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Equity Mutual Funds Performance Persistence Analysis: Systematic Behavior Identification

TESI DI LAUREA MAGISTRALE IN
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Abstract

This thesis comprises four chapters that comprehensively explore the landscape of equity mutual funds and their performances. Starting from the foundational aspects of mutual funds, including their types, role of fund managers, market evolution, with a connection to the Efficient Market Hypothesis (EMH), the study will be going in depth with the analysis of the classic literature for mutual funds. Firstly, examining multifactor models such as Fama & French's 3 factors and Carhart's 4 factors, alongside performance consistency studies by Hendricks, Patel, Zeckhauser, then Titman, and Wermers, till more recent studies of Berk, Van Binsbergen (2015) and Cogneau, P., Hübner, G., (2017). Once the main concepts of mutual funds theory are introduced, it is then conducted an empirical analysis of a survivorship bias-free sample of global equity open-end funds with the objective of shedding light on the persistent theme in the literature that superior fund performance is primarily a result of chance rather than skills. Right after, the study takes a forward-looking approach, extending the previous sample of funds aiming to identify if a substantial subset of funds consistently outperforms a specific benchmark (MSCI World TR Index) across time, trying to be in line with what recent studies have discovered. In the end, the previously identified subgroup of funds (called "Top Performers") is further analyzed in order to find a common pattern among the selected funds, in terms of their structural characteristics and investment strategies, putting the accent on the impact that the benchmark selection and manipulation phenomena have on the presented performance persistence results, between the first and the second half of the study.

Key-words: equity, mutual fund, global, managers, consistency, systematic, multi-factors, luck, skill, performance.

Abstract in lingua italiana

Questa tesi è composta da quattro capitoli che esplorano in modo completo il panorama dei fondi comuni azionari e le loro performance. Partendo dall'analisi degli aspetti fondamentali dei fondi, tra cui i loro diversi tipi, il ruolo dei gestori di fondi, l'evoluzione del loro mercato, con un collegamento alla Teoria del Mercato Efficiente (EMH), lo studio va poi nel dettaglio analizzando una parte della letteratura sui fondi comuni azionari. Inizialmente, esamina modelli multifattoriali come il modello a 3 fattori di Fama & French e quello a 4 fattori di Carhart, insieme agli studi sulla consistenza delle performance di Hendricks, Patel, Zeckhauser, poi Titman e Wermers, fino agli studi più recenti di Berk & Van Binsbergen, e Cogneau, P., Hübner, G., (2017). Una volta introdotti i concetti principali della teoria dei fondi comuni azionari, viene presentata un'analisi empirica di un campione di fondi azionari globali e open-end, mettendo in luce il tema persistente nella letteratura classica secondo cui le performance superiori dei fondi sono principalmente il risultato del caso (fortuna) piuttosto che delle abilità dei managers dei fondi. Subito dopo, lo studio adotta un approccio prospettico, estendendo il precedente campione di fondi con l'obiettivo di identificare se una parte sostanziale di fondi superi costantemente uno specifico benchmark (MSCI World TR Index) nel tempo, cercando di essere in linea con le scoperte degli studi più recenti. Alla fine, il sottoinsieme di fondi (chiamato "Top Performers") precedentemente identificato viene ulteriormente analizzato per scoprire un pattern comune, in termini di caratteristiche strutturali e strategie di investimento, mettendo in evidenza come i risultati di persistenza delle performance possano essere influenzati dai fenomeni di selezione e manipolazione del benchmark, tra la prima e la seconda metà dello studio.

Parole chiave: fondi, azionari, globali, manager, consistenza, costanza, sistematico, multi-fattoriale, fortuna, abilità, performanti.

Contents

Introduction

The mutual funds sector offers investors a variety of options to engage in capital markets, making it a crucial player in the global financial scene. In particular, equity mutual funds garner a lot of interest because of their potential to outperform conventional investment vehicles in terms of returns. But evaluating the performance of mutual funds is a complicated process with many moving parts that calls for a deep comprehension of the different aspects that affect how well or poorly the funds perform. Examining performance persistence—the propensity of funds to hold onto their relative performance over time—is a crucial component of assessing mutual fund performance. The notion of performance persistence prompts significant inquiries regarding the efficacy of fund managers in consistently surpassing market benchmarks and the consequences for investors who strive for long-term gains. Investors struggle to find funds that can consistently outperform market benchmarks amidst the wide variety of equity mutual funds available. The pursuit of this kind of steady outperformance—also referred to as performance persistence—raises important concerns regarding what constitutes success in the field of fund management. Are some funds able to consistently outperform the market, or are they merely short-lived and vulnerable to changes in the dynamics of the market?

By building a sample of equity, global, open-end and actively managed mutual funds, the purpose of this thesis is to conduct a comprehensive survivorship bias free analysis of performance persistence across time (from 2000 to 2022), with a focus of understanding the factors that contribute to generate an outperformance or an underperformance, extending the current literature, which has been subject to much debate. In the first chapter, I will start from the definition of mutual funds, describing the different forms of funds that exist in the financial markets, going in details with the explanation of the role and main functions of fund's managers, and why the prospectus is fundamental for both potential investors and the manager itself. The focus will then move to the analysis of the evolution of the market for mutual funds across time, trying to analyze how the variation of the macroeconomic factors and the financial crises have impacted on both the expansion of mutual funds and the behavior of the investors, starting from the 80s till today. At this point, I will introduce the concept of Efficient Market Hypothesis (EMH) and how it is connected to the mutual funds sector. According to EMH, asset prices accurately reflect all available information. Stated differently, the Efficient Market Hypothesis postulates that financial markets are efficient and that consistently achieving above-average returns through information analysis and trading is next to impossible. According to the hypothesis, investors have little chance of outperforming the market because prices move swiftly in response to fresh information. The idea that mutual fund managers can regularly beat the market by selecting stocks or timing the market is contested by EMH. This theory will be somehow contested in the conclusions of this study. In the following chapter, it will be created the bridge between classic and modern mutual funds literature, in order to set the stage for the last part of this thesis. Initially, I will introduce and explain two multi-factorial theories that are always used as the starting point to conduct any kind of mutual funds analysis; the three factors model by Fama & French (1990) and the four factors model by Carhart (1997). Then, I will be more specific with the introduction of other classic papers whose focus is the analysis of performance persistence of mutual funds, both short term by Hendricks, Patel, and Zeckhauser (1990) and longer term by Grinblatt and Titman (1992). They assert that investment strategies that target purchasing historically high-performing stocks—dubbed "Hot-Hands" (Hendricks, Patel, and Zeckhauser, 1990) in the sports world—

can explain the persistence of short-term performance. According to their analysis, mutual funds that did well the year before are still better in the short term (four months to two years), exposing an exploitable flaw in the efficient market theory. Additionally, other writers such as Grinblatt and Titman (1992) explain the phenomenon in terms of fund managers' capacity to generate abnormal returns that last for five to ten years. Beyond these initial findings, Carhart determines every element that conceivably permits performance persistence, coming to the conclusion that skills and strategies are not among them, in favor of other factors such as momentum and luck. For this reason, I will then present more recent studies by Berk, J., & Van Binsbergen, J. H. (2015) and Cogneau, P. and Hübner, G. (2017), according to which it is possible to identify specific performance measures that can explain how some mutual funds have the ability to consistently outperform other funds and their benchmarks across time, not as result of chance, but as a consequence of specific investment strategies and abilities of fund's managers.

After the presentation of the "fundamentals" that represents the pillars of this study, in the third chapter it is presented an empirical survivorship bias free analysis on a sample of 5148 equity, global, open-end and actively managed mutual funds that were born between 2009 and 2022 (built gathering data from Thomson Reuters Refinitiv Eikon database). In this chapter it will be presented the distinction between skills and luck, intended as two crucial generators of results for mutual funds, with the objective of understanding from a numerical point of view, if the results showed by the classic literature are still valid and applicable to modern market for mutual funds, or if they should be instead disproved. In this first analysis, the performances of the selected funds will be analyzed in terms of a group of indicators such as Jensen's Alpha (computed in relation to the specific benchmark of the funds), Beta, R-squared, correlation and standard deviation across a period of 10 years divided in: last 1 year, last 3 years, last 5 years and last 10 years, considering as a last period of observation of the analysis the 31st of December 2012. From this first analysis, first small evidence of outperformance is presented, but it will not be considered as significant, since the largest part of the sample will show results of underperformance instead, being in line with the classic studies. Since I strongly believe that the positive performances of mutual funds cannot be attributed to pure luck only, but it is possible to identify more interesting reasons and factors to explain those superior performances, I will go further with the analysis in the last chapter, whose focus will move to the identification of a systematic behavior of constant outperformance of a slightly different sample of 2086 funds (with the same previously introduced characteristics), considering also those funds that were born after 31/12/1999. This time, the performances of the selected funds will be evaluated in terms of percentage variation of their NAV, that will be compared with the percentage variation of the results of one single strong benchmark in the same period of time, the MSCI World TR Index. I believe that this different approach is crucial as a consequence of the phenomenon of "benchmark selection and manipulation", according to which it could happen that the results of mutual funds are not representative of their real potential and quality, that is the reason why I will use only the MSCI World TR Index. The objective is to highlight the impact that this phenomenon has on the performance persistence of the equity mutual funds. Benchmarks for mutual funds should be stable over time, and they should always be aligned with the objectives and characteristics of the fund, otherwise this could lead to misleading results. According to Hougaard, J., L., & Tvede, M. (2002), the selection of benchmarks and the possibility of manipulation in benchmarking procedures have come to light as important variables impacting the validity of research findings. In order to guarantee the validity and relevance of research findings, it is critical to comprehend and tackle benchmark selection issues and manipulation as algorithms become more and more integrated into different fields. If the funds will be able to beat such a strong index, their positive results will be in that case “absolute”, making the benchmark manipulation phenomena less meaningful. Finally, I will present how a subgroup of funds, that I will call “Top Performers” have been able to consistently beat the selected benchmark across time (over a 15 years period). The final goal will consist in the identification of a common pattern between these funds, in terms of structural characteristics, in order to give an explanation to their superior performances, that is not related to pure luck; presenting, according to recent studies, a different result compared to the classic literature.

Chapter One

Mutual Funds Introduction (Structure and Market)

The ever-changing financial markets are a result of the dynamic interaction between investor behavior and economic forces. Mutual funds play a crucial role in this complex web, representing the goals of all investors who want capital to grow, be diversified, and be professionally managed. This chapter provides an introduction to mutual funds by describing their complex structure, tracing the history and the evolution of the market they are a part of, and examining the theoretical foundations that impact their performance according to how mutual funds are directly connected to the Efficient Market Hypothesis.

1.1 Mutual Funds

Mutual funds are investment vehicles run by asset management firms, that pool the capital of many investors and invest it in a single portfolio of diversified financial assets (shares, bonds, government securities, etc.) or, in some cases, real estate, as it is listed in the prospectus of the fund. They are split up into a large number of equally weighted units known as shares, which are purchased by investors who subscribe to the fund. Depending on how well the underlying assets perform, the value of the shares will change, and shareholders of the fund participates proportionally in the gains and losses of the fund. Investors may sell their shares at any moment, but depending on the fund's current valuation, they might not get the same price they paid. The same investment activity can be carried out by variable capital investment companies (SICAV) or fixed capital investment companies (SICAF), in addition to the conventional form, SGR/mutual fund. The primary danger of investing in mutual funds is that the share value could increase as well as decrease, because of the fluctuations in the underlying assets' values. Because of this, before making an investment in mutual funds, investors should be informed of the risks. There are various types of funds:

- Open-end mutual funds which allow investors to subscribe or redeem shares at any time. These funds typically invest in publicly traded financial assets.
- Closed-end mutual funds typically only redeem shares at maturity and only permit investors to register for shares during the offering period, which occurs prior to the fund's actual activities. Closed-ended funds are mostly used for illiquid and long-term investments (e.g., real estate, loans, unlisted firms).
- Open-end Harmonized mutual funds. Due to their wide distribution, harmonized funds founded in European Union nations and investing mostly in listed securities (shares, bonds, etc.) are particularly significant among open-ended funds. The word "harmonized" refers to their adherence to standardized guidelines and standards designed to safeguard depositors' interests by capping and dividing the risks that funds can take. Authorities in the nation of origin are responsible for overseeing harmonized funds.

Based on their investment policies, harmonized funds are divided into:

- Equity funds – they are characterized by the highest level of risk, because they invest mostly in shares.
- Bond funds – they have a lower level of risk because they invest in government and corporate bonds.

- Balanced funds – they invest both in bonds and shares, generating an overall level of risk that is proportional to the percentage of shares invested through the portfolio.
- Money market funds – they invest in short term money market financial instruments (no longer than 6 months)

The performance of the securities that the mutual fund invests in determines the value of the fund. Investors purchase the performance of a mutual fund's portfolio—or, more specifically, a portion of the value of the portfolio—when they purchase a unit or share of the fund. Purchasing shares of a mutual fund is distinct from purchasing stock. Mutual fund shares do not grant their owners any voting rights, in contrast to stock. A mutual fund share is an investment in a variety of stocks or other securities, and it may charge shareholders or annual running fees that are paid directly by the investors when purchasing or selling the fund. The expense ratio, which typically ranges from 1 to 3 percent of the funds under administration, represents the annual proportion of annual fund operating fees. An investment fund's expense ratio is calculated by adding its advisory or management charge and operating expenses. These managed funds typically charge greater fees than "index" or "tracker" funds (which replicate changes in broad market indexes), as the majority of funds are "active" in that they either aim to select "winner stocks" or they engage in market timing (i.e., projecting relative returns of large asset classes).

