Christie and Huang (1995) and Chang et al. (2000) state that herding tends to be more present in the emerging markets instead of developed peers such as the U.S. In his study, Spyrou (2013) also notes that the CSAD model used does not necessarily comply with developed markets. Contradicting these previous studies, Bekiros et al. (2017) observed herding in the U.S. The evidence of these papers suggests that herding behavior may be more context-specific or masked by the more rational investor behavior of fund managers in developed markets.

In addition to previous literature, the regression results for the whole sample period also have significance in terms of theory. Interestingly, the obtained results are consistent with the Efficient Market Hypothesis. The EMH supposes that market prices in developed markets such as the US reflect all available information, meaning that the markets are efficient. Additionally, the reason for the absence of herding might also relate to agency theory, which was mentioned in the second chapter. In this scenario, agency theory would suggest that human fund managers could participate in a herd for reputational concerns. However, the results indicate the opposite. This could imply that these incentives fail to produce significant herding or that this kind of behavior is severely limited in the U.S. fund sector.

Even though evidence of herding was not detected in any of the fund categories. It is still important for this thesis and the analysis of the H1 to compare fund performance metrics. Table 3 below shows the mean returns, cumulative returns, and Sharpe ratios of the funds.

Table 3. Fund performance metrics for the full sample period

Full Sample Period							
	AI	All Human	Growth	Value	Value-Added	Balanced	Income
Mean Return	0,03 %	0,02 %	0,04 %	0,02 %	0,02 %	0,02 %	0,01 %
Cumulative Return	45,14 %	35,47 %	67,02 %	32,31 %	33,59 %	33,32 %	7,24 %
Sharpe Ratio	0,021	0,018	0,031	0,014	0,015	0,020	-0,010

Multiple notable insights can be derived based on the fund performance metrics over the full sample period. As shown in Table 3 above, AI-managed funds outperform their human-managed peers in both mean and cumulative returns, the Growth fund category being an exception. With a mean daily return of 0,03% and a cumulative return of 45,14%, the AI fund category portrays higher returns than the average of all human funds, which documented a 0,02% mean return and cumulated a return of 35,47%. Among the human-managed categories, Growth funds stand out with the highest performance in mean returns (0,04%) and cumulative returns (67,02%), demonstrating the strongest long-term performance.

When adapting for risk using the Sharpe ratio, AI funds again outperform the overall human-managed fund group with a Sharpe ratio of 0,021 against 0,018. The Growth fund category posts the highest Sharpe ratio of 0,031, indicating the best return per unit of risk. Moreover, Income funds not only portray the lowest mean and cumulative returns (0,01% and 7,24%), but also a negative Sharpe ratio of -0,010. This implies that the returns of the Income funds are insufficient to compensate for their risk exposure. In line with the performance metrics results, Grobys et al. (2022) also found that hedge funds with more automation had higher performance in comparison with the funds with a lower amount of automation. This supports the fact that AI and funds with automation tend to show more stable Sharpe ratios.

To conclude, the empirical evidence provides inconclusive support for H1. These results cannot posit that herding behavior negatively impacts the long-term performance of human-managed funds compared to AI-managed funds. Even though AI funds outperform most human-managed categories in all fund performance metrics, the CSAD regression results do not confirm the presence of herding, as the y_3 coefficients were positive and significant across all fund types. This indicates the absence of traditional herding behavior as defined by Chang et al. (2000). Furthermore, the Growth funds category outperforms all others in terms of cumulative return (67.02%) and Sharpe ratio (0.031). The Growth fund category even surpasses AI funds, which challenges the fact that AI's performance advantage is based on the absence of behavioral biases. These scattered results indicate that herding behavior alone does not explain performance differences and that other factors, for example, investment style, market exposure, and risk preferences, may play a significant role. Thus, the results do not provide clear empirical support for Hypothesis 1.

6.2 Herding Behavior During Subperiods

As previously noted in this thesis, herding behavior tends to intensify during market stress. Multiple sources are cited in chapter 3.7, which covers this topic. Next, this concept will be studied by testing herding behavior for each subperiod: COVID-19, the Russia-Ukraine war, the Silicon Valley Bank collapse, and the Israel-Gaza conflict. These four crisis periods will be examined by addressing the second hypothesis:

H2: Herding behavior is more prevalent during times of significant market volatility, leading to a greater performance divergence between human-managed and AI-managed funds.

The method for the regressions for each subperiod is the same as in testing the H1, the equation (3). Also, whether or not evidence of herding is found, the fund performance metrics will still be calculated similarly to the previous chapter, using equations (5), (6), and (7). The regression results for the first subperiod, the COVID-19 pandemic, are found in Table 4 below.

Table 4. Regression results of herding behavior during the COVID-19 period

COVID-19

	y_0		y_1	y_2		y_3		R^2
AI Funds	0,006 (2,688)	***	0,008 (0,187)	0,914 (5,568)	***	3,473 (1,973)	*	0,799
All Human Funds	0,006 (3,019)	**	0,027 (0,689)	0,720 (5,011)	***	3,452 (2,239)	**	0,785
Growth	0,006 (3,302)	***	0,006 (0,171)	0,584 (4,372)	***	3,620 (2,526)	**	0,768
Value	0,010 (3,375)	***	0,012 (0,211)	0,747 (3,631)	***	4,403 (1,995)	**	0,688
Value-Added	0,009 (3,273)	***	0,031 (0,597)	0,651 (3,460)	***	5,443 (2,698)	***	0,724
Balanced	0,003 (1,917)	*	0,042 (1,511)	0,742 (7,330)	***	1,800 (1,659)		0,850
Income	0,002 (1,626)		0,040 (1,556)	0,911 (9,810)	***	1,799 (1,806)	*	0,904

*The coefficient is significant at the 10 % level
**The coefficient is significant at the 5 % level
***The coefficient is significant at the 1 % level

Interestingly, in line with the regression results for the whole sample period, clear evidence of herding behavior was not found during COVID-19. For both AI funds (y_3=3,473, *) and All Human Funds (y_3=3,452, **) categories, the y_3 coefficient is positive and significant. Additionally, in other categories as well, including Growth, Value, Value-Added, and Income funds, the y_3 is significant and positive, implying no herding behavior in an economic sense. The only exception is the Balanced funds category, where the y_3 coefficient is not significant. The regression results indicate that the dispersion has increased as returns have moved away from the mean. Therefore, despite the timeframe being during volatile market conditions, the regression results for the COVID-19 subperiod do not support the presence of herding.