In comparison to other financial institutions that serve the requirements of consumers, mutual funds have a high level of operating openness. Unlike banks and insurance companies, mutual funds do not assume credit and insurance risks, therefore they are not required to build actuarial reserves against potential insurance claims or to make subjective provisions against non-performing loans. Mutual funds are able to value their assets according to a "mark-to-market" methodology and invest in marketable securities. However, it is the investors who take on the investment risk since they are exposed to significant losses when markets decline as well as the upside potential of corporate equities, particularly in the case of equity funds.

It is worth noticing the difference between ETF (Exchange Traded Funds) and Mutual funds. Both are pools of investment that provide investors with a share in a diverse portfolio. As detailed in the fund's prospectus, investors have a multitude of fund options from which to choose to expose themselves to a broad range of markets, industrial sectors, locations, asset classes, and investing methods. They are both pretty liquid. Investors in mutual funds can typically easily redeem their shares on a daily basis. ETFs and mutual funds can both lose money, and a fund's historical performance does not guarantee that it will continue to perform well.

They incur costs and fees, known as cost ratios (and represented as a percentage). "Annual Fund Operating Expenses" are fees levied by both mutual funds and exchange-traded funds (ETFs). In addition, there are typically brokerage commissions when buying or selling an ETF, and mutual funds frequently impose additional fees. Both funds are available in active and passive forms. As mandated by law, mutual funds price their shares at NAV every business day, usually following the closure of the major U.S. exchanges. The value of the mutual fund's assets less its obligations is expressed in terms of a single share, or NAV, or net asset value. ETFs, on the other hand, are traded like individual stocks on a stock market, and their prices change all day long. Every day, ETFs also compute their NAV; however, during the trading day, an ETF's per-share price may differ from the per-share NAV. A more minor distinction is that investors can buy and redeem mutual fund shares directly from the fund or via a brokerage company that sells the fund. In the meantime, "intraday liquidity" is made possible by ETF investors purchasing and selling shares of an ETF on an exchange just like they would any other publicly listed stock. To put it briefly, end-of-day mutual fund pricing can be unpredictable, but not with an ETF as pricing is ongoing.

ETFs offer investors greater control over their tax obligations. When selling ETF shares, an investor essentially decides whether or not a capital gains liability arises. But when you do eventually decide to sell, you'll have to pay taxes on any realized capital gains and file any dividends and interest you get. It is also up to investors when to sell their mutual fund shares. However, when the fund manager sells securities with embedded capital gains, there may also be a tax burden related to mutual funds.

1.2 The role of Mutual Funds Managers

Mutual funds are operated by professional money managers, who are supported by investment advisers and analysts who allocate the fund's assets and attempt to produce capital gains or income for the fund's investors, and who are legally obligated to work in the best interest of mutual fund shareholders. The fund manager has a vital role between the organization and investors, offering continuing management, a customized portfolio, and tailored support to their clients. Clients no longer have to contest a broker's decisions to buy or sell their shares because, in fee-based management as opposed to transaction-based management, they and their adviser are on the same team. Professional money managers are compensated as a proportion of the assets they are responsible for managing, rather than receiving commissions on transactions.

A fund manager oversees the trading of the fund's portfolio and puts the investment strategy into action. The fund may be run by a single manager, two co-managers, or a group of three or more people. Putting your trust in the pros to make investment management decisions is the primary advantage of investing in a fund. Fund managers are crucial in the investing and financial industries because of this. They provide investors comfort in knowing that their money is in the hands of professionals. The performance of a fund is influenced by a variety of factors, including market dynamics and manager talent. A well-trained fund manager can outperform both the benchmark indexes and the fund's rivals. Those that use a more passive approach are referred to as passive fund managers, whereas this type of manager is known as an active or alpha manager. Typically, fund managers supervise the direction and oversight of mutual funds or pensions. In addition, they oversee a group of investment analysts. This means that the fund manager needs to be extremely skilled in people, arithmetic, and business. Meeting with team members and new and current clients is one of the fund manager's primary responsibilities. The fund manager is in charge of the fund's performance, hence they must investigate businesses, look into the financial sector, and analyze the state of the economy. The goal of active fund managers is to beat benchmark indices and their colleagues. Managers that actively manage funds research market patterns, evaluate economic information, and keep up with corporate news. They purchase and sell securities—stocks, bonds, and other assets—based on this research in an effort to increase their profits. Because they take a more active role in managing their funds by regularly shifting their holdings, these fund managers typically demand higher fees. The reason why mutual fund fees are typically high is because they are often actively managed. Conversely, managers of passive funds engage in trading stocks that are included in a benchmark index. The portfolio weighting of this type of fund manager is identical to that of the underlying index. Passive fund managers often aim to replicate the performance of the index rather than surpass it. Passively managed funds include a large number of index mutual funds and exchange-traded funds (ETFs). Due to the fund manager's lack of experience, fees for these investments are typically substantially lower.

1.3 Prospectus

A mutual fund's portfolio is structured and maintained to match the investment objectives stated in its prospectus. A prospectus is a formal document that contains information regarding a public offering of securities. For offerings of stocks, bonds, and mutual funds, a prospectus is submitted. Because it offers a wealth of pertinent information about the investment or security, the prospectus can assist investors in making more educated investing decisions. Specifically for mutual funds, the aims, tactics, performance, distribution rules, costs, and fund management are all covered in the prospectus. So, a prospectus is an agreement that binds the fund and the investor. According to U.S. Securities and Exchange Commission (SEC), although the content in a fund's prospectus may differ from one fund to another, all prospectuses are required by law to include the following crucial sections:

- Investment Objectives that are the financial objectives of the fund, and the securities selected to meet those objectives reflect those objectives. Investment goals can take many different forms, such as high total return, steady income, and long-term capital growth. Fund companies are not allowed to alter these goals unless fund investors approve the changes by voting.
- Investment Strategies. This section of the prospectus describes how a fund manages and distributes its assets in order to meet its investment goals. Setting objectives for net asset value, allocating assets, imposing investment constraints (such solely investing in specific industries), and deciding whether or not to use derivatives are all factors taken into account while creating such a plan.
- Risk of investing in the fund. This risk section that outlines the risks associated with a given fund, including credit risk, interest rate risk, market risk, and so forth, since investors have different levels of risk tolerance.

- Distribution Policy, to outline how revenue from securities and investing activities, such as realized capital gains, dividends, interest, and other income, is distributed to investors. Certain funds pay returns to unitholders directly, while others reinvest the distributions back into the fund, purchasing additional units for fundholders.
- Fees and Expenses.
- Fund Management, containing various information for the fund, such as how long the fund manager has overseen it.

1.4 Evolution of Mutual Funds Market

Closed-end investment trusts, resembling the initial manifestation of mutual funds, emerged in the final quarter of the nineteenth century. The inaugural open-end mutual fund took shape in Boston in 1924. Both closed and open-end mutual funds witnessed robust expansion during the 1920s, only to face a significant setback due to mismanagement, fraud, and the stock market crash of 1929. From 1930 to 1970, mutual funds experienced modest growth, notwithstanding a surge in interest in equity funds amid the stock market boom of the early and mid-1960s. However, this momentum was reversed in the 1970s, marked by the first oil crisis and lackluster equity market performance. The collapse of International Overseas Services, a fraudulent fund management group in the late 1960s, contributed to a loss of investor confidence in mutual funds. A pivotal innovation unfolded in the 1970s with the introduction of money market mutual funds. Specializing in money market instruments, these funds competed with banks by offering market-related returns and narrower spreads compared to traditional bank deposits, all while ensuring liquidity and easy access. The launch of money market mutual funds in the United States during the 1970s was a response to regulatory restrictions preventing US banks from providing market rates of interest on retail deposits, particularly during a period of high inflation. This regulatory environment forced banks to operate within ceilings on interest rates. Money market mutual funds also gained significant traction in countries with stringent restrictions on bank deposit rates, such as France, Greece, and Japan. Even in the absence of regulatory constraints, the invention of money market mutual funds led to their growth, meeting the demand from sophisticated investors seeking a convenient avenue for parking their liquid investment balances.

The expansion of equity and bond funds recommenced in the early 1980s as macroeconomic performance and equity markets began to show signs of improvement. However, the real surge in growth did not occur until the early 1990s.

In most nations during the 1990s, mutual funds experienced tremendous growth, with a few notable outliers, mostly in Asia. In Anglo-American nations, equity funds dominated; most of Continental Europe and middle-income nations used bond funds. The key drivers of mutual fund growth were the expansion of the capital markets (which reflected investor confidence in market integrity, liquidity, and efficiency), as well as financial system orientation. Money market and (short-term) bond funds developed as a result of limitations on competing products.

The rapid expansion of mutual funds was one of the most intriguing financial trends of the 1990s. This was especially true in the United States, where total mutual fund net assets increased by USD 1.6 trillion from 1992 to 1998, or an average annual growth rate of 22.4%[1]. The total mutual fund assets of the 15 nations that make up the European Union increased at an average annual growth rate of 17.7%[2].

Greece had the highest growth rate among EU members, coming in at 78 percent, followed by Italy at 48 percent and Belgium, Denmark, Finland, and Ireland at about

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[1] Data from ICI (Investment Company Institute) report (2002).

[2] Data from ECB (European Central Bank) report (2003).

35 percent each. Even higher growth rates were recorded in certain developing nations, such as Morocco, although from considerably lower starting positions. Over this time, not only did mutual fund assets in the United States expand rapidly, but so did household ownership of mutual funds. According to survey results published by the Investment Company Institute (the trade organization for US mutual funds), more US households now own mutual funds than did so in 1980 (ICI 2002).

The expansion of huge international financial firms' operations throughout a wide range of nations, as well as the robust performance of the equities and bond markets for the majority of the 1990s, all contributed to the global growth of mutual funds. The demographic aging of most high- and middle-income countries' populations and the increasing demand from investors for financial products that are safe, liquid, and offer strong long-term returns were likely the third and fourth factors.

It is quite clear that, under the right circumstances, the asset management companies (owners of mutual funds) could surpass banks and insurance providers to become the most significant financial institutions for households. While equity funds are typically employed by pension funds run by small businesses, this is frequently the case with money market mutual funds and short-term bond funds, which satisfy the liquidity requirements of tiny organizations.

The popularity of mutual funds in the US and other high-income nations has sparked an extensive and growing body of research on the variables that influence the success of mutual funds. These studies are often focused on the performance of mutual funds in a single nation. Few studies have looked at the growth and effectiveness of mutual funds across various nations. The Otten and Schweitzer (1998) study that contrasted the mutual fund businesses in the US and Europe is an exception. Otten and Schweitzer discovered that, in terms of total assets, average fund size, and capital market prominence, the European mutual fund business lagged behind the American industry. According to Fernando, Deepthi and Klapper, Leora F. and Sulla, Victor and Vittas, Dimitri (May 2003), while mutual fund markets in various European countries are dominated by a few large local firms, most of which are bank-centered, suggesting maybe a lower amount of competition, European investors have a predilection for fixed income mutual funds.

Several studies focused on the expansion of mutual fund market from 2000 to 2020, as a consequence of many key trends, such as rising incomes, increasing financial literacy, and the growing popularity of passive investing. As it is shown in the report "The evolution of the global mutual fund industry: 2000-2020 - Investment Company Institute (ICI). (2021)", in 2000, the global mutual fund industry had assets under management (AUM) of $7.6 trillion. By 2021, AUM had grown to $112.3 trillion (Figure 1.4.1).

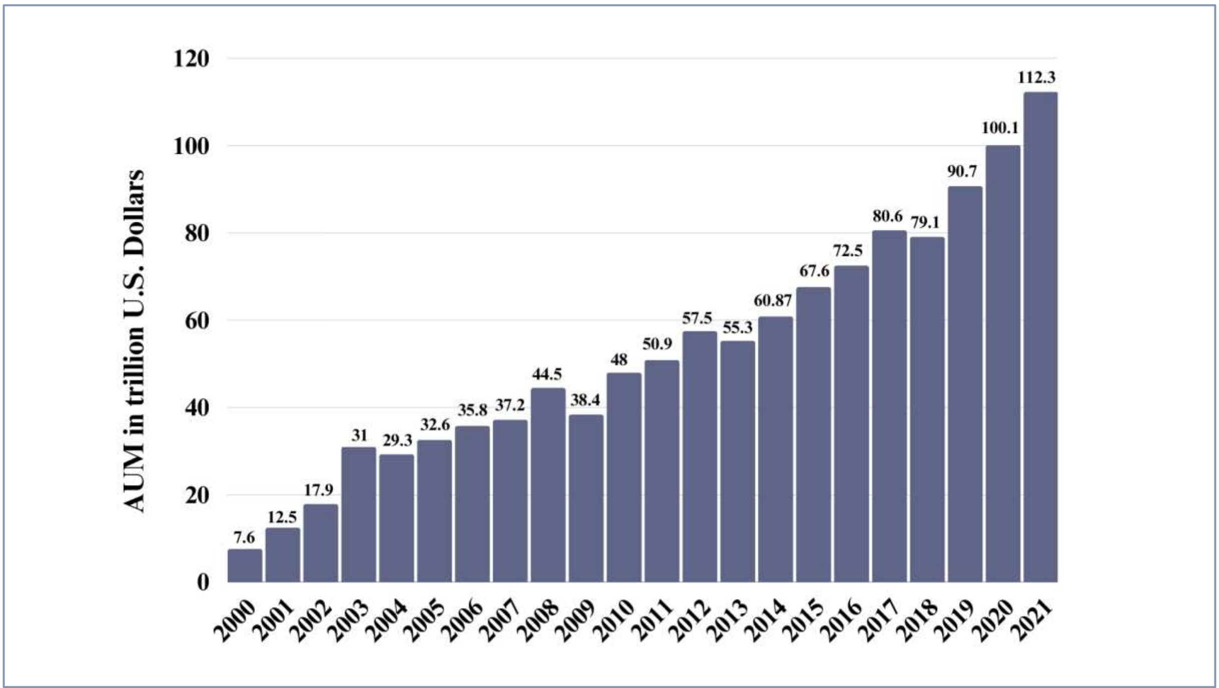

Figure 1.4.1: AUM value increase between 2000 and 2021 (ICI, 2021).

In order to explain the phenomena, "The future of the mutual fund industry" article by McKinsey & Company (2019), provides the analysis of several factors, so that mutual fund demand has increased as a result of rising income levels and rising financial literacy. People all throughout the world have been able to save and invest more money as they have gotten more prosperous and financially astute. Both novice and seasoned investors find mutual funds to be an accessible and affordable option to invest in a diverse range of assets. This has made them an attractive option for many investors, particularly those who are looking for a hands-off approach to investing.

Several significant occurrences over the previous 20 years, including as the dot-com boom, the global financial crisis, and the COVID-19 epidemic, have also had an impact on the worldwide mutual fund industry. Although these occasions caused market instability, growth and innovation have been the overarching trends. Many actively managed funds suffered huge losses when the dot-com bubble broke in 2000, resulting into investor losing confidence in mutual funds. In spite of this, the sector recovered in the years that followed the crisis. The 2008 global financial crisis caused the stock market to drop significantly once more and investors' faith in mutual funds to erode. The mutual fund sector, nevertheless, remained robust. In fact, investor interest and market engagement have surged as a result of the COVID-19 epidemic. Mutual funds were one of the alternatives that investors looked for as traditional investment opportunities, such real estate, and fixed deposits, faced uncertainty during the pandemic. As more investors dedicate their money to these investment vehicles because of the rising demand, mutual fund assets have expanded. Additionally, the epidemic has sped up the adoption of internet investing and digital platforms. Investors used internet channels to access and manage their investments in the face of lockdowns and social isolation policies.

Nowadays, with new products and services emerging to fulfill the demands of investors in many nations and regions, the global mutual fund market is likewise diversifying. For instance, there is rising interest in sustainable mutual funds, which make investments in businesses dedicated to environmental, social, and governance (ESG) objectives. Technology advancements are also having an effect on the mutual fund sector. For instance, the emergence of robo-advisors has made it simpler for investors to buy mutual funds directly from the market without using a traditional financial advisor. In general, the mutual fund industry is well-positioned to continue expanding in the years to come, expecting from 2023 to 2030 to expand at a CAGR (Compound Annual Growth Rate) of 5.3%[3], as presented in Figure 1.4.2:

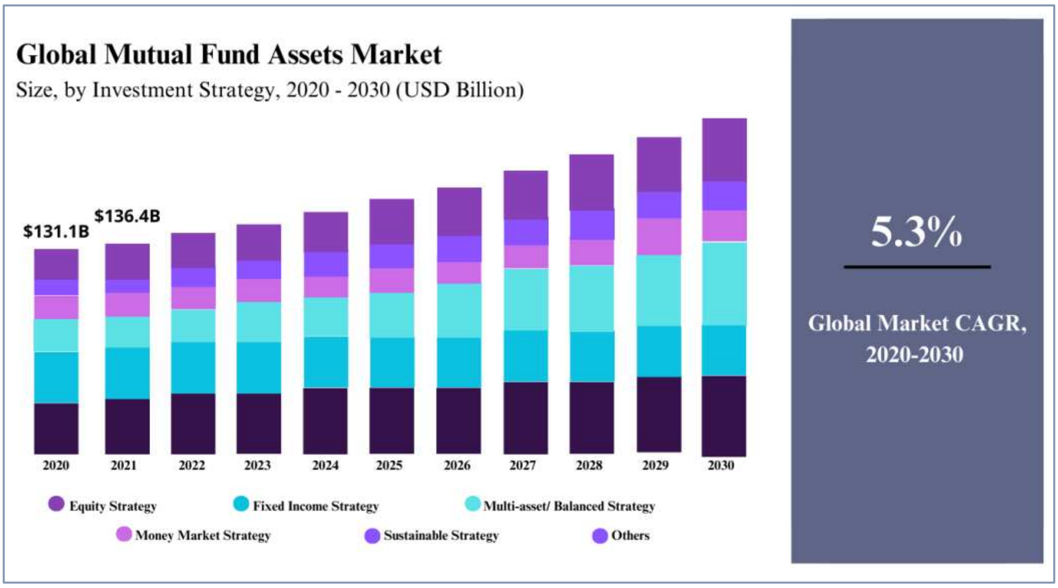

Figure 2.4.2: Mutual Funds Global Market increase expectations between 2020 and 2030 (McKinsey & Company, 2019).

Specifically for Equity funds (that are the subject of this study), they command a substantial presence in Hong Kong and the United States, surpassing 30 percent of GDP. In the United States, this prominence is reflective of the investing public's strong inclination toward corporate equities, although this preference may wane following recent downturns in equity markets. The net assets of equity funds range from 10 to 20 percent of GDP in select countries,

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[3] Mutual Fund Assets Market Size, Share & Trends Analysis Report By Investment Strategy, By Type, By Distribution Channel, By Investment Style, By Investor Type, By Region, And Segment Forecasts, 2023 – 2030.

including Belgium, Canada, the Netherlands, Sweden, Switzerland, and the United Kingdom. In much of Continental Europe, equity funds were relatively underdeveloped in 1998, although notable growth was observed in France, Italy, and Spain. In most middle-income countries, including Brazil and Chile, where equity markets are reasonably well-developed, equity funds have a limited presence. This can be attributed to a combination of factors such as lack of confidence in the integrity of local markets, low risk tolerance among investors, and the preference of wealthier and more sophisticated investors for overseas mutual funds. The modest representation of equity funds in Australia and New Zealand can be explained by residents' easy access to overseas mutual funds operating in offshore centers like Hong Kong, Singapore, the United States, and the United Kingdom.

1.5 Efficient Market Hypothesis (EMH)

According to Eugene Fama (1970), the degree to which market prices accurately reflect all available, pertinent information is referred to as market efficiency. There is no way to "beat" the market if markets are efficient since there are no assets that are undervalued or overvalued because all information is already factored into prices. Because no one has a clear idea of how to completely define or accurately measure this thing called market efficiency, the term is a little deceptive. Despite these restrictions, the phrase is used to refer to the Efficient Market Hypothesis (EMH), for which Fama is most well-known. According to the EMH, it is impossible for an investor to outperform the market, and market anomalies shouldn't exist since they would be quickly arbitraged away. Investors that embrace this notion frequently invest in index funds that follow the performance of the entire market and advocate for passive portfolio management. The market gets more efficient as information quality and quantity rise, lowering prospects for arbitrage and above-market gains, resulting into three levels of market efficiency.

Because it is impossible to accurately estimate future prices based on historical price changes, market efficiency is weak. If current prices take into account all relevant information that is currently known, then all knowledge that can be learned from past prices is already considered by current prices. Future price changes can only result from the availability of fresh information, therefore. According to this version of the hypothesis, it is not reasonable to anticipate that investing techniques like momentum or any rules based on technical analysis will consistently produce above-average market returns. This version of the hypothesis still leaves open the potential that employing fundamental analysis, excess returns could be obtained. Although this point of view is no longer maintained with such fervor, it has long been widely taught in academic finance courses. The semi-strong form of market efficiency makes the assumption that stocks quickly adjust to take in new information that is made public, making it impossible for an investor to outperform the market by trading on that knowledge. Because any knowledge gleaned from fundamental analysis will already be available and hence already incorporated into current pricing, it follows that neither technical analysis nor fundamental analysis would be trustworthy tactics to attain greater returns. Only privately held knowledge that is not available to the public will be valuable for gaining a trading advantage, and only to those who have it before the rest of the market does. The strong form of market efficiency, which builds on and incorporates the weak form and the semi-strong form, claims that market prices reflect all information, both public and private. Assuming that stock prices represent all information, both public and private, no investor, not even a corporate insider, would be able to make more money than the ordinary investor, even if he had access to fresh insider information.[4]

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[4] Mutual Fund Assets Market Size, Share & Trends Analysis Report By Investment Strategy, By Type, By Distribution Channel, By Investment Style, By Investor Type, By Region, And Segment Forecasts, 2023 – 2030

A more recent study by Wolla, Scott A. (2016) shows how strong form efficiency proponents concur with Fama, and they frequently include passive index investors. Active trading can produce anomalous profits through arbitrage, according to proponents of the weak version of the EMH, whereas semi-strong believers fall somewhere in the middle. Value investors, for instance, are at the other end of the spectrum from Fama and his adherents and hold the opinion that stocks can become undervalued or priced below what they are really worth. Investing in equities at a discount and selling them when their price increases to equal or above their inherent value is how successful value investors make their money.

People who reject the idea of an efficient market emphasize the existence of active traders. There should be no incentive to become an active trader if there are no opportunities to make profits that outperform the market. Furthermore, because the EMH states that an efficient market has minimal transaction costs, the fees levied by active managers of mutual funds with good results which outperform the benchmark are considered as evidence that the EMH is incorrect.

1.6 Mutual Funds And Market Efficiency

Examining whether mutual funds yield positive risk-adjusted returns, or they tend to replicate abnormal returns overtime is an indirect technique to determine whether financial markets are efficient. Let $q_{p,t}$ stand for the price per share of mutual fund p at the conclusion of period t. The fund's time-weighted rate of return for period t is provided by equation 1.6.1:

$$r_{p,t} = \frac{q_{p,t}}{q_{p,t-1}} - 1 \qquad (1.6.1)$$

Let $\tilde{r}_{p,t}$ denote the realized return on mutual fund p observed in periods t = 1, · · · ,T and Let $\tilde{r}_{m,t}$ and $\tilde{r}_{f,t}$ denote the realized returns on the market portfolio and the safe asset observed in periods t = 1, · · · ,T, we can define the Jensen's Alpha for mutual fund p as the intercept α_p in the linear regression of the fund excess return, $\tilde{r}_{p,t} - r_{f,t}$, over the market portfolio excess return, $\tilde{r}_{m,t} - r_{f,t}$ (equation 1.6.2):

$$\tilde{r}_{p,t} - r_{f,t} = \alpha_p + \beta_p(\tilde{r}_{m,t} - r_{f,t}) + \tilde{\epsilon}_{p,t} \tag{1.6.2}$$

The Jensen's alpha is defined using a linear regression that directly arises from the CAPM. The Jensen's alpha is a risk-adjusted performance indicator that assesses a fund manager's ability (also known as selectivity) to choose assets with superior performance.

The Jensen's alpha OLS estimate is computed as in equation 1.6.3:

$$\hat{\alpha}_p = (\bar{r}_p - \bar{r}_f) - \hat{\beta}_p(\bar{r}_m - \bar{r}_f) \tag{1.6.3}$$

where $\hat{\beta}_p$ is the OLS estimate of the fund's beta, so the difference between the mean excess return on the fund, $\bar{r}_p - \bar{r}_f$, and the estimated fund's beta times the mean excess return on the market portfolio, $\hat{\beta}_p(\bar{r}_m - \bar{r}_f)$.

The fund beta measures the amount of systematic risk associated with the fund portfolio. Then, the Jensen's alpha, $\hat{\alpha}_p$, indicates whether the fund returns on average are larger (smaller) than the equilibrium value consistent with its amount of systematic risk; the fund is located above (below) the security market line.

Jensen (1968) used data from the 1945–1964 period to determine the alphas for a group of 115 mutual funds. He discovers that, net of expenses, 72 funds have a negative alpha, 43 have a positive alpha, and only 3 have a statistically significant positive alpha using the S&P500 index as a proxy for the market portfolio. As a result, actively seeking public and private data only makes enough money to pay for itself.

According to Grinblatt M. and Titman S. (1992), if a fund's returns are higher than a benchmark, represented by a market index, for at least two consecutive periods, the fund is said to have positive persistence in performance. But, is positive persistence in the performance of a generic fund consequence of skill or chance? Suppose that we observe returns over periods {1, 2,… ,t,…,T} for funds {1, 2,… , p,…, n}. For any fund p the probability of beating the benchmark, B, in any period t is 50%. This implies that the fund managers are not particularly skillful and can beat the benchmark only by chance.

Suppose now that we observe returns over periods {1, 2, … ,T1, T1 + 1, … ,T = T1 + T2} for funds {1, 2, … , p, … , n}. Let $\bar{r}_{p,1}$ denote the mean return on fund p over the first interval {1, 2, … ,T1}; Let $\bar{r}_{p,2}$ denote the corresponding mean return over the second interval {T1 + 1,T1 + 2, · · · ,T}; Let $\bar{r}_{B,1}$ and $\bar{r}_{B,2}$ denote the mean returns on the benchmark B over the two intervals. Using this data, we can perform a linear cross-section regression as it showed in equation 1.6.4:

$$\bar{r}_{p,2} - \bar{r}_{B,2} = \delta_0 + \delta_1(\bar{r}_{p,1} - \bar{r}_{B,1}) + \tilde{\epsilon}_p \tag{1.6.4}$$

where the persistence in the average performance of the n funds is given by the coefficient δ_1. The fact that funds that outperformed the benchmark in the first interval tend to repeat their strong performance in the second interval is evidenced by a significantly positive coefficient, δ_1. Instead of using a benchmark, the cross-section method evaluates performance in relation to the market portfolio. Suppose that we observe returns over periods {1, 2, … ,T1, T1 … ,T = T1 + T2} for funds {1, 2, … , p, … , n} and for the market portfolio m. Then, Let $\hat{\alpha}_{p,1}$ denote the estimated alpha of fund p over the first interval {1, 2, · · · ,T1}and let $\alpha\hat{}p,2$ denote the corresponding alpha estimated over the second interval {T1 + 1,T1 + 2, · · · ,T}, it is possible to obtain the coefficient δ_1 through a linear cross section regression presented in equation 1.6.5:

$$\hat{\alpha}_{p,2} = \delta_0 + \delta_1 \hat{\alpha}_{p,1} + \tilde{\epsilon}_p \tag{1.6.5}$$

As it is showed in Table 1.6.1, the cross-section method is used by Goetzmann and Ibbotson (1994) to analyze the estimated alphas of 828 US funds spanning different bi-annual periods between 1976 and 1987.