In contrast to these findings, the study by Alexakis et al. (2023) finds a clear presence of herding behavior during the COVID-19 pandemic in the US. Similarly, Ferreruela & Mallor (2021) record signs of herd activity in their study, focusing on Europe. Also, Jiang et al. (2022) discovered herding behavior during the crisis in the Asian stock market. This further strengthens the notion by Christie and Huang (1995) and Chang et al. (2000) that herding tends to be more prevalent in emerging markets. Even though Alexakis et al (2023) find evidence from the US, the difference in results might stem from fund-specific behavior or limitations of the CSAD method in fund-level analysis.

Table 5. Regression results of herding behavior during the Russia-Ukraine War period

Russia-Ukraine War

	y_0		y_1		y_2		y_3		R^2
AI Funds	0,011	***	0,095	*	0,155		15,921	**	0,398
	(6,771)		(1,908)		(0,641)		(2,201)		
All Human Funds	0,006	***	0,073	**	0,360	**	7,549		0,540
	(5,984)		(2,219)		(2,238)		(1,569)		
Growth	0,011	***	0,061		0,178		7,001		0,227
	(7,490)		(1,376)		(0,821)		(1,082)		
Value	0,007	***	0,073	*	0,338	*	6,726		0,401
	(5,760)		(1,812)		(1,726)		(1,148)		
Value-Added	0,007	***	0,083	**	0,347	*	9,040		0,459
	(5,628)		(2,014)		(1,727)		(1,507)		
Balanced	0,004	***	0,070	***	0,390	***	7,133	*	0,660
	(4,607)		(2,665)		(3,032)		(1,856)		
Income	0,003	***	0,079	***	0,589	***	8,341	**	0,790
	(3,661)		(3,019)		(4,607)		(2,183)		

*The coefficient is significant at the 10 % level
**The coefficient is significant at the 5 % level
***The coefficient is significant at the 1 % level

In Table 5 above are the regression results for the Russia-Ukraine War subperiod. Similarly to COVID-19, with only three fund categories recording significant y_3 coefficients, none of the fund categories portrays evidence of herding behavior. Even though the high y_3 coefficients again imply heightened dispersion during market stress, they are inconsistent with herding activity, which would call for negative y_3 values. Thus, no evidence of herding is present among the fund categories during the Russia-Ukraine War period.

Interestingly, studying the Russia-Ukraine war period, Blasco et al. (2024) do not find any evidence of herding behavior during the crisis in the United States. However, the authors do find that in the markets of Canada, New Zealand, Singapore, the UK, and Italy, herding behavior was detected. These results, consistent with this thesis, indicate that the US has not been affected by this crisis in terms of herding behavior. Moreover, Blasco et al.

(2024) clarify that Italy is among the biggest Russian energy importers in all of Europe, which might have had an impact on the significance of herding there. These findings indicate that herding behavior tends to depend on the relations of markets to the originated area of the crisis.

Table 6. Regression results of herding behavior during the SVB Collapse period

	SVB Collapse						
	γ_0		γ_1	γ_2		γ_3	R^2
AI Funds	0,006	***	0,107	0,807		-8,640	0,391
	(3,168)		(1,174)	(1,394)		(-0,275)	
All Human Funds	0,004	***	0,060	0,511		0,601	0,401
	(3,134)		(0,855)	(1,155)		(0,025)	
Growth	0,005	***	-0,023	0,637		-18,143	0,160
	(3,143)		(-0,301)	(1,295)		(-0,679)	
Value	0,006	***	0,128	0,409		-1,182	0,184
	(3,023)		(1,262)	(0,636)		(-0,034)	
Value-Added	0,006	***	0,156	0,519		-1,296	0,275
	(2,880)		(1,582)	(0,828)		(-0,038)	
Balanced	0,002	***	-0,010	0,523	*	6,263	0,703
	(2,875)		(-0,220)	(1,895)		(0,418)	
Income	0,002	***	0,015	0,530	*	16,393	0,817
	(2,891)		(0,357)	(2,019)		(1,150)	

*The coefficient is significant at the 10 % level
**The coefficient is significant at the 5 % level
***The coefficient is significant at the 1 % level

During the Silicon Valley Bank collapse, the regression results produced some negative y_3 values. For instance, AI funds y_3= -8,640, Growth y_3= -18,143, Value y_3= -1,182, and Value-Added y_3= -1,296 all had negative coefficients, which in theory might be a signal of herding. However, none of the y_3 coefficients have statistical significance, indicating no robust evidence of herd activity even during this period of market turbulence. Moreover, negative values in the AI funds category create additional inconsistency concerning the H2. Furthermore, Balanced and Income funds had positive y_3 coefficients, which again imply increasing dispersion in returns.

In contrast to the results in this thesis from the Silicon Valley Bank collapse period, the study by Bekiros et al. (2017) finds evidence of herding behavior from the U.S market, focusing on multiple crisis periods. The authors note that during the global financial crisis in 2008, herding tended to be the most significant at the start of the crisis and faded toward the later stages. Even though Bekiros et al. studied different crisis periods, both the global financial crisis and the SVB collapse highly affected the banking industry, which adds relevance to the results from this thesis. The mentioned evidence further clarifies that herding behavior is highly dependent on multiple factors, such as the type of crisis.

Table 7. Regression results of herding behavior during the Israel-Gaza Conflict period

Israel-Gaza Conflict						
	y_0		y_1	y_2	y_3	R^2
AI Funds	0,005	***	-0,010	0,496	4,176	0,373
	(4,726)		(-0,158)	(1,609)	(0,228)	
All Human Funds	0,005	***	-0,020	0,195	9,990	0,274
	(5,921)		(-0,416)	(0,789)	(0,681)	
Growth	0,004	***	-0,047	0,401	-6,159	0,157
	(4,563)		(-0,780)	(1,311)	(-0,339)	
Value	0,006	***	-0,020	-0,038	13,609	0,075
	(6,791)		(-0,343)	(-0,134)	(0,801)	
Value-Added	0,006	***	-0,005	0,115	11,219	0,137
	(5,868)		(-0,079)	(0,362)	(0,593)	
Balanced	0,003	***	-0,016	0,301	8,636	0,426
	(4,423)		(-0,372)	(1,392)	(0,672)	
Income	0,003	***	-0,031	0,319	23,891	0,544
	(3,925)		(-0,570)	(1,159)	(1,461)	

*The coefficient is significant at the 10 % level
**The coefficient is significant at the 5 % level
***The coefficient is significant at the 1 % level

During the last subperiod, the Israel-Gaza conflict, the regression results are no different from the rest. All fund types have positive y_3 coefficients, apart from the Growth funds category. However, again, none of the y_3 values are significant statistically speaking. Therefore, no presence of herding surfaces from this period either, providing no support for Hypothesis 2.