Intervals	$\hat{\boldsymbol{\delta}}_0$	$\hat{\boldsymbol{\delta}}_1$	**t-student**
78-79 76-77	0.10	0.34	4.99
80-81 78-79	-0.02	0.25	12.08
82-83 80-81	0.08	0.12	1.48
84-85 82-83	-0.09	0.15	2.26
86-87 84-85	0.00	0.60	10.49

Table 1.6.1: Goetzmann and Ibbotson cross-section.

The coefficient δ_1 is highly positive for the majority of intervals, providing strong support for positive persistence. Underperforming mutual fund companies frequently shut or rename their funds very soon. As a result, sampling of fund returns over lengthy periods only apply to the best-performing funds. As a result, there is an introduction of a survivorship bias into the examination of mutual fund performance, leading to an overestimation of the abilities of the portfolio management sector.

According to Brown et al. (1992), survivorship bias can result in erroneous indications of performance improvement over time. Suppose we observe the realized returns, $\tilde{r}_{p,1}$ and $\tilde{r}_{p,2}$ over two subsequent periods for funds {1, 2, … , p, … , n}. We define a winner (loser) in the first (second) period a fund whose return is in the top (bottom) 50% of the distribution of returns.

If a performance is simply the result of chance, the winner-loser joint distribution should look like the following Table 1.6.2:

First Period	**Second Period**	
	Winner	**Loser**
Winner	0.25	0.25
Loser	0.25	0.25

Table 1.6.2: Winner-Loser joint distribution.

The study of Brown et al. (1992), focused on the simulation of the returns of 600 mutual funds mimicking historical US data, over a 4-year period, then the computation of mutual funds performance over 2-year intervals, finally building the empirical joint distribution of winners and losers for 3 scenarios:

- All 600 funds survive in both periods;
- The bottom 5% of the performers are removed from the sample every year;
- Where the bottom 10% of the performers are removed from the sample every year;

The process is at the end repeated for thousands of simulations. In the following Table 1.6.3 managers are classified by risk adjusted returns over successive intervals:

	Second-period Winners	**Second-Period Losers**
A. No cut-off (n=600)		
First-period winners	150.09	149.51
First-period losers	149.51	150.09
B. 5% cut-off (n=494)		
First-period winners	127.49	119.51
First-period losers	119.51	127.49
C. 10% cut-off (n=398)		
First-period winners	106.58	92.42
First-period losers	92.42	106.58

Table 1.6.3: Classification of managers by risk adjusted returns.

If every penny is still in the sample, the joint distribution resembles a random drawing. If the worst funds are eliminated, there is evidence of persistence since there is a higher than 50% chance that first-period winners (or losers) will also be winners (or losers) in the subsequent period. The use of an index proxy for the market portfolio raises the customary identification issues when assessing the alphas of funds. In a similar vein, Roll's criticism of the CAPM (1977) is still relevant. Finally, the data presented by Fama and French (1990) raises the possibility that the CAPM may not be the best model for calculating risk-adjusted returns. The benchmark used to measure fund performance in the persistence analysis is a contentious decision. As a benchmark, a number of other market indexes can often be utilized, which may produce somewhat varied outcome. Moreover, the field of active management is significantly impacted by the EMH, especially when it comes to mutual funds. Portfolio managers that use active management actively choose stocks and time the market in an effort to beat the market. It becomes difficult to consistently outperform the market in an efficient market because prices react quickly to new information. The EMH is closely related to the idea of a "random walk," in which stock prices fluctuate arbitrarily and future price changes are unpredictable. This calls into question the efficacy of mutual funds that are actively managed and make an effort to forecast short-term price fluctuations. For this reason, the popularity of passive investing has increased in part because of the EMH, especially when using index funds. Using passive strategies, you don't actively choose individual stocks; instead, you just track a market index. It is believed that investing passively in the overall market, as opposed to trying to beat it, may make more sense if markets are efficient.

Chapter 2

Classic Literature for Mutual Funds

This chapter delves into a thorough examination of influential theories and research that have influenced the conversation around mutual funds as it attempts to understand the complex dynamics that drive their performance. Starting with the multi-factor models put out by Fama and French (1993) and Carhart (1997), the study goes further with the analysis of crucial performance persistence studies by Hendricks, Patel, and Zeckhauser (1990), Titman S., and Wermers R., (1997), introducing more recent studies by Berk, J., & Van Binsbergen, J. H. (2015) and Cogneau, P. and Hübner, G. (2017). The objective of this chapter is to make an initial comparison between the findings of the classic literature for mutual funds and the recent discoveries, in order to create a solid base that is going to be use in the following chapters. Hence, this second chapter attempts to make connections between these previously introduced models and theories. I set the stage for a comprehensive method of studying and interpreting mutual fund behavior by objectively assessing the advantages and disadvantages of each model, laying the foundation for a sophisticated understanding that goes beyond specific theories.

2.1 Multi-Factoral Models

2.1.1 Fama And French 3 Factors Model

The "mean-variance model" created by Harry Markowitz in 1959 served as the foundation for the Capital Asset Pricing Model (CAPM), which was created by Sharpe and Lintner in 1964 and 1965, respectively. The CAPM model suggested a positive linear relationship between the asset's anticipated risk and return. Systematic risk, which is calculated using beta, is the sole linked risk metric. The beta factor predicts how the rate of return on the shares or portfolio will change in relation to changes in the market. Fama and French (1992) used a sample of non-financial equities listed on the NYSE, NASDAQ, and AMEX between 1963 and 1990 in their original study, resulting into an alternative perspective (or extension) on CAPM in their following study in 1993. This study sought to explain the relationship between expected excess returns and the market premium as well as the value factor measured by the book-to-market equity ratio, which is calculated by subtracting the average excess return on a portfolio with a high ratio of book-to-market stocks from the average excess return on a portfolio with a low ratio of book-to-market stocks. The study also sought to explain the relationship between company size measured by market capitalization, which is determined by taking the average return on the book-to-market equity. In addition to equities, Fama and French (1993) broadened the analysis to include corporate and U.S. government bonds. They confirmed that the Fama and French three-factor model (1993) is successful in explaining the cross-section of average returns on U.S. stocks and that portfolios built based on a market component, book-to-market equity (BE/ME), and size have significant effects on stock returns.

So, the three factors model has been developed by Fama & French (1993), adding two more elements to the one-factor model CAPM (Capital Asset Pricing Model) previously developed by Sharpe (1964). Based on the general market risk, market size, and market value, investors can forecast their return on investment in this situation.

So, it is based on the observation that small-cap and value shares typically beat large-cap and growth shares, respectively. The Fama-French Three Factor model incorporates size risk and value risk into the calculation rather than only measuring market risk as the CAPM does. Based on three factors—general market risk, the extent to which small businesses beat big businesses, and the extent to which high-value businesses outperform low-value ones—the Fama-French Three Factors model determines the anticipated rate of return on an investment. The approach compares small-cap enterprises to large-cap firms by using market capitalization to determine a company's size. It compares high book-to-market value firms to low book-to-market value companies in order to determine a company's value. The book-to-market ratio is just the price-to-book ratio inverted. Value stocks and growth equities are distinguished from one another using the third factor.

Fama and French started with the observation that two classes of stocks have tended to do better than the market as a whole: (i) small caps and (ii) stocks with a high book-to-market ratio (B/P, customarily called value stocks, contrasted with growth stocks). They then added two factors to CAPM to reflect a portfolio's exposure to these two classes, generating the following formula (equation 2.2.1):

$$r = R_f + \beta(R_m - R_f) + b_s \cdot SMB + b_v \cdot HML + \alpha \tag{2.2.1}$$

Where r is the portfolio's expected rate of return[5], Rf is the risk-free return rate[6], and Rm is the return of the market portfolio. The "three factor" β is analogous to the classical β but not equal to it, since there are now two additional factors to do some of the work. SMB stands for "Small [market capitalization] Minus Big" and HML for "High [book-to-market ratio] Minus Low".

In particular, SMB is the performance of small-cap companies vs. large-cap companies, while HML is the performance of high book-to-market (or "value") stocks vs. low book-to-market (or "growth") stocks. Under the CAPM model, the return on your

[5] The return expected by a portfolio made up of all the shares available in the market.

[6] The return expected by an investment with no risk.

investment is estimated based entirely on overall market risk. The Fama-French Three Factor model instead estimates an investment's return based on market risk, market size and investment value.

The Fama-French Three Factor model's last variable, α (alpha) stands for the investment's risk. More officially, this is referred to as the investment's alpha. This variable is used somewhat infrequently. An investment's capacity to outperform the market is measured by alpha. An investment has value that an investor's market research hasn't recognized if a particular investment or portfolio manages to produce higher returns than comparable investments in the overall market. For unforeseen weak returns, the same is true in reverse. It is described as the investment's alpha. When an investment outperforms what the Fama-French model predicts, it means that its returns were higher than what an investor may have anticipated given its composition in relation to the market's overall risk, size, and value. (Again, the contrary would be accurate). This is what we would refer to as the investment's "alpha," which is often determined as the percentage by which the investment exceeded expectations. The alpha is typically not employed in predictive Fama-French Three Factor models unless there are specific reasons to think an investment will outperform or underperform the market.

Small businesses typically outperform large businesses in terms of stock market returns over the long run, according to one of the two main findings of the Fama-French Three Factor model. This model component reflects that finding.

The SMB factor of the model assesses how much historically small-cap enterprises have outperformed large-cap firms in terms of returns. The model also predicts that investment portfolios with smaller firms will have greater rates of return than portfolios with larger companies, which helps to tilt the model in favor of small-cap enterprises. The Fama-French model's second important finding is that businesses with higher book-to-market values often generate higher returns than those with lower book-to-market values. This model's factor accurately represents the finding. The HML component of the model compares the average return on value portfolios—those with high book-to-market value—against the average return on growth portfolios—those with low book-to-market value—in order to determine which returns are more favorable.

Finally, the Fama-French Three Factor model predicts that investment portfolios with value stocks will have greater rates of return than portfolios with growth stocks, which helps to tilt the model in favor of value stocks.

2.1.2 Carhart 4 Factors Model

One of the most thorough and comprehensive analyses on the subject is that by Carhart. He explores how the momentum component, which Jegadeesh and Titman (1993) describe but which Hendricks, Patel, and Zeckhauser (1993) did not take into account, can account for a significant portion of the excess return of mutual funds by beginning with their findings. In particular, the one-year momentum impact of Jegadeesh and Titman (1993) is primarily responsible for Hendricks, Patel, and Zeckhauser's (1993) "hot hands" result; nevertheless, individual funds do not see higher returns when investing in equities using the momentum method. The strongest underperformance by the mutual funds with the poorest returns is the only notable persistence that cannot be explained. The findings don't suggest that knowledgeable or professional mutual fund portfolio managers exist.

Although certain mutual funds just so happen to maintain substantially greater positions in the winning equities from the previous year, this does not explain why some funds have higher one-year returns than others. Rarely do hot-hands funds repeat their abnormal performance. Wermers (1996) contends that momentum strategies alone produce short-term persistence, in contrast to Grinblatt, Titman, and Wermers (1995), who find that funds that use momentum strategies outperform their peers before management fees and transaction costs. Individual mutual funds that look to follow the one-year momentum approach have much lower anomalous returns after expenses. Its dataset is made up of monthly results from 1892 various US-domiciled funds, including inactive and merged funds, and is hence survivorship bias-free, analyzed using mainly wo models: the Capital Asset Pricing Model (CAPM) described in Sharpe (1964), and the (Carhart (1995)) 4-factor model, that is built using the Fama & French's (1993) 3 factors model and adding another factor capturing Jegadeesh and Titman's (1993) one-year momentum anomaly.

Performance in comparison to the CAPM, 3-factor, and 4-factor models is calculated as it is showed by the following equations 2.3.1, 2.3.2, 2.3.3:

$$r_{it} = \alpha_{iT} + \beta_{iT} VWRF_t + e_{it} \qquad t = 1,2,\dots,T \tag{2.3.1}$$

$$r_{it} = \alpha_{iT} + b_{iT} RMRF_t + s_{iT} SMB_t + h_{iT} HML_t + e_{it} \quad t = 1,2,\dots,T \tag{2.3.2}$$

$$r_{it} = \alpha_{iT} + b_{iT} RMRF_t + s_{iT} SMB_t + h_{iT} HML_t + p_{iT} PR1YR_t + e_{it} \quad t = 1,2,\dots,T \tag{2.3.3}$$

where r, is the return on a portfolio in excess of the one-month T-bill return; VWRF is the excess return on the CRSP value-weighted portfolio of all NYSE, Amex, and Nasdaq stocks; RMRF is the excess return on a value-weighted aggregate market proxy; and SMB, HML, and PRlYR are returns on value weighted, zero-investment, factor-mimicking portfolios for size, book-to-market equity, and one-year momentum in stock return. Tts momentum factor (i.e. PR1YRt) is constructed as the equal-weight average of firms with the highest 30 percent eleven-month returns lagged one month minus the equal-weight average of firms with the lowest 30 percent eleven-month returns lagged one month.

In the following Table 2.1.2.1[7] it is reported that the 4-factor model may adequately account for significant returns variance. First, observe the low correlations between the SMB, HML, and PRlYR zero-investment portfolios and their comparatively high variation compared to the market proxies. This indicates that the 4-factor model can account for significant time-series variation. Second, the significant cross-sectional variation in the mean return on stock portfolios may be explained by the high mean returns on SMB, HML, and PRlYR. The low cross-correlations also suggest that multicollinearity has little impact on the predicted 4-factor model loadings.

				Cross-Correlations				
Factor Portfolio	**Monthly Excess Return**	**Std Dev**	**t-stat for Mean=0**	**VWRF**	**RMRF**	**SMB**	**HML**	**PR1YR**
VWRF	0.44	4.39	1.93	1.00				
RMRF	0.47	4.43	2.01	1.00	1.00			
SMB	0.29	2.89	1.89	0.35	0.32	1.00		
HML	0.46	2.59	3.42	-0.36	-0.37	0.10	1.00	
PR1YR	0.82	3.49	4.46	0.01	0.01	-0.29	-0.16	1.00

Table 2.1.2.1: 4-Factors Model for significant returns variance.

Since the 3-factor model takes into account both size and book-to-market equity characteristics, it is not surprising that it reduces average pricing errors from the CAPM. The 3-factor model errors, however, are highly negative for the portfolios of losing stocks from the previous year and strongly positive for the portfolios of winning stocks. In contrast, compared to both the CAPM and the 3-factor model, the 4-factor model significantly lowers the average price errors. The mean absolute errors from the

[7] VWRF is the Center for Research in Security Prices (CRSP) value-weight stock index minus the one-month T-bill return. RMRF is the excess return on Fama and French's (1993) market proxy. SMB and HML are Fama and French's factor-mimicking portfolios for size and book-to-market equity. PRlYR is a factor-mimicking portfolio for one-year return momentum

CAPM, three-factor, and four-factor models are 0.35 percent, 0.31 percent, and 0.14 percent each month, respectively, for the purposes of comparison.

The 4-factor model also virtually removes all pricing error patterns, showing that it accurately captures the cross-sectional diversity in average stock returns.

The establishment of 10 portfolios, held for the next year, and then rebalanced, forms the basis of the research. Each January, funds are categorized in the portfolios based on the decile distribution of their prior year's annualized return. This yields a time series of monthly returns on each decile portfolio from 1963 to 1993. In the previous winners portfolio, he discovers evidence of a definite performance persistence in the form of a monthly spread between top and bottom performers' returns of about 67 basis points. He then runs the CAPM and the 4-factor model regression on the returns of these portfolios and examines the results; the CAPM doesn't seem to be able to explain the relative returns, as the market beta is almost the same for all portfolios. Instead, its 4-factor model generates a much more valuable output because the momentum and size coefficients can more accurately capture the differences between the two portfolios. In particular, the momentum factor accounts for nearly half of the spread, indicating that the portfolio with the best performance can gain from the performance of the best-performing stocks in its assets. The fact that the alphas don't seem to deviate much from 0, though, emphasizes how irrelevant managerial abilities are to this theory.

Carhart's study takes a step further by attempting to determine whether the remaining portion of unexplained persistence can be linked to particular fund characteristics. He discovers that expense ratios and portfolio turnover by themselves are unable to fully account for the remaining gap between the performance of low and high decile portfolios identified by the regression, but at least he shows that the losers portfolios have higher than average expenses, which may be a factor in their poor performance.

The next analytical exercise he completes entails assessing the impact of these fund features on the performance of each particular fund.

To do this, he estimates a supplemental regression using the 4-factor model's single fund alphas as well as the expense ratio and turnover in turns as explanatory variables. The results of this intricate approach point to a significant relationship between fund attributes and performance. In particular, he can attest that funds typically do not recover their transaction costs through improved returns, which is more evidence against the idea that management decisions have a favorable impact.

Since investors are paying for the quality of the manager's knowledge and because managers only trade to increase expected returns net of transactions costs, mutual fund managers contend that fees and turnover do not have an adverse effect on performance. As opposed to what was implied in the previous section, costs and turnover should instead have a neutral or positive impact on performance. In order to explain such a claim, he measures the marginal effect of specific variables on abnormal performances performing a monthly cross section regression, then average the coefficient estimates across the complete sample period. The result is that performance is closely related to size, expense ratios, turnover, and load fees. Moreover, the correlation between performance, expense ratios, and modified turnover points to the possibility that mutual funds do not, on average, provide returns that cover their investing costs.

The last section of Carhart's research examines consistency in fund ranking using a contingency table that shows how fund decile membership has changed over time. This led to the uninteresting conclusion that winners are more likely to stay winners and losers are more likely to perish; however, the noteworthy finding is that the top decile's fund composition varies significantly each year with a turnover rate of roughly 80%. Additionally, prior champions frequently turn into losers the next year.

Finally, Carhart examines whether the degree of ex- planation for the spread in mean returns between ranks of portfolios is impacted by extending the estimation time for the decile portfolios creation to two, three, four, and five years. This means that the 4-factor model is essentially unable to explain the differences in returns after an extension to a 3-year estimation period, and the remaining spread is attributable only to expense ratios (for about 1/3) and mostly to unidentifiable variables. He concludes that a larger estimation period clearly reduces this spread, but its absolutely unexplained quantity remains unchanged. Therefore, the profits from using a momentum approach in equities are offset by transaction expenses. Turnover has a detrimental effect on performance as well as that expenses have a negative influence on fund performance that is at least one-for-one. Calculations show that trading reduces performance by about 0.95 percent of the market value of the trade. The variation in transaction costs between mutual funds also contributes to the performance's consistency. Additionally, it is shown the existence of a large and negative correlation between fund performance and load fees, which is likely caused by load funds' higher total transaction costs. What little evidence there is in this article to demonstrate the existence of mutual fund manager stock-picking skill is obscured by the joint-hypothesis difficulty of assessing market efficiency conditional on the enforced equilibrium model of returns. High historical alpha funds show relatively higher alphas and predicted returns in the future. However, because the same model is used to rank funds in both eras, these results are susceptible to model misspecification. These funds also generate predicted future alphas that are little different from zero. Therefore, even though the majority underperform by roughly their investing costs, the top past-performance funds seem to recoup their costs and transaction fees. This article goes a long way toward explaining how common factors like stock returns and investing fees might explain short-term persistence in equity mutual fund returns.

Mutual funds from last year's top decile and bottom decile can be purchased and sold to generate an annual return of 8%. Differences in the market value and momentum of the stocks held account for 4.6 percent of this gap, while variations in expense ratios account for 0.7 percent and variations in transaction expenses account for 1 percent. Smaller spreads in mean returns are obtained by grouping mutual funds according to longer time periods of historical returns; all but about 1% of these differences can be attributed to common factors, such as expense ratios and transaction expenses. Performance is strongly and negatively correlated with expense ratios, portfolio turnover, and load fees. Performance seems to be decreased by expense ratios slightly greater than one-for-one. Unexpectedly, load funds perform significantly worse than no-load funds. After adjusting for the association between costs and loads and excluding the quintile of funds with the lowest performance, it is shown that the average load fund underperforms the average no-load fund by about 80 basis points annually.

High 4-factor alpha mutual funds exhibit above-average alphas and anticipated returns in subsequent periods. Since the same model is employed to estimate performance in both periods, these results are not resistant to model misspecification. In addition, as high-alpha funds do not generate considerably positive predicted future alphas, the better expected performance for these funds is merely relative.

Finally, the evidence in this article points to three key guidelines for investors in mutual funds who want to maximize their wealth: (1) Avoid funds with consistently poor performance; (2) Funds with high returns last year have higher-than-average expected returns next year, but not in years after; and (3) Investment costs such as expense ratios, transaction costs, and load fees all have a direct, detrimental effect on performance. While the mainstream media will undoubtedly continue to glorify the top mutual fund managers, practically all of the crucial predictability in mutual fund returns can be attributed to the boring explanations of strategy and investment expenses.

The research offers proof that the relative performance of mutual funds exhibits short-term persistence. Short-term outperformance is expected to persist for funds that have performed well recently. However, the data points to a long-term reversal in performance, even in the face of short-term persistence. Mutual funds that perform well relative to their peers for a short while typically see a drop in performance in the following years. The study admits that not all mutual funds exhibit the same level of performance persistence. Certain funds are persistent in the short term, but others don't show a consistent pattern of outperformance over time. Although certain research endeavors to pinpoint proficient fund managers, chance continues to play a part, particularly in the near run. When analyzing fund performance, academics and investors frequently struggle to separate the benefits of talent from chance.

2.2. Performance Persistence Theories

2.2.1 First Evidence Of Short-Term Persistence

Hendricks, Patel, and Zeckhauser (1990) examine the performance of open-end, no-load funds from 1974 to 1987 using standard Jensen and Sharpe measures on methods that take advantage of the identification of funds with "hot hands," and they find compelling evidence supporting that mutual funds that perform well over the course of a year (short term) are likely to continue to perform well the following year. The hot hands strategy's success is unrelated to choosing superior investments during the study period. Knowing when to choose which fund involves time, which is important.

Practically, they evaluate whether a hot-hands strategy enhances performance unambiguously relative to the benchmark in a mean-variance framework (given the selection of the risk-free asset) in accordance with Dybvig and Ross (1985). These findings hold up well against alternative benchmarks for equity portfolios, such as those that take firm-size effects and mean reversion into consideration. An investor could have made a big, risk-adjusted excess return of 10% a year by taking advantage of the hot hands phenomena.

First of all, they assess fund performance as the α of the Capital Asset Pricing Model applied to excess returns:

$$(R_{it} - R_{ft}) = \alpha_{it} + \beta_i(R_{mt} - R_{ft}) + \epsilon_{it} \; with \; i = 1, \dots, N, t = 1, \dots, T \tag{2.1.1}$$

Where $(R_{it} - R_{ft})$ is the difference between the return by fund i over quarter t, net of all fees and assuming dividend reinvestment and the risk-free return over quarter ((which we proxy by the yield on 90-day U.S. treasury bills). R_{mt} is the return to the market (benchmark) portfolio over quarter t. α_{it} is the Jensen's alpha that measure the superiority of fund i in period t relative to the benchmark portfolio m in a mean-variance framework. Then β_i is 'beta' of fund, which is assumed to be time-invariant for convenience: measures systematic risk of fund i within the Capital Asset Pricing Model (CAPM). Finally, ϵ_{it} is the ex-post idiosyncratic component of the return, which would be unpredictable under a joint hypothesis of the CAPM and the EMH (Efficient Market Hypothesis).

Since they are interested in the dynamic properties, if any, of the α parameter for mutual funds, they introduce three main hypotheses:

- H1: $\alpha_{it|t-1} = 0, for\ all\ i$ → This is the traditional null hypothesis that states that performance is unpredictable, and $|t-1$ means that information is available ex-ante.
- H2: $\alpha_{it|t-1} = \mu_i, with\ \mu_i \neq 0\ for\ some\ i$ → some funds have a constant nonzero ex-ante excess performance.
- H3: $\alpha_{it|t-1} = \mu_i + f_i(\alpha_{t-j}; j > 0), with\ f_i \neq 0\ for\ some\ i\ and\ some\ t$ → the conditional mean is nonzero and time varying.

Even if the unconditional mean, μ_i, is zero, they reject H1 as long as the conditional prediction is nonzero for some t. H3 admits funds that have hot hands, that is, funds that are expected to be superior performers in the near term.

In the next step, they consider a sample of 96 no load equity funds with growth objective (i.e. investment funds that stated they sought growth, aggressive growth, or growth plus income) because they are more practical since the transaction costs associated with investing in (and switching between) them are negligibly different from zero, neglecting tax consequences. Considering this sample, they test the previously introduced hypothesis for the excess returns, deciding to reject the joint hypothesis of zero α's in all tests when testing H1 vs. H2, despite the fact that the majority of fund α's are not significantly different from 0, primarily because they focus their analysis on growth-funds that consistently achieve positive excess returns. However, they are unable to identify a feasible investment strategy that could produce significant excess returns in response to this finding, rendering it without application. In testing H2 vs H3 instead, the approximate autoregressive order is of relevance in order to identify a practical exploitation of this persistence, since under H3 the residuals ε_{it} (which under H2 would represent white noise in the CAPM formula) would be serially auto correlated. To assess this auto-correlation, they use the modified Q-statistics, following Harvey, (1990, p.211), according to equation 2.1.2:

$$Q = T(T+2)\sum_{j=1}^{L}[\ \dot{\rho}_j^2/(T-j)] \tag{2.1.2}$$

Where $\dot{\rho}_j^2$ is the estimated residual autocorrelation at lag j and T is the number of observation. The Q-statistic tests the hypothesis that all of the autocorrelations of a series up to lag L are zero. In order to understand three years' worth of results, they give their data a lag period of 12 and discover that around one-third of it has a significant Q-statistic at the 10% level, discarding H2 in favor of H3. The approximate autoregressive order of Jensen's alpha under H3 is of interest for a practical exploitation of short-term persistence in performance. The order denotes the appropriate time frame for projecting performance in the future. Considering an optimal time period for predicting future performance of four quarters (1 year), they find that the sums of squared partial correlations (equation 2.1.3) can be used to draw preliminary conclusions:

$$q_k = T\sum_{i=1}^{N}\ \dot{\rho}_{(i)kk'}^2 \tag{2.1.3}$$

Where $\dot{\rho}_{(i)kk'}^2$ is the estimate of the k^{th} partial autocorrelation in the residuals of fund i. The pattern of q_k's, setting low p-values up to k=4, indicate that an AR (4) process adequately approximates the time-dependence in the market model residuals. Practically, performance data from the previous four quarters appears sufficient for accurate performance forecast.