Using the same CSAD model as this thesis, Belhoula and Naoui (2011), as opposed to the results from the Israel-Gaza conflict period, do find significant evidence of herding behavior during major market price movements. However, inconsistent with the study by Belhoula and Naoui and supporting the results of this thesis, Gleason et al. (2004) do not detect herding behavior during extreme market movements when focusing on US-based sector ETFs. These results and previous literature again create inconclusiveness among the results of herding behavior in the US as well as the world.

Across all four crisis periods addressed, none of the regression results provide statistically significant negative y_3 values, the key coefficient for detecting herding behavior among the data. While some fund categories and subperiods portray high dispersion (high y_3 coefficients), this reflects more separation in returns rather than herding. Also, while some fund types and periods record negative y_3 values, they lack statistical significance. The evidence on the subperiods reinforces the conclusion that herding behavior was not prevalent during these events of market turbulence, regardless of the fund manager. Additionally, the absence of herd activity reinforces the aspect that fund managers are acting rationally and are not influenced by herding behavior during market turbulence. In contrast to traditional finance, behavioral finance implies that investors are inclined to behavioral biases during times of market uncertainty (Bikhchandani & Sharma, 2000; Banerjee, 1992). Notably, these regression results do not support this claim. Institutional fund managers might be less influenced by herding, or the CSAD model may fail to capture subtle signs of herding from this sample period. However, even though herding was not present during these periods, the fund performances between fund categories are still compared. Below is Table 8, portraying the performance metrics for each fund type.

Table 8. Fund performance metrics for the subperiods

COVID-19 Pandemic

	AI	All Human	Growth	Value	Value-Added	Balanced	Income
Mean Return	0,06 %	-0,06 %	0,03 %	-0,11 %	-0,15 %	-0,03 %	-0,02 %
Cumulative Return	4,16 %	-7,75 %	2,48 %	-13,64 %	-17,05 %	-4,17 %	-3,10 %
Sharpe Ratio	0,009	0,007	0,018	0,006	0,006	0,009	-0,004

Russia-Ukraine War

	AI	All Human	Growth	Value	Value-Added	Balanced	Income
Mean Return	-0,05 %	-0,06 %	-0,11 %	-0,05 %	-0,04 %	0,00 %	-0,06 %
Cumulative Return	-7,27 %	-8,06 %	-14,16 %	-6,97 %	-5,11 %	0,30 %	-8,10 %
Sharpe Ratio	0,016	0,014	0,020	0,013	0,014	0,015	-0,009

SVB Collapse

	AI	All Human	Growth	Value	Value-Added	Balanced	Income
Mean Return	-0,03 %	0,04 %	0,15 %	-0,01 %	-0,03 %	0,06 %	0,02 %
Cumulative Return	-1,52 %	1,52 %	6,36 %	-0,43 %	-1,57 %	2,45 %	0,97 %
Sharpe Ratio	0,025	0,022	0,040	0,017	0,018	0,029	-0,015

Israel-Gaza Conflict

	AI	All Human	Growth	Value	Value-Added	Balanced	Income
Mean Return	-0,02 %	0,01 %	0,05 %	0,05 %	-0,02 %	0,01 %	-0,01 %
Cumulative Return	-1,48 %	0,57 %	3,46 %	4,92 %	-1,39 %	0,36 %	-0,52 %
Sharpe Ratio	0,036	0,023	0,041	0,021	0,021	0,024	-0,010

Throughout the COVID-19 pandemic, with a mean return of 0,06% and a cumulative return of 4,16%, AI-managed funds surpassed human-managed funds that mostly experienced negative returns. Value-added and Value funds were the poorest performers, declining cumulatively by -17,05% and -13,64%. While AI funds displayed a higher Sharpe ratio (0,009) in comparison with most human-managed categories, Growth funds had the best risk-adjusted performance with a Sharpe ratio of 0,018. Income funds experienced major difficulties, recording a negative cumulative return of -3,10% and the lowest Sharpe ratio of -0,004, highlighting significant volatility and insufficient returns.

Moving on to the Russia-Ukraine War period, Balanced funds are interestingly the only category that does not have a negative mean and cumulative returns. AI funds category recorded a mean return of -0,05% and a cumulative return of -7,27%, slightly outperforming all human-managed funds with -0,06% and -8,06% in the same metrics. Notably, the Growth funds category took the greatest hit with a mean return of -0,11% and a cumulative return of -14,16%. This poor performance implies that the Growth funds have heightened sensitivity to geopolitical stress. However, in line with COVID-19, AI funds recorded a Sharpe ratio of 0,016, being the close second in risk-adjusted performance among all categories. These metrics indicate that none of the funds were protected from the conflict, although the AI funds category once again surprises with their high Sharpe ratio.

The fund performance metrics for the Silicon Valley Bank collapse period differ from previous subperiods with scattered positive and negative returns. Notably, Growth funds outperform all other funds, with a mean return of 0,15% and a cumulative return of 6,36%. This indicates sector-specific positioning to benefit from market movements. Another noteworthy insight can be made from the AI funds category performance. The category performed second-to-worst in both mean (-0,03%) and cumulative returns (-1,52%). The Balanced funds category also surprises with a solid mean (0,06%) and cumulative returns (2,45%). In line with returns, Growth funds recorded the highest risk-adjusted returns with a Sharpe ratio of 0,040. However, AI funds once again had a compelling Sharpe ratio (0,025) among all the funds, consistently proving to perform when accounting for risk. Overall, during the SVB collapse, it seems that human-managed categories performed slightly better than AI funds.

Lastly, while examining the performance metrics for the Israel-Gaza conflict period, several interesting insights can be made. For this period, most fund categories posted modest returns, apart from AI (-0,02%; -1,48%), Value-Added (-0,02%; -1,39%), and Income funds (-0,01%; -0,52%) with negative values. The top performers during the conflict were Growth and Value funds with mean returns of 0,05% for both and cumulative returns of

3,46% and 4,92%. The central insight from the returns is that more traditional investment philosophies performed favorably during the conflict. Following the theme of previous crises, Income funds had a negative Sharpe ratio (-0,010). On the other hand, Growth funds had again the highest Sharpe ratio of 0,041. However, although the cumulative return (-1,48%) of AI funds was the lowest, the Sharpe ratio again proved to be the second highest, suggesting low volatility relative to returns. This yet again implies that whether or not AI funds record high or low returns, they offer better risk management during times of crisis.

The empirical evidence from the duration of the subperiods COVID-19, the Russia-Ukraine War, the Silicon Valley Bank Collapse, and the Israel-Gaza Conflict does not support the second hypothesis. Although volatility was seemingly heightened during the crisis periods, no significant herding behavior was detected according to the regression results, since only positive or insignificant negative values for the y_3 coefficient were found. However, notable differences in performance metrics between AI- and human-managed funds did surface during the subperiods. For instance, the AI funds category outperformed during COVID-19, implying more stable returns during broader events of volatility across the market. On the contrary, human-managed fund categories such as Growth, Value, and Balanced performed strongly during the Russia-Ukraine war, SVB collapse, and the Israel-Gaza conflict, suggesting better returns during shorter or sector-specific crises. These results resonate with the study by Abis (2020). Abis highlights that discretionary funds tend to have superior performance compared to quantitative funds during market downturns.

While the main focus of the hypothesis was to compare returns between AI- and human-managed funds in events of herding behavior, the results also revealed notable differences across fund strategies. For instance, Growth funds outperformed during the SVB collapse and the Israel-Gaza conflict, while also providing solid Sharpe ratios during all the subperiods. Even though this was not directly hypothesized, this notion implies that investment strategies affect how different funds react during crisis periods. This has applications for future research. Nevertheless, while herding was the key topic of concentration and was not statistically significant during these periods, the return differences between AI- and human-managed funds cannot be explained by it. Thus, although volatility correlated with return separation, the second hypothesis is still unsupported by these results.

7 Limitations and Suggestions for Future Research

While this thesis provides valuable insights into the topic of herding behavior related to human-managed fund returns in comparison with AI, there remain multiple limitations. The main limitations concern data and methodology. Next, an overview of the limitations and suggestions for future research is provided.

7.1 Sample and Data Limitations

One central limitation of the thesis is the selection process of the funds. While a broad set of funds and fund categories was selected, there might have been a selection bias in choosing the funds. The selection bias consists of data availability, and some fund categories might have been under- or overrepresented in this thesis. Most of the funds utilized had multiple categories based on the investor target group. Some funds had subfunds targeting, for instance, pension investors, individual investors, high-net-worth individuals, or institutional investors. Another limitation related to the sample and data is the availability of the data. Some funds had incomplete returns for certain periods during the whole sample period. Since AI funds are a rather new concept, some funds lacked returns following the start of the sample period. The incomplete data might have twisted some calculations, providing a false weight distribution between funds and fund categories. Additionally, factors such as transaction fees and other costs were not accounted for, which may have affected the actual returns of the funds. Lastly, due to data restrictions, the volumes of buying and selling stocks were not available. This would have eased the measurement of herding behavior during the sample periods. In the current state of the thesis, the only measurement for herding activity remains the Cross-Sectional Absolute Deviation model, further limiting the study.

7.2 Herding Measurement Limitations

Moving on from the sample and data limitations, the chosen methodology for the study also carries a few limitations. As stated by Spyrou (2013), the Christie and Huang (1995) herding model (and other similar models) uses just a small part of the total return to detect herding behavior toward the consensus of the investors. Spyrou further clarifies that these types of measures (CSAD included) assess only one type of herding and disregard herding in other environments. Additionally, according to Xie et al. (2015), the CSAD model by Chang et al. (2000) assumes factors that do not portray reality.

Another limitation addressed by Spyrou (2013) is detecting the herding behavior of institutional investors. According to Spyrou, among institutional investors, there are various investment strategies. For instance, proving herding behavior among momentum, growth, value, emerging markets, and diversified equity can be very hard. To provide context, fund managers might herd on varying investment strategies. However, when they are examined as a group, herding may not be detected due to the investment styles countering each other. This thesis utilizes multiple funds and strategies, so this might have particularly influenced the results. Next, as previously discussed in this thesis, Spyrou mentions the distinction between spurious and intentional herding. The question remains: over time, do people invest in the same direction for the same reasons? Whether herding is studied as spurious or intentional, the evidence might provide varying results based on the applied method or dependent variable. Lastly, to conclude the herding-related limitations, Spyrou notes that when attempting to capture active herding, passive herding is often disregarded. Bikhchandani and Sharma (2000) further emphasize that for an individual to herd, they must know and be affected by other investors' decisions. However, it is also called herding when an investment is made without others affecting the decision. According to Spyrou, empirical studies do not account for this. This may be since it is almost impossible to capture it.

7.3 Other Limitations

Although the primary focus of the thesis is herding behavior, other behavioral biases could have been accounted for. As previously mentioned, humans are affected by multiple behavioral aspects constantly. For instance, overconfidence, anchoring, and loss aversion might have influenced investor and fund manager decisions, especially during turbulent subperiods. It is difficult to say which one or multiple of the behavioral biases have affected investors during the sample period. Finally, limiting the generalization of the results, only the U.S. market and U.S.-based funds were used for the thesis. This thesis does not consider global markets, and investor behavior may deviate based on the researched geographical area. Factors such as market structure, regulation, and human psychology may vary based on these.

7.4 Suggestions for Future Research

This thesis provides valuable information on the performance impact of herding behavior in fund management, but it also leaves several questions open for future research. As mentioned above, further research could be done that exploits other behavioral biases. Suitable for fund management space, overconfidence, anchoring, loss aversion, and disposition effect are a few examples. Future research could also focus on the methods for detecting herding behavior. Since the current models assume certain factors and cannot capture herding effectively, further considerations could be made. Also, this study focuses only on the U.S. market and provides a narrow outlook on the whole financial market. This same topic could be further examined in an international setting. Finally, future studies could focus on the transparency and access to the data. While this study does not provide the buying and selling volumes of funds, future studies could create a more comprehensive outlook on the topic by using data that considers these aspects. By exploring these areas, future papers can continue to provide material for a deeper understanding of behavioral biases and their disadvantages or advantages in comparison with artificial intelligence.

8 Conclusions

This thesis aims to examine the presence of herding behavior and its impact on human-managed funds in comparison to AI-managed funds. The study utilizes data from the U.S. financial market from 01.01.2019 to 26.09.2024. This window includes the COVID-19 pandemic, the Russia-Ukraine war, the Silicon Valley Bank collapse, and the Israel-Gaza conflict, since herding behavior tends to be more prevalent during market stress. The whole sample period and the subperiods are tested for herding behavior separately, to provide a comprehensive outlook on the topic of the thesis. The research is motivated by the growing presence of artificial intelligence in asset management and finance in general. The thesis also draws motivation from the inconclusive research and empirical evidence on behavioral biases, particularly herding behavior. By utilizing behavioral finance theory, regression model, and performance metrics, this study investigates whether the absence of herding behavior in AI funds has a performance advantage when compared with human-managed funds, with a particular focus on periods of high volatility.