Finally, by examining alpha persistence over various sub-period lengths and selecting a weighted mix of the best mutual funds, which is updated at the end of each holding period, they analyze various investment strategies, employing the time-series regression approach discussed in Grinblatt and Titman (1989) as well as contingency table analysis. The relative validity of H2 and H3 will determine the relationship between the size of the persistence and the duration of the subsample. If H2 is correct, the greater the relationship between the alphas from various periods will be because the sampling variance of the estimate will be reduced the longer the time used to estimate alpha. On the other hand, under H3, the relations will fluctuate in a complex way but degenerate exponentially after a certain maximum subperiod length if the unconditional mean of alpha is zero but its conditional mean is time variable.

The results for the ideal balance of estimating and holding periods are presented in the Table 2.2.1.1 below, where "4E 4H" denotes an estimation period of four quarters and a holding term of four quarters (each lasting one year). In addition, the α's estimate appears to be statistically significant and indicates an excess annualized return greater than 10%, which is an exceptional finding given that the Efficient Market Theory EMH postulates a 0 α. The Table also displays a quarterly average return spread of more than 5% between the best and worst performers and a difference of 0.4 in Sharpe's Measure[8].

			Jensen's Alpha (%) Benchmarks			
			S&P 500		EWMF	
4E 4H Strategy	**Mean Return**	**Sharpe's Measure**	**Value**	**t-statistics**	**Value**	**t-statistics**
Worst Fund	-0.55	-0.05	-2.26	-2.15	-2.51	-2.76
Best Fund	4.78	0.40	3.10	2.67	2.77	2.88
Best - Worst	5.33	0.52	5.36	3.55	5.28	3.49

Table 2.2.1.1: Ideal balance of Estimating (E) and holding periods (H).

The Table compares the best and worst fund measures according to calculations made after 4 quarters of Estimation (4E) and 4 quarters of Holding (4H). The measures

[8] Sharpe's Measure is the mean of the quarterly returns divided by the standard deviation of the quarterly returns

discussed are the average quarterly return, the Sharpe's Measure, and the alphas derived using the S&P 500's value weighted market index and the Dow Jones Industrial Average's equally weighted market index benchmarks, respectively, along with their t-statistics. Positive investment techniques, however unreported, that take advantage of the rejection of H1 in favor of H2 do not, as Grinblatt and Titman (1987) found, produce appreciable additional returns (either statistically or economically). Despite a statistically substantial rejection of H1, the failure to uncover meaningful ex-ante performance techniques is consistent with sample survivorship bias. In conclusion, even though we can statistically rule out H1 in favor of H2, that result seems to be of little practical significance.

Finally, they assess the time frame for which historical performance is significant. The signal of better performance owing to talent is drowned out by chance factor noise if the evaluation period is too brief. The importance of "hot hands" decreases over an extended examination time. The assessment period of one year yields the best findings, which is consistent with the lag-length beyond which partial autocorrelations in excess returns are no longer meaningfully different from zero.

2.2.2 Mutual Funds performance analysis with Characteristic-Based Benchmarks

The study by Titman S., and Wermers R., (1997), makes a valuable contribution to the filed of mutual fund performance evaluation by introducing characteristic-based benchmarks and incorporating detailed quarterly portfolio holdings data. Considering all U.S. equity mutual funds that existed during any given quarter between December 31, 1974 and December 31, 1994, the objective of the authors is to use benchmarks based on characteristics to assess mutual fund performance. The writers concentrate on figuring out how well mutual funds do in comparison to benchmarks that are created using the unique attributes of the funds, like momentum, size, and book-to-market ratio. By constructing characteristic-based benchmarks[9] for each mutual fund in the sample, they evaluate the performance of mutual funds against both traditional benchmarks such as market indices and the characteristic-based benchmarks, trying to provide a more nuanced assessment that considers the specific attributes of each fund. The usage of these newly introduced characteristic based benchmarks is an important contribution to mutual funds theory, as it recognizes that mutual funds may have unique investment styles. The information presented in this article indicates that, indeed, the average mutual fund achieves success in this particular aspect. Nevertheless, the article reveals that the margin by which the average mutual fund outperforms a mechanical strategy is relatively modest and roughly equivalent to the average management fee. It is likely that aggressive-growth and growth funds, which demonstrate superior performance, also incur higher associated costs. However, the outperformance of aggressive-growth and growth funds compared to growth-income funds cannot be solely attributed to momentum investing. Despite these funds selecting stocks with higher momentum, the residual performance, after accounting for momentum, remains somewhat higher for aggressive-growth and growth funds than for growth-income and balanced funds.

Additionally, the measure of selectivity based on characteristics does not assign significant abnormal performance to investors who consistently adhere to the same mechanical characteristic-based strategy throughout the entire period, even if that strategy performs exceptionally well. However, abnormal performance is attributed to portfolio managers who alter their investment styles over time, adopting styles with the highest expected returns.

[9] These benchmarks are designed to reflect the fund's specific investment style and characteristics, and they are designed to measure whether mutual funds pick stocks that outperform simple mechanical rules.

In conclusion, the study's findings suggest that the "hot hands" phenomenon documented by Hendricks, Patel, and Zeckhauser (1993) can be elucidated by considering these distinct benchmarks.

2.2.3 Recent Performance Persistence Theories

The more recent study on mutual funds performance persistence conducted by Berk, J., & Van Binsbergen, J. H. (2015) shows that the Null Hypothesis that mutual fund managers have no skill is rejected. Starting from a comprehensive dataset of U.S. mutual funds, both active and passive, and covering multiple years, the primary objective is to examine whether mutual fund managers possess skill in generating superior returns relative to their benchmark and, if so, measuring and identifying that skill. Even though the initial findings of this study are in line with the classic literature[10], the authors are able to identify a subset of fund managers who demonstrate skills, as indicated by their consistent outperformance relative to random portfolios. These skillful managers are characterized by a positive ACI. This ACI (Alpha Consistency Index)[11] is a quantitative measure of skill. Funds with higher ACI scores are more likely to have skillful managers who generate consistent positive alpha. As a consequence, funds managed by skillful managers, as measured by their ACI scores, tend to generate higher returns for investors. The main contribution of this study is given by three main innovations. First, the introduction of the ACI parameter

[10] The majority of mutual fund managers do not exhibit statistically significant skill in generating returns that consistently surpass random chance. This implies that, for many funds, their performance may be attributed more to luck than skill.

[11] This index has been introduced for the first time by the authors to conduct the analysis and it is measured as the difference between the alpha of the analyzed sample of mutual funds and the alpha of another sample of randomly generated mutual funds, comparing then the fund's actual alpha to the distribution of alphas generated by random portfolios. The ACI metric provides a quantifiable measure of skill. Funds with higher ACI scores are more likely to have skillful managers who generate consistent positive alpha.

to assess the skill of mutual fund managers. Second, they used a Vanguard benchmark to calculate fund alphas, rather than relying on a risk model. Third, they used a full cross-section of mutual funds available to a U.S. investor, including global funds. The discovered evidence of skill cannot be attributed solely to luck since variations in skill persist cross-sectionally for up to a decade. Moreover, investors seem capable of recognizing and appropriately rewarding this skill. Improved funds not only accumulate higher overall fees, but present aggregate fees prove to be a more reliable indicator of future value addition than past performance. In their research, the authors discover that the average abnormal return for investors hovers around zero. Moreover, there is limited evidence indicating that investors can achieve a positive net alpha by aligning with the top-performing funds. The study, both theoretically and empirically, demonstrates why conventional alpha-based metrics for assessing managerial skill fall short, contributing to the lack of support for such skill in prior literature. The authors clarify the functions of traditional measures present in existing literature. The net alpha gauge reflects the rationality of investors and the competitiveness of capital markets. A positive net alpha suggests a lack of competitiveness in capital markets, while a negative net alpha implies some investors' irrationality in allocating excessive funds to active management. The authors argue that due to substantial cross-sectional variation in Assets Under Management (AUM), the gross alpha serves no purpose—it neither gauges managerial skill nor the returns to investors.

Another important recent study was developed by Cogneau, P. and Hübner, G. (2017). Analyzing a sample of 1625 international equity mutual funds (between 1984 and 2016), they have been able to isolate 147 portfolio performance measures (and their variations) that can explain the persistence of the performances of those selected funds. The study's main conclusion is that performance persistence is not a common occurrence. Rather, it is contingent upon the performance measure selected. In comparison to metrics that concentrate on total returns, like the Sharpe ratio, metrics that highlight downside risk, like the Sortino ratio, typically show less persistence. Accordingly, when assessing mutual funds, investors ought to give careful thought to the performance metric they select. The fact that persistence is typically stronger in the short term than in the long term is another significant finding. This suggests that, particularly over longer time horizons, past performance is not a good indicator of future performance. When choosing investments, investors should consider the long term and exercise caution when extrapolating past performance to predict future results. Persistence is stronger for funds with higher fees, according to the study. This implies that prior to investing, investors ought to carefully evaluate a fund's fees. Even if a fund shows persistence, higher fees could limit its potential return. The study also discovered that more actively managed funds have weaker persistence. This suggests that performance is not always sustained by active management. Before making an investment, investors should carefully consider the fund's investment style and be aware that active management may not always result in higher returns. The study concluded by showing that funds that allocate their investments to more volatile asset classes have lower persistence. This implies that buyers and sellers of volatile asset classes need to be informed about the risks involved. Diversification among asset classes may lower risk and even improve performance over the long run.

Chapter 3

Empirical Analysis

Having in mind the pillars for mutual funds theory, this third chapter aims to introduce the first analysis on the performance of a sample of mutual funds, built under some specific constraints. After explaining how and why this sample of equity mutual funds has been created, I delve firstly into the introduction and then computation and analysis (across different time horizons, both short and long term) of the most important parameters for mutual funds (Alpha, Beta, R-squared, Correlation, Sharpe Ratio). The objective in this case is to compare the results obtained through the analysis of a modern sample of mutual funds with the classic literature findings, in order to understand whether they are similar or not, and why. Finally, I went further in the analysis to verify if a relevant portion of this sample of funds is able to beat their own benchmark or not, making a distinction between performances generated as a consequence of skills of the fund managers, and those performances that are the consequence of luck.

3.1 Data

With the objective of having a broader perspective for the analysis, without focusing only on the European, American or Asian market, I decided to consider global open-end actively managed equity mutual funds during the period 2009 - 2022, for a total number of 5148 mutual funds. The term "Global" means that all the selected funds are focused on a global investment strategy. Mutual funds that invest in a diverse portfolio of securities from multiple nations worldwide are referred to as "global mutual funds". The goal of these funds is to expose investors to global markets so they can take part in the success of businesses and economies that are located outside of their own nation. In this context, "global" refers to a wide-ranging and inclusive investment plan that crosses several geographical areas.

The analysis is survivorship bias-free, as I included both active and dead funds during the period of observation. Furthermore, I considered only common equity mutual funds and excluded sectoral, hedge and short funds, as well as pure index funds, ETFs and ETNs. I decided to consider equity mutual funds starting from January 2009 and not before because the performances of previous born mutual funds may be negatively affected by the 2008 financial crisis, without specifically showing a real implication of the fund manager investment strategy.

The database that has been used to gather all the needed data to conduct the study is Refinitiv Eikon web platform by Thomson Reuters[12], using the advanced fund screener tool that gave me the possibility to build the sample on the basis of all the previously mentioned constraints.

3.2 Fund performance vs Benchmark Analysis

In order to conduct the first part of the analysis, I decided to divide the overall sample of 5148 global equity mutual funds into four different groups on the basis of data availability (e.g., Return, NAV, Correlation):

- Group 1, mutual funds with at least 1 year of life, so the overall sample (5148).
- Group 2, mutual funds with at least 3 years of life, for a total of 3680, excluding the funds born after September 2020.

12 https://eikon.refinitiv.com/

- Group 3, with at least 5 years of life, for a total of 2522, excluding the funds born after September 2018.
- Group 4, with at least 10 years of life, for a total of 812, excluding the funds born after September 2013.

The objective in this case is to understand how the performances of the same mutual fund vary over time, by analyzing the variation of a specific group of performance parameters of the mutual funds of the last 12 months (1 year) to last month end (31st December 2022), going then further considering also the last 36 (3 years), 60 (5 years), 120 (10 years) months to last month end[13]. The final goal relies on understanding whether these mutual funds have been or not able to "beat" their benchmark.[14] I am also including in the previously mentioned groups those mutual funds that "died" before 1 year, 3 years, 5 years, 10 years (survivorship bias-free)[15].

The relevant parameters computed for this part of the analysis are Alpha, Beta, R-Squared, Sharpe Ratio, Correlation, Standard deviation. Each one of them is calculated for each single mutual fund of the four groups on the different considered time horizons. For Group 1, the indicators are computed on a 1-year basis, for Group 2 on a 3-years basis, for Group 3 on a 5-years basis, for Group 4 on a 10-years basis. The

[13]"Last Month End" means that that the computation of the parameters of the analysis is performed considering the last 12 months (in case of 1 year), 36 months (in case of 3 years), 60 months (in case of 5 years), and 120 months (in case of 10 years), leading up to the last month for which data is available, that is always the 31st of December 2022.

[14]When a mutual fund is said to "**beat the benchmark**", it means that the fund has generated a higher return on investment compared to a specific index or benchmark that is used as a standard for measuring its performance. Benchmarks are typically well-known and widely followed indices, such as the S&P 500 for U.S. stocks or the Barclays Aggregate Bond Index for bonds. This suggests that the fund's management team has made investment decisions or employed strategies that have led to better returns for investors compared to simply investing in the benchmark index.

[15]Practically, I am considering the same mutual funds for all the groups, but the number is smaller from one group to the other because I am excluding some funds from the overall sample. For example, taking Group 4, I need to consider 10 years old funds minimum, because otherwise I could end up considering thousands of other younger funds for which it is impossible to have data, affecting the results. This does not mean that all the funds of the group are still "alive" (survivorship bias-free).

final part of the computation consists in the definition of the annualized average Alpha, Beta, R-Squared, Sharpe Ratio, Correlation, Standard deviation for the four groups.

3.2.1. Indicators definitions

To be more specific, I would like to explain why these parameters are at the basis of the Modern Portfolio Theory (MPT) to determine the risk-return profile of an investment strategy/mutual fund, and why they are more relevant than others for this kind of analysis.

- The ability of an investment strategy defined by a trader of a portfolio manager to outperform the market, or its "edge", over a certain period of time, is referred to in the investing world as **Alpha**[16]. Thus, when risk is taken into account, alpha is also frequently referred to as "excess return" or the "abnormal rate of return" in reference to a benchmark. In particular, alpha is computed as the difference between the return/performance of an investment strategy and the return/performance of the market index or benchmark that is considered to represent the market's movement as a whole. So, alpha is the excess return of an investment relative to the return of a benchmark index, ending up having a value that can be either positive or negative. In relation to mutual funds, it is often considered to represent the value that a portfolio manager adds to or subtracts from a fund's return. Alpha, then, is the return on an investment that does not originate from a broad trend in the larger market. As a result, an alpha of zero would mean that the portfolio or fund is perfectly mirroring the benchmark index and that the management has not gained or lost any

[16] Fidelity Report: https://www.fidelity.com/learning-center/investment-products/etf/smart-beta

additional value throughout the course of the general market. Finally, the classic formula used for Alpha is presented in equation 3.2.1.1:

$$Alpha = \frac{End\ Price + DPS - Start\ Price}{Start\ Price} \tag{3.2.1.1}$$

Where DPS is the Distribution per share.

In particular, the type of alpha that I use to carry out the analysis is computed over the different time horizons (1, 3, 5, 10 years) until the end of the last month (September 2023 in this case). It means that, for example the alpha 1 year to last month end is computed as in the following equation 3.2.1.2:

$$Alpha = Actual\ Return\ fund\ 1\ year - Actual\ Return\ benchmark\ Index\ 1\ year \tag{3.2.1.2}$$

Where the first item of the formula is calculated as showed in the following equation 3.2.1.3:

$$Actual\ Return\ fund\ 1\ year = \frac{Ending\ Value - Beginning\ Value + Income}{Beginning\ value} \tag{3.2.1.3}$$

Ending value is the value of the NAV[17] in Euro in September 2023 (last month end), and Beginning Value is the value of the NAV 1 year before (September 2022). The Income accounts for any income generated by the investment during the time period, such as interest, dividends, or capital gains.[18]

[17] The Net Asset Value (NAV) of a mutual fund is the per-share market value of all the securities held in the fund's portfolio, minus any liabilities, divided by the total number of outstanding fund shares. It represents the price at which investors buy and sell mutual fund shares.

[18] The same logic is applied in case of alpha 3, 5, 10 years to last month end. The Ending value is always the same (NAV of the fund as of September 2023), while the beginning value is the NAV of the fund as of September of 3, 5, 10 years before.

The second item of the formula ($Actual\ Return\ benchmark\ Index\ 1\ year$) is computed following the same logic, but taking into account the benchmark index.

- **Beta**, often known as the beta coefficient, is a measure of a stock's, a fund's, or a stock portfolio's volatility relative to the market as a whole. Investors can assess whether a stock is worth the risk by understanding how volatile its price is. 1 is the default value for beta, meaning that the security's price moves in lockstep with market trends. A security's price is less volatile than the market if its beta is less than 1, and the opposite is true if its beta is bigger than 1. A stock is regarded as 50% more volatile than the market as a whole if its beta value is 1.5. While a positive alpha is always preferable than a negative alpha, the situation with beta is less straightforward. Lower beta is appealing to risk-averse investors, including seniors looking for a consistent income, while higher beta equities are frequently acceptable to risk-tolerant investors looking for greater returns. The formula to compute the beta is the following (equation 3.2.1.4):

$$Beta = \frac{CR}{Variance\ of\ Market's\ Return} \qquad (3.2.1.4)$$

Where CR is Covariance of asset's return with market's return, that is used to calculate the correlation between the price changes of any two stocks. A positive covariance indicates that the stocks often move in unison, whereas a negative covariance indicates that they typically move in opposition. The variance describes how much a stock deviates from its mean. It is regularly employed to gauge the price volatility of a stock over time.

- The correlation between any change in an asset's price and a benchmark is gauged by **R-squared**[19], that is measured on a scale between 0 and 100; the higher the R-squared number, the more correlated the asset is to its benchmark. A hypothetical mutual fund with an R-squared of 0 has no correlation to its benchmark at all. A mutual fund with an R-squared of 100 matches the performance of its benchmark precisely.
- According to the CAPM (Capital Asset Pricing Model) developed by Sharpe (1994)[20], the Sharpe Ratio is a measure of an investment’s risk adjusted performance, calculated by comparing its return to that of a risk-free asset. The idea that excess returns over time may indicate greater volatility and risk rather than investment expertise is expressed mathematically in this way. The formula for its computation is presented in equation 3.2.1.5:

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p} \tag{3.2.1.5}$$

Where R_p is the return of the overall portfolio and R_f is the risk-free rate (return expected from an investment with no risk), and σ_p is the standard deviation of the portfolio’s excess return. So, the Sharpe ratio's numerator is the difference over time between realized, or expected, returns and a benchmark such as the risk-free rate of return or the performance of a particular investment category. Its denominator is the standard deviation of returns over the same period of time, a measure of volatility and risk. This is one of the most popular tools for calculating risk-adjusted relative returns. It contrasts the past or anticipated variability of such returns with the fund's historical or projected performance

[19] Morningstar Report: https://www.morningstar.com/investing-definitions/r-squared%EF%BB%BF
[20] Sharpe, W. F. (1994). The Sharpe Ratio. Journal of Portfolio Management, 21(1), 49-58.

in relation to an investment benchmark. The risk-free rate was initially employed in the calculation to represent the fictitious low borrowing costs for an investor. It stands for the risk premium of an investment in comparison to a secure asset like a Treasury bill or bond more broadly. The Sharpe ratio offers a measurement of risk-adjusted performance unrelated to such ties when compared to the returns of an industrial sector or investing strategy. The Sharpe ratio can be used to determine if an excess return on a portfolio is due to wise investment choices or just luck and risk. For instance, during the Dot-Com Bubble or, more recently, the meme stocks mania, low-quality, extremely speculative equities were able to outperform blue chip shares for extended periods of time. The Sharpe ratio of a portfolio determines how well it performs while adjusting for risk. A portfolio's return is likely to be negative if the Sharpe ratio is negative, which indicates that the risk-free or benchmark rate is higher than the portfolio's historical or forecast return.

- In the financial and investment sectors, **correlation** is a statistic that gauges how closely two assets (e.g., stock and its benchmark index) move in tandem. Advanced portfolio management makes use of correlations, which are calculated as the correlation coefficient, whose value must fall between the range of -1.0 and +1.0. This parameter is particularly relevant in the context of the theory of portfolio diversification according to which investing in assets that are not correlated is a tool to mitigate the risk of the overall portfolio/fund. A perfect positive correlation means that the correlation coefficient is exactly 1. This implies that as one security moves, either up or down, the other security moves in lockstep, in the same direction. A perfect negative correlation means that two assets move in opposite directions, while a zero correlation implies no linear relationship at all. According to Pearson (1920) the formula is the following (equation 3.2.1.6):

$$r = \frac{n * (\sum(X,Y) - (\sum(X) * \sum(Y)))}{\sqrt{(n * \sum(X^2) - \sum(X)^2) * (n * \sum(Y^2) - \sum(Y)^2)}} \tag{3.2.1.6}$$

Where r is the correlation coefficient and n is the number of observations.

- Investment analysts look first and foremost at a mutual fund's **standard deviation** to determine the risks involved. The standard deviation of a data collection determines how much the numbers deviate from the average value. Analysts can determine how stable a portfolio's returns are over time by calculating the standard deviation of its yearly rate of return. Low standard deviation indicates a mutual fund with a long history of steady performance. The volatility and standard deviation of a growth- or emerging-markets-focused fund will probably be higher, resulting into a higher price volatility. But, for instance, while a mutual fund with an annual return between 5% and 7% has a lower standard deviation than a rival fund with an annual return between 6% and 16%, that doesn't necessarily mean it is a superior investment. It is crucial to remember that standard deviation simply illustrates the range of annual returns for a mutual fund and does not guarantee continued stability over time. Changing interest rates and other economic conditions can always have an impact on a mutual fund's performance.

When combined, Alpha, Beta, R-squared, Sharpe Ratio and standard deviation, it is possible to define the risk-return profile of a mutual fund, allowing investors to determine how effective a fund manager is at capturing profit when a benchmark is also profiting, having a complete picture of asset managers' performance.

3.2.2 Results of the analysis

The results of the calculations are showed in the following Table 3.2.2.1[21]:

GROUP 1 (5148 funds)	Avg Alpha 1y	Avg Beta 1y	Avg R-squared 1y	Avg Sharpe Ratio 1y	Avg Correlation 1y	Avg Std Dev 1y
Average	-0.289777531	0.782135919	70.45%	0.06082404	0.791973851	16.180%
GROUP 2 (3680 funds)	**Avg Alpha 3y**	**Avg Beta 3y**	**Avg R-squared 3y**	**Avg Sharpe Ratio 3y**	**Avg Correlation 3y**	**Avg STD 3y**
Average	-0.283129142	0.82042928	71.87%	0.092074466	0.814729268	15.893%
GROUP 3 (2522 funds)	**Avg Alpha 5y**	**Avg Beta 5y**	**Avg R-squared 5y**	**Avg Sharpe Ratio 5y**	**Avg Correlation 5y**	**Avg STD 5y**
Average	-0.223847832	0.874257763	78.16%	0.080004138	0.864783131	17.186%
GROUP 4 (812 funds)	**Avg Alpha 10y**	**Avg Beta 10y**	**Avg R-squared 10y**	**Avg Sharpe Ratio 10y**	**Avg Correlation 10y**	**Avg STD 10y**
Average	-0.166322696	0.864724773	77.10%	0.136583443	0.859945901	14.463%

Table 3.2.2.1: Average values of the analyzed parameters for each group of mutual funds across the different considered time horizons.

First, analyzing the Alpha, the table shows that the AVG (Average) Alpha over the different groups is always negative, but quite constant between -0.16 and -0.28, meaning that, on average, these mutual funds have underperformed their benchmark indices over time, generating returns that did not adequately compensate investors for the level of risk they have taken. Investors could have achieved better returns by simply investing in the benchmark index, and this is also showed by the fact that the Alpha is getting worse from the last 10 years to the last 1 year of observation.

Looking at the Beta results, the average for all the groups is lower than 1, ranging between 0.78 and 0.87, sequentially decreasing from 5 years time horizon to last 1 year.

[21] 1y stands for last 1 year; 3y stands for 3 years; 5y stands for last 5 years; 10y stands for last 10 years.

For all the groups the Beta is "Defensive"; it shows that these mutual funds have been having a moderate level of sensitivity to movements in their respective benchmark indices over time. During the observation of the last 1 year, on average, the considered mutual funds were 21.79% less volatile than the average on the market, 17.96% less volatile than the average of the market in the last 3 years, 12.57% less volatile in the last 5 years and 13.53% less volatile in the last 10 years. It seems that, in terms of Beta, over the different considered time horizons, the mutual funds performed steadily. So, the average systematic risk given by the beta has been consistently lower than the average risk associated to the market benchmark, so lower has been the volatility. Given this constant behavior, over the analyzed time horizons, it is clear that the mutual funds had not fully captured the benchmark's gains during the strong market upswings, offering at the same time more protection during market downturns.

Furthermore, the performance, in terms of R-squared, of the different groups is also steadily, ranging between 70% and 78%, sequentially increasing from 1 year time horizon to 5 years time horizon, and then slightly decreasing at 10 years.

This suggests that the mutual funds had a relatively high level of correlation with their respective benchmark indices over time. In other words, about 70% to 78% of the variation in the funds' returns can be explained by the movements of their benchmark indices, showing that the funds tended to move in sync with their benchmarks. This result is in line with the constraints of the analysis, since ETF are not included in the considered sample of mutual funds[22].

Considering the Sharpe ratio, it ranges between +0.06 and +0.13, meaning that these mutual funds have generated slightly positive risk-adjusted returns, so returns that exceed the risk-free rate[23] over time. Even though the average Sharpe ratio for all the

[22] The main objective of the ETF is to keep a level of R-squared close to 100.