The first hypothesis was constructed to investigate whether herding behavior among human-managed funds had an impact on the performance in comparison with AI funds during the whole sample period. The regression results based on this hypothesis revealed no evidence of statistically significant herding behavior in any of the human-managed fund categories. Notably, the regression results for the whole sample period seem to follow a pattern, where no evidence of herding is found in the developed market of the US (Chang et al., 2000; BenSaïda et al., 2015). However, the study by Bekiros et al. (2017) opposes these results with evidence of herding in the U.S. market. Supporting the results of this thesis, in an early study on herding, Lakonishok et al. (1992) do not find herding activity among U.S. fund managers. However, Wylie (2004) provides contradicting evidence, since in his study, herding among mutual fund managers is detected. Moreover, the results from the whole sample period align with the EMH, as no herding was detected. Agency theory also offers a useful lens to the results, since fund managers may have been affected by reputational concerns. Despite the absence of herding, inconclusive literature, and the relation to theory, the performance metrics did show differences. AI funds provided the second-highest mean and cumulative returns as well as a stable Sharpe ratio during the whole sample period. The only fund type that outperformed AI in those three categories was the Growth fund category. Regardless, the fact that no herding was observed in any of the human-managed fund categories indicates that the performance results cannot be explained by herding behavior specifically. Thus, Hypothesis 1 can be rejected by the empirical evidence.

The second hypothesis concentrated on the subperiods, which consisted of periods of high volatility. Even though the expectations were that periods of market stress would reveal herding behavior among human-managed funds, no statistically significant herding was found across all four subperiods. Opposing the regression results for the subperiods, Alexakis et al. (2023) find evidence of significant herding activity during the COVID-19 pandemic. Similarly, herding has been prevalent during multiple other crisis periods in the U.S., for example, the global financial crisis (Bekiros et al., 2017; Belhoula & Naoui, 2011). However, supporting the results from the Russia-Ukraine war period, Blasco et al. (2024) also fail to capture herding in the United States market. Additionally, Gleason et al. (2004) similarly fail to detect herding behavior in the U.S. Again, while no herding was revealed, the performance metrics provided notable results. The AI funds category managed to outperform the human-managed funds during the COVID-19 pandemic in both mean and cumulative returns. However, during the other three subperiods, Growth, Value, and Balanced funds provided higher returns and Sharpe ratios compared to AI. Another noteworthy mention based on the performance metrics is that AI funds consistently showed high and stable Sharpe ratios, although the returns were negative during most periods. These results indicate specific advantages for each category, but again, herding behavior was not the reason. Therefore, in line with the first hypothesis, Hypothesis 2 is also rejected due to the absence of herding.

In conclusion, this thesis contributes to the growing literature on AI in asset management and the comparison between a machine and a human. While artificial intelligence might be free of behavioral biases and provide stable, risk-adjusted returns, it is not superior during all market conditions. Measured by the CSAD model, the absence of herding indicates that herding might be less pronounced in modern-day fund management, or other methods are needed to detect herding behavior among funds. The performance differences between fund categories seem to be dependent on the fund type, strategy, and the nature of the crisis period.

While the empirical evidence of this thesis follows a pattern of inconclusive results with previous literature, it does provide value for both academics and practitioners. The study's main contribution is that it focuses on an unexplored gap in the literature by directly comparing the impact of herding behavior on the performance of human-managed funds with AI-managed peers. During the making of the thesis, no other papers addressing the same topic and methodology were found. For investors and fund managers, these results indicate that AI-managed funds have the potential to offer more consistent risk-adjusted returns, especially during systemic crises. However, the evidence also implies that human-managed strategies and investment philosophies still can outperform artificial intelligence under certain market conditions. These insights may affect how portfolios are constructed in the future, especially when artificial intelligence continues to evolve. For fund management companies in particular, the performance results obtained by this paper encourage further investigation regarding investment approaches. These approaches would combine the data-processing abilities of AI and human expertise in interpreting non-quantifiable aspects. For policymakers and regulators, this paper emphasizes the importance of creating more transparency around the use of AI in financial markets. This improvement of transparency should have a focus particularly on crisis periods. Understanding the logic behind AI systems’ decision-making is crucial in assessing their possible systemic impact on the market. It is also important in creating possible supervision as AI adoption continues to grow. Ultimately, this thesis provides practical insights on how investment strategies, portfolio construction, and regulatory frameworks might progress in the future in response to the growing adoption of AI in asset management.

References

Abis, S. (2020). Man vs. Machine: Quantitative and Discretionary Equity Management. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3717371

Adams, A. (2019, October 8). *Book and book chapter references: No location required*. APA Style Blog. Retrieved 2019-12-17 from https://apastyle.apa.org/blog/publisher-locations-in-book-references

Adcock, R., & Gradojevic, N. (2019). Non-fundamental, non-parametric Bitcoin forecasting. Physica a Statistical Mechanics and Its Applications, 531, 121727. https://doi.org/10.1016/j.physa.2019.121727

Alexakis, C., Chantziaras, A., Economou, F., Eleftheriou, K., & Grose, C. (2023). Animal Behavior in Capital markets: Herding formation dynamics, trading volume, and the role of COVID-19 pandemic. The North American Journal of Economics and Finance, 67, 101946. https://doi.org/10.1016/j.najef.2023.101946

Arora, A., Barrett, M., Lee, E., Oborn, E., & Prince, K. (2023). Risk and the future of AI: Algorithmic bias, data colonialism, and marginalization. Information and Organization, 33(3), 100478. https://doi.org/10.1016/j.infoandorg.2023.100478

Avery, C., & Zemsky, P. (1998). Multidimensional uncertainty and herd behavior in financial markets. American economic review, 724-748.

Aziz, S., & Dowling, M. (2018). Machine learning and AI for risk management. In Palgrave studies in digital business & enabling technologies (pp. 33–50). https://doi.org/10.1007/978-3-030-02330-0_3

Barberis, N., & Thaler, R. (2003). Chapter 18 A survey of behavioral finance. Handbook of the Economics of Finance, 1053–1128. https://doi.org/10.1016/s1574-0102(03)01027-6

Barocas, S., Hardt, M., & Narayanan, A. (2023). Fairness and machine learning: Limitations and opportunities. MIT press.

Barras, L., Scaillet, O., & Wermers, R. (2010). False Discoveries in Mutual Fund Performance: Measuring luck in estimated alphas. The Journal of Finance, 65(1), 179–216. https://doi.org/10.1111/j.1540-6261.2009.01527.x

Bartram, S. M., Branke, J., & Motahari, M. (2020). Artificial intelligence in asset management. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3510343

Bazley, W. J., Dayani, A., & Jannati, S. (2020). Transient emotions, perceptions of well-being, and mutual fund flows. Finance Research Letters, 41, 101825. https://doi.org/10.1016/j.frl.2020.101825

Bekiros, S., Jlassi, M., Lucey, B., Naoui, K., & Uddin, G. S. (2017). Herding behavior, market sentiment and volatility: Will the bubble resume? The North American Journal of Economics and Finance, 42, 107–131. https://doi.org/10.1016/j.najef.2017.07.005

Belhoula, M., & Naoui, K. (2011). Herding and positive feedback trading in American stock market: a two co-directional behavior of investors. International Journal of Business and Management, 6(9). https://doi.org/10.5539/ijbm.v6n9p244

BenSaïda, A., Jlassi, M., & Litimi, H. (2015). Volume-herding interaction in the American market. American J of Finance and Accounting, 4(1), 50. https://doi.org/10.1504/ajfa.2015.067837

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. Journal of Political Economy, 100(5), 992–1026. https://doi.org/10.1086/261849

Bikhchandani, S., & Sharma, S. (2000). Herd behavior in financial markets. IMF Staff Papers, 47(3), 279–310. https://doi.org/10.2307/3867650

Blasco, N., Casas, L., & Ferreruela, S. (2024). Does war spread the herding effect in stock markets? Evidence from emerging and developed markets during the Russia-Ukraine war. Finance Research Letters, 63, 105365. https://doi.org/10.1016/j.frl.2024.105365

Briggs, R. (2014). Normative Theories of Rational choice: expected utility. Stanford Encyclopedia of Philosophy. https://digitalcollections.anu.edu.au/handle/1885/29474

Brown, N. C., Wei, K. D., & Wermers, R. (2014). Analyst recommendations, mutual fund herding, and overreaction in stock prices. Management Science, 60(1), 1–20. https://doi.org/10.1287/mnsc.2013.1751

Cao, L. (2021). AI in Finance: Challenges, Techniques and Opportunities. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3869625

Cao, S., Jiang, W., Wang, J., & Yang, B. (2024). From Man vs. Machine to Man + Machine: The art and AI of stock analyses. Journal of Financial Economics, 160, 103910. https://doi.org/10.1016/j.jfineco.2024.103910

Chang, E. C., Cheng, J. W., & Khorana, A. (2000). An examination of herd behavior in equity markets: An international perspective. Journal of Banking &Amp; Finance, 24(10), 1651–1679. https://doi.org/10.1016/s0378-4266(99)00096-5

Chen, R., & Ren, J. (2022). Do AI-powered mutual funds perform better? Finance Research Letters, 47, 102616. https://doi.org/10.1016/j.frl.2021.102616

Chen, M., Challita, U., Saad, W., Yin, C., & Debbah, M. (2019). Artificial Neural Networks-Based Machine Learning for Wireless Networks: A tutorial. IEEE Communications Surveys & Tutorials, 21(4), 3039–3071. https://doi.org/10.1109/comst.2019.2926625

Chiang, T. C., & Zheng, D. (2010). An empirical analysis of herd behavior in global stock markets. Journal of Banking & Finance, 34(8), 1911–1921. https://doi.org/10.1016/j.jbankfin.2009.12.014

Choi, R. Y., Coyner, A. S., Kalpathy-Cramer, J., Chiang, M. F., & Campbell, J. P. (2020). Introduction to Machine Learning, Neural Networks, and Deep Learning. Translational Vision Science & Technology, 9(2), 14. https://doi.org/10.1167/tvst.9.2.14

Christie, W. G., & Huang, R. D. (1995). Following the Pied Piper: Do Individual Returns Herd around the Market? Financial Analysts Journal, 51(4), 31–37. https://doi.org/10.2469/faj.v51.n4.1918

D'Acunto, F., Prabhala, N., & Rossi, A. G. (2019). The promises and pitfalls of Robo-Advising. Review of Financial Studies, 32(5), 1983–2020. https://doi.org/10.1093/rfs/hhz014

De Bondt, W. F., & Thaler, R. H. (1995). Chapter 13 Financial decision-making in markets and firms: A behavioral perspective. In Handbooks in operations research and management science (pp. 385–410). https://doi.org/10.1016/s0927-0507(05)80057-x

De Bondt, W. F. M., & Forbes, W. P. (1999). Herding in analyst earnings forecasts: evidence from the United Kingdom. European Financial Management, 5(2), 143–163. https://doi.org/10.1111/1468-036x.00087

De Camargo Fiorini, P., Seles, B. M. R. P., Jabbour, C. J. C., Mariano, E. B., & De Sousa Jabbour, A. B. L. (2018). Management theory and big data literature: From a review to a research agenda. International Journal of Information Management, 43, 112–129. https://doi.org/10.1016/j.ijinfomgt.2018.07.005

DeMiguel, V., Garlappi, L., & Uppal, R. (2009). Optimal Versus Naive Diversification: How Inefficient is the 1/NPortfolio Strategy? Review of Financial Studies, 22(5), 1915–1953. https://doi.org/10.1093/rfs/hhm075

Devenow, A., & Welch, I. (1996). Rational herding in financial economics. European Economic Review, 40(3–5), 603–615. https://doi.org/10.1016/0014-2921(95)00073-9

Dixon, M. F., & Halperin, I. (2019). The four horsemen of Machine learning in finance. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3453564

Fabozzi, F. J., Gupta, F., & Markowitz, H. M. (2002). The legacy of modern portfolio theory. The journal of investing, 11(3), 7-22.

Fama, E. F. (1970). Efficient Capital Markets: A review of theory and Empirical work. The Journal of Finance, 25(2), 383. https://doi.org/10.2307/2325486

Fama, E. F., & French, K. R. (1988). Permanent and temporary components of stock prices. Journal of Political Economy, 96(2), 246–273. https://doi.org/10.1086/261535

Fama, E. F., & French, K. R. (2004). The Capital Asset Pricing Model: Theory and evidence. The Journal of Economic Perspectives, 18(3), 25–46. https://doi.org/10.1257/0895330042162430

Feldman, F. (2006). Actual Utility, The Objection from Impracticality, and the Move to Expected Utility. Philosophical Studies, 129(1), 49–79. https://doi.org/10.1007/s11098-005-3021-y

Ferreruela, S., & Mallor, T. (2021). Herding in the bad times: The 2008 and COVID-19 crises. The North American Journal of Economics and Finance, 58, 101531. https://doi.org/10.1016/j.najef.2021.101531

Fishburn, P. C. (1981). Subjective expected utility: A review of normative theories. Theory and Decision, 13(2), 139–199. https://doi.org/10.1007/bf00134215

Galariotis, E. C., Krokida, S., & Spyrou, S. I. (2016). Herd behavior and equity market liquidity: Evidence from major markets. International Review of Financial Analysis, 48, 140–149. https://doi.org/10.1016/j.irfa.2016.09.013

Galariotis, E. C., Rong, W., & Spyrou, S. I. (2015). Herding on fundamental information: A comparative study. Journal of Banking & Finance, 50, 589–598. https://doi.org/10.1016/j.jbankfin.2014.03.014

Gleason, K. C., Mathur, I., & Peterson, M. A. (2004). Analysis of intraday herding behavior among the sector ETFs. Journal of Empirical Finance, 11(5), 681–694. https://doi.org/10.1016/j.jempfin.2003.06.003

Grobys, K., Kolari, J. W., & Niang, J. (2022). Man versus machine: on artificial intelligence and hedge funds performance. Applied Economics, 54(40), 4632–4646. https://doi.org/10.1080/00036846.2022.2032585

Harvey, C. R., Rattray, S., Sinclair, R., & Hemert, O. V. (2017). Man vs. machine: Comparing discretionary and systematic hedge fund performance. Journal of Portfolio Management, 43(4), 55-69. https://doi.org/10.3905/jpm.2017.43.4.055

Hirshleifer, D. (2020). Presidential address: Social transmission bias in economics and finance. Journal of Finance, 75(4), 1779-1831. https://doi.org/10.1111/jofi.12855

Holmes, P., Kallinterakis, V., & Ferreira, M. P. L. (2013). Herding in a Concentrated Market: a Question of Intent. European Financial Management, 19(3), 497–520. https://doi.org/10.1111/j.1468-036x.2010.00592.x

Hwang, S., & Salmon, M. (2004). Market stress and herding. Journal of Empirical Finance, 11(4), 585–616. https://doi.org/10.1016/j.jempfin.2004.04.003

IBM. (2023). Shedding light on AI bias with real world examples. What is bias in artificial intelligence? https://www.ibm.com/think/topics/shedding-light-on-ai-bias-with-real-world-examples

Indārs, E. R., Savin, A., & Lublóy, Á. (2019). Herding behaviour in an emerging market: Evidence from the Moscow Exchange. Emerging Markets Review, 38, 468–487. https://doi.org/10.1016/j.ememar.2018.12.002

Jagannathan, R., & Ma, T. (2003). Risk reduction in large portfolios: Why imposing the wrong constraints helps. The Journal of Finance, 58(4), 1651–1683. https://doi.org/10.1111/1540-6261.00580

Jain, J., Walia, N., Kaur, M., & Singh, S. (2021). Behavioural biases affecting investors' decision-making process: a scale development approach. Management Research Review, 45(8), 1079–1098. https://doi.org/10.1108/mrr-02-2021- 0139

Jiang, H., & Verardo, M. (2018). Does herding behavior reveal skill? An analysis of mutual fund performance. The Journal of Finance, 73(5), 2229–2269. https://doi.org/10.1111/jofi.12699

Jiang, R., Wen, C., Zhang, R., & Cui, Y. (2022). Investor's herding behavior in Asian equity markets during COVID-19 period. Pacific-Basin Finance Journal, 73, 101771. https://doi.org/10.1016/j.pacfin.2022.101771

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. Econometrica, 47(2), 263. https://doi.org/10.2307/1914185

Kolanovic, M., & Krishnamachari, B. (2017). Big data and AI strategies: Machine learning and alternative data approach to investing. J.P. Morgan Research.

Krauss, C., Anh, X., DO, & Huck, N. (2017). Deep neural networks, gradient-boosted trees, random forests: Statistical arbitrage on the S&P 500. European Journal of Operational Research, 259(2), 689–702. https://doi.org/10.1016/j.ejor.2016.10.031

Kumar, S., & Goyal, N. (2015). Behavioural biases in investment decision making – a systematic literature review. Qualitative Research in Financial Markets, 7(1), 88–108. https://doi.org/10.1108/qrfm-07-2014-0022

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1992). The impact of institutional trading on stock prices. Journal of Financial Economics, 32(1), 23–43. https://doi.org/10.1016/0304-405x(92)90023-q

Linnainmaa, J. T., Melzer, B. T., & Previtero, A. (2021). The misguided beliefs of financial advisors. The Journal of Finance, 76(2), 587–621. https://doi.org/10.1111/jofi.12995

Lotfi, I., & Bouhadi, A. E. (2021). Artificial intelligence Methods: toward a new decision making tool. Applied Artificial Intelligence, 36(1). https://doi.org/10.1080/08839514.2021.1992141

Malkiel, B. G. (2003). The efficient Market hypothesis and its critics. The Journal of Economic Perspectives, 17(1), 59–82. https://doi.org/10.1257/089533003321164958

Markowitz, H. (1952). PORTFOLIO SELECTION*. The Journal of Finance, 7(1), 77–91. https://doi.org/10.1111/j.1540-6261.1952.tb01525.x

Maug, E. G., & Naik, N. Y. (1995). Herding and Delegated Portfolio Management: The impact of relative performance evaluation on asset allocation. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.7362

McGee, V. (1991). We turing machines aren't expected-utility maximizers (even ideally). Philosophical Studies, 64(1), 115–123. https://doi.org/10.1007/bf00356093

Nofsinger, J. R., & Sias, R. W. (1999). Herding and feedback trading by institutional and individual investors. The Journal of Finance, 54(6), 2263–2295. https://doi.org/10.1111/0022-1082.00188

Poterba, J. M., & Summers, L. H. (1988). Mean reversion in stock prices. Journal of Financial Economics, 22(1), 27–59. https://doi.org/10.1016/0304-405x(88)90021-9

Ratanabanchuen, R., & Saengchote, K. (2020). Institutional capital allocation and equity returns: Evidence from Thai mutual funds' holdings. Finance Research Letters, 32, 101085. https://doi.org/10.1016/j.frl.2018.12.033

Ritter, J. R. (2003). Behavioral finance. Pacific-Basin Finance Journal, 11(4), 429–437. https://doi.org/10.1016/s0927-538x(03)00048-9

Schwert, G. W. (2003). Chapter 15 Anomalies and market efficiency. In Handbook of the economics of finance (pp. 939–974). https://doi.org/10.1016/s1574-0102(03)01024-0

Shiller, R. J. (2003). From efficient markets theory to behavioral finance. The Journal of Economic Perspectives, 17(1), 83–104. https://doi.org/10.1257/089533003321164967

Sias, R. W. (2004). Institutional herding. Review of Financial Studies, 17(1), 165–206. https://doi.org/10.1093/rfs/hhg035

Spyrou, S. I. (2013). Herding in financial markets: a review of the literature. Review of Behavioral Finance, 5(2), 175–194. https://doi.org/10.1108/rbf-02-2013-0009

Stier, C. (2022). Artificial Intelligence: The next frontier in investment management. Deloitte. https://www.deloitte.com/global/en/Industries/financial-services/perspectives/ai-next-frontier-in-investment-management.html

Stone, P., Brooks, R., Brynjolfsson, E., Calo, R., Etzioni, O., Hager, G., ... & Teller, A. (2022). Artificial intelligence and life in 2030: the one hundred year study on artificial intelligence. arXiv preprint arXiv:2211.06318.

Tappe, A. (2020). Wall Street's 11-year bull market comes to a screeching halt: stocks plummet. CNN, https://edition.cnn.com/business/live-news/stock-market-news-today-031220/index.html.

Ţiţan, A. G. (2015). The Efficient Market Hypothesis: Review of specialized literature and empirical research. Procedia Economics and Finance, 32, 442–449. https://doi.org/10.1016/s2212-5671(15)01416-1

USTR (2020). United States Trade Representative. https://ustr.gov/about-us/policy-offices/press-office/press-releases/2019/december/united-states-and-china-reach

Von Neumann, J., & Morgenstern, O. (1945). Theory of games and economic behavior. The Journal of Philosophy, 42(20), 550. https://doi.org/10.2307/2019327

Wang, H., Li, S., & Ma, Y. (2021). Herding in Open-end Funds: Evidence from China. The North American Journal of Economics and Finance, 57, 101417. https://doi.org/10.1016/j.najef.2021.101417

Welch, I. (2000). Herding among security analysts. Journal of Financial Economics, 58(3), 369–396. https://doi.org/10.1016/s0304-405x(00)00076-3

Wylie, S. (2005). Fund Manager Herding: A test of the accuracy of empirical results using U.K. data. The Journal of Business, 78(1), 381–403. https://doi.org/10.1086/426529

Xie, T., Xu, Y., & Zhang, X. (2015). A new method of measuring herding in stock market and its empirical results in Chinese A-share market. International Review of Economics &Amp; Finance, 37, 324–339. https://doi.org/10.1016/j.iref.2014.12.004

Appendices

Appendix 1. Fund List

AI Funds

QRAFT AI-ENHANCED US LGCP.MMTM.ETF
QRAFT AI-ENHANCED US LARGE CAP ETF
QRAFT AI-ENHANCED US HIGH DIVIDEND ETF
QRAFT AI-ENHANCED US NEXT VALUE ETF
AMPLIFY AI POWERED EQUITY ETF
MERLYNAI BULL-RIDER BEAR-FIGHTER ETF
MERLYNAI TACTICAL GROWTH AND INCOME ETF

Growth Funds

FIDELITY CONTRAFUND
T ROWE PRICE BLUE CHIP GROWTH FUND I
T ROWE PRICE BLUE CHIP GROWTH FUND Z
AMERICAN FUNDS GROWTH FUND OF AMERICA A
FIDELITY MAGELLAN K6 FUND
FID.MAGELLAN FD.CLASS K
FIDELITY MAGELLAN
BLACKROCK ADVANTAGE LARGE CAP GROWTH FUND K
BLACKROCK ADVANTAGE LARGE CAP GROWTH FUND R

Value Funds

AMERICAN CENTURY VALUE CL.C
AMERICAN CENTURY VALUE FUND I
AMERICAN CENTURY VALUE FUND R5
AMERICAN CENTURY VALUE FUND Y
AMERICAN CEN.VAL.FD.A CL.
AMERICAN CEN.VAL.FD.R6 CL.
AMER.CEN.VAL.FD.R CL.
ROWE T PRICE VALUE FD.
T ROWE PRICE VALUE FUND I
T ROWE PRICE VALUE FUND Z
DODGE & COX STOCK FUND I
DODGE & COX STOCK FUND X
OAKMARK FUND INVESTOR
OAKMARK FUND ADVISOR
OAKMARK FUND R6
VANGD.WINDSOR FD.

Value-Added Funds

FIDELITY EQ.INC.RLST.
FIDELITY EQ.INC.SHS.BEN. INT.
FIDELITY EQUITY-INCOME K6 FUND
FID.EQ.INC.FUND CLASS K
T ROWE PRICE EQUITY INCOME FUND I
T ROWE PRICE EQUITY INCOME FUND Z
T ROWE PRICE EQ.INC.FD.
T ROWE PRICE EQ.INC.FD. ADVI.CL.
T ROWE PRICE EQ.INC.FD. R CL.
VANGD.EQ.INC.FD.ADMIRAL SHS.
JPMORGAN EQUITY INCOME FUND R6
JPMORGAN EQ.INC.FD.CL.A
JPMORGAN EQ.INC.FD.CL.C
VANGUARD INTERNATIONAL DIVIDEND GROWTH FUND INV

Balanced Funds	Income Funds
VANGD.WELLINGTON INC.FD.	VANGD.WELLESLEY INC.FD.
T ROWE PRICE BALANCED FUND I	FIDELITY STGC.DIV.& INC. FD.
JNL/T ROWE PRICE BALANCED FUND A	T ROWE PRICE SPECTRUM INCOME FUND I
JNL/T ROWE PRICE BALANCED FUND I	T ROWE PRICE SPTM.INC. FD.
T ROWE PRICE BAL.FD.	DODGE & COX INCOME FUND I
MFS TOTAL RETURN FUND R6	FIDELITY MULTI-ASSET INCOME FUND
MFS TOR.FD.C	BLACKROCK MULTI-ASSET INCOME PORTFOLIO K
MFS TOR.FD.CL.R1	
MFS TOR.FD.CL.R2	
MFS TOR.FD.CL.R3	
MFS TOR.FD.CL.R4	
MFS TOR.TST.B	
FIDELITY BALANCED K6 FUND	
FIDELITY ADVISOR BALANCED FUND I	
FIDELITY ADVISOR BALANCED FUND M	
FIDELITY BALANCED ALLOCATION FUND	
AMERICAN BAL.FD. CL.A SHS.	
AMERICAN FUNDS AMERICAN BALANCED FUND F3	
AMERICAN FUNDS AMERICAN BALANCED FUND R2E	
AMERICAN FUNDS AMERICAN BALANCED FUND R5E	