[23] To better understand the meaning of this sentence, look at the previous paragraph.

groups is positive, there are some differences that should be considered. A higher Sharpe ratio (closer to 0.13) implies better risk-adjusted performance, indicating that the fund has generated relatively strong returns for the level of risk it has taken. Conversely, a lower Sharpe ratio (closer to 0.06) suggests that the fund's risk-adjusted returns are less favorable, since the value is very close to 0, so the return offered by the funds was, on average, similar to the return obtained investing into risk free bonds.
The Correlation coefficient ranges between 0.79 and 0.86, that is quite close to 1 (maximum value of positive correlation), meaning that when one fund's returns increased or decreased, the others tended to move in a similar direction. This indicates that these funds have been influenced by similar markets conditions and economic factors. The average standard deviation for the different considered time horizons ranges between 14% and 17%, resulting into steadily performances over time.
These values of standard deviation suggest that, on average, these funds had a moderate level of volatility or risk in their returns, meaning that their returns tended to fluctuate over time. In terms of performances, over time, these funds have provided the potential for greater returns, but they also came with a higher likelihood of experiencing large losses.

3.2.3. Comments on the Results

From the previous analysis, it is clear that, over time, ranging from 1 year to 10 years time horizons, the considered mutual funds did not show a significant variation of their performances, on average. The variation of the same average parameter from one group to the other is relatively small, suggesting that the funds characteristics in terms of risk-return profile over time have been relatively consistent. This result shows that, on average, large part of the considered funds adhered to a stable investment strategy that has not significantly changed over the different time periods. This result could negatively affect the diversification strategy of investors, because the stable correlation values suggest that the funds have maintained consistent relationships with each other or their benchmarks, impacting the diversification benefits of holding multiple funds from the same sample, as they are not likely to exhibit significant changes in correlation over time. When funds in a portfolio have high positive correlations, the portfolio may not effectively reduce risk because all funds are likely to react similarly to market movements. Assuming that the underlying investment strategy and management remain constant, investors may expect these funds to continue behaving in a consistent manner with their historical patterns, that is positive for those investors who value consistency in their investment choices. However, the average values highlight a pattern of underperformance relative to benchmarks, and their risk-adjusted returns vary within a moderate range, being at the same time conservative in terms of market exposure (higher stability) because of the beta values. Lastly, considering the "beat the benchmark" phenomena, it is possible to conclude that:

- The average alpha for the sample of mutual funds is consistently negative, ranging between -0.16 and -0.29 on average. This means that the mutual funds in the sample have failed to beat their respective benchmarks over various time horizons.
- Since one of the primary goals of active mutual fund management is to deliver returns that exceed the benchmark's performance, investors typically expect active fund managers to use their expertise to select securities and make investment decisions that lead to positive alpha. When funds consistently show negative alpha, it raises questions about the effectiveness of their active management strategies.

3.2.4. T-test on Alpha

Looking at the simple average of the alpha parameter across time, it is possible to affirm that the analyzed funds do not show a significant variation of their performances (in terms of percentage variation of their return) across time. In order to be more specific, it is convenient to conduct a One-sample T-test, to understand whether the average alpha for the four groups is significantly lower than zero.

The first step of the T-test consists in setting the hypothesis:

- Null Hypothesis (H0) according to which the sample mean is significantly higher or equal to the hypothesized population mean (in this case, zero):

  $$H_0\text{: } \mu \geq 0$$

  Where μ is the sample mean.
- Alternative Hypothesis H1, stating that the sample mean is significantly lower than the hypothesized population mean (in this case, zero):

  $$H_1\text{: } \mu < 0$$

On the basis of these two hypotheses, the objective of the following T-test is to check if this H0 can be rejected or not; making valid or not valid H1, as a consequence. Since the population mean is zero, the T-test is characterized by one single tail, specifically a left tail test, in order to check if the specific group of funds has a mean value significantly lower than zero (so on the left side). The significance value[24] in this case is set at 0.05.

[24] The significance value is a predetermined threshold that is set to determine the level of evidence required to reject the null hypothesis H0, so it is the probability of rejecting H0 when it is actually true (Type 1 error). It is commonly set at 0.05.

The following Table 3.2.4.1 shows the result of the test:

	Alpha 1y	Alpha 3y	Alpha 5y	Alpha 10y
Mean	-0.29	-0.2831	-0.2238	-0.1663
Variance	0.58	0.3140	0.1155	0.0646
Sample	5148	3635	2458	812
Hypothesized Mean	**0.00**	**0.0000**	**0.0000**	**0.0000**
df	5147.00	3634.0000	2457.0000	754.0000
t-statistic	**-27.39**	**-30.4612**	**-32.6550**	**-17.9842**
P(T<=t) one-tail (p-value)	**0.00**	**0.0000**	**0.0000**	**0.0000**
t Critical one-tail	**1.65**	**1.6453**	**1.6455**	**1.6469**
P(T<=t) two-tail	0.00	0.0000	0.0000	0.0000
t Critical two-tail	1.96	1.9606	1.9609	1.9631
Rejecting Area (Reject H0 if)	t-statistic < 1.6469	t-statistic < 1.6454	t-statistic < 1.6453	t-statistic < 1.65
Rejecting Area (Reject H0 if)	p-value < 0.05	p-value < 0.06	p-value < 0.07	p-value < 0.08
Result	**H0 must be rejected**			

Table 3.2.4.1: T-test result for each of the four groups of mutual funds, showing why H0 must be rejected.

Analyzing the results of this T-test, it is clear that for all of the four groups, the null hypothesis H0 must be rejected (validating H1) since in all the cases the p-value[25] is always lower than the significance level initially set at 0.05. In any case, being more restrictive setting a significance value lower than 0.05 (e.g., 0.01) does not change the result, showing the robustness of the analysis. Moreover, the t-statistic[26] for all the groups is always lower than the critical value, confirming once more the final result. These findings are in in line with what discovered in the previous paragraph, so the mutual funds in the sample have failed to beat their respective benchmarks over

[25] The p-value shows the probability of obtaining the observed data assuming that the null hypothesis is accurate. It serves as a measure to assess the strength of evidence against the null hypothesis. In hypothesis testing, a p-value below a selected significance level (e.g., 0.05) indicates that there is enough evidence to reject the null hypothesis.

[26] The t-statistic represents how far the sample mean is from the hypothesized population mean in terms of standard errors.

various time horizons (consistent pattern of underperformance), since the average alpha of each group is significantly lower than zero. The negative alphas across all groups may raise doubts about the skills or effectiveness of fund managers in selecting securities and managing portfolios. In this sense, the next paragraph will be developed with the objective of making a clear distinction between skill of the fund manager and luck. Another relevant issue may be connected to the benchmark selection, since a benchmark serves as a standard against which the fund's performance is compared, and it should be relevant to the fund's investment objectives, strategy and asset class. The objective of the setting a right benchmark (always aligned to the fund's asset class and risk of the adopted investment strategy) is to represent the market that the fund aims to outperform. For this reason, a constant underperform may be related to wrong selection of the benchmark.

3.2.5. Luck vs Skills

Even though the considered mutual funds did not show, on average, a significant variation of their performances, I decided to go further in the analysis, setting the goal of understanding if there is a relevant percentage of the overall sample for each group that is anyway able to beat their own benchmark. Doing so, it is possible to identify whether the positive performance of some mutual funds is due to the skills and the right investment strategy of the fund manager, or it is the result of luck.

In order to conduct this kind of analysis, I decided to use a statistical approach (Tuckey Method[27]) according to which it is possible to identify the so called "Outliers" of the sample, both positive and negative.

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[27] The statistical procedure known as the Tukey method (developed by the American statistician John Tuckey), is used to find possible outliers in a dataset. A range that falls outside of this range is identified as a possible outlier using the technique, which use the Interquartile Range (IQR) to establish the typical range of data points.

The first step of this method consists in the calculation of the Quartiles[28] for each of the four considered groups of funds. The computation of the Quartiles is useful to understand the distribution of the values of the sample around the median. Then, on the basis of the Interquartile Range (IQR) it is possible to compute how many negative and positive Outliers compose the overall sample.

For this part of the study, I apply the statistical method only to Alpha, since as previously presented, it is the parameter that is able to show the direct connection between the fund performance and its benchmark's.

[28] The total number of Quartiles is three. The First Quartile (Q1) is the 25th percentile of the sample, meaning that, once the Q1 value is computed, it is possible to affirm that the 25% of the values of the sample are below the Q1 value. The second Quartile (Q2) is the 50th percentile of the sample, meaning that the 50% of the values of the sample are below Q2 value. The third Quartile (Q3) is the 75th percentile of the sample, so in this case the 75% of the values of the sample are below the Q3 value. Q2 is also the Median value of the sample.

The numerical results are presented in the following Table 3.2.4.1:

	Alpha 1y	Alpha 3y	Alpha 5y	Alpha 10y
Total Sample	5148	3635	2458	812
Q1	-0.53773205	-0.5206899	-0.376392425	-0.28836835
Q2 (Median)	-0.20779405	-0.2164979	-0.19887705	-0.1519722
Q3	0.04781415	-0.0147713	-0.042850775	-0.024514
Q4 (Max)	5.8521636	7.0288653	4.2950452	1.4224449
IQR	**0.5855462**	**0.5059186**	**0.33354165**	**0.26385435**
# of funds in Q1	1287	909	615	189
# of funds in Q2	1287	909	614	189
# of funds in Q3	1287	908	614	188
# of funds in Q4	1287	909	615	189
# of Positive values	1488	844	429	142
% out of the Total sample	28.90%	23.22%	17.45%	17.49%
Outliers 1 Threshold	**-1.41605135**	**-1.2795678**	**-0.8767049**	**-0.684149875**
# of Outliers 1	**213**	**119**	**52**	**14**
% out of the total sample	**4.14%**	**3.27%**	**2.12%**	**1.72%**
Outliers 2 Threshold	**0.92613345**	**0.7441066**	**0.4574617**	**0.371267525**
# of Outliers 2	**87**	**55**	**25**	**9**
% out of the Total sample	**1.69%**	**1.51%**	**1.02%**	**1.11%**

Table 3.2.5.1: Identification of Negative and Positive Outliers, respectively Outliers 1 and Outliers 2.

In the beginning of the table, the value of the specific Quartile is reported for each of the four groups. The Quartile value merely represents a threshold that divide the total sample is four parts (25% each). The next measure is the IQR computed following the next Equation 3.2.5.1:

$$IQR = Q3 - Q1 \tag{3.2.5.1}$$

The number (#) of funds in each Quartile is always the same for each of the four parts of the specific sample, since it simply represents the number of funds that compose the 25% of the total sample[29].

At this point, I want to highlight the number of funds characterized by a positive Alpha because they represent those potential funds able to outperform their own benchmark across time. For this reason, this number is going to be compared with the Real Positive Outliers at the end. The "# of Positive Values" is the number of funds with a value of the Alpha parameter higher than zero. While the "%out of the Total sample" has been computed as it is showed in equation 3.2.5.2:

$$\%out\ of\ the\ sample = \frac{\#\ of\ Positive\ Values}{Total\ sample\ of\ the\ Group} \tag{3.2.5.2}$$

Finally, the last part of the table shows the identification of the Outliers. First of all, it is crucial to compute a threshold for both Outliers type 1 and type 2. The two thresholds are computed using the Equations 3.2.5.3 and 3.2.5.4:

$$Outliers\ 1\ Threshold = Q1 - (1.5 * IQR) \tag{3.2.5.3}$$

$$Outliers\ 2\ Threshold = Q3 + (1.5 * IQR) \tag{3.2.5.4}$$

Then, the first threshold is useful to understand the number of Negative Outliers (type 1), since the "# of Outliers 1" represents all those funds with a value of Alpha lower

[29] Considering Group 1, the # of funds in Q1 is 1287 that is the 25% of the total Group 1 sample (5148). The # of funds in Q2 is another 25% because it represents the number of funds with an Alpha value higher than Q1 and lower or equal to Q2. The same logic for all the others. The # of funds in Q4 represents those funds with an Alpha value higher than Q3 but lower or equal to the maximum value of the sample.

than the threshold. The "# of Outliers 2" is the number of funds with a value of the Alpha higher than the second threshold, giving the number of Positive Outliers.

In particular, the term "Outliers" refers to those funds that are sensibly different (in terms of Alpha value) by the median funds (those funds inside the second Quartile Q2), so those funds that are distinguishing themselves because of a strongly worse (type 1) or strongly better performance than the others.

Looking at the number of Positive Outliers (type 2), it is worth to notice the strong difference if compared with the Number of positive values only. The latter is 1488 (28.90%) for Group 1, 844 (23.22%) for Group 2, 429 (17.45%) for Group 3, 142 (17.49%) for Group 4. Even though a large portion of funds for each group is showing a negative alpha, so a negative performance in terms of return if compared with the benchmark, it is important to say that more than 20% for Group 1 and Group 2 and slightly less than 20% for Group 3 and 4 are able to outperform the benchmark. In reality, this result is not completely true, since more than the half of them have a value of Alpha that is inside the second Quartile (Q2) group, so it does not significantly differ from the median value. The Positive Outliers are those funds with a value of Alpha that is significantly higher than the median value, so on the very right side of the distribution (those funds with a strong positive performance).

As a consequence, the real result comes up when looking at this last value, according to which, for all the four groups, the number of Outliers type 2 represents always less than 2% of the total sample, showing that there is not a significant variation of the performances of the funds over the analyzed time horizons.

Looking at the number of Negative Outliers, this last finding is even stronger, since the number of Negative Outliers is always higher than the number of Positive ones. is true that the largest part of the sample shows a negative performance, but on the other side a very small portion of positive Outliers can be still identified, but it cannot be considered as a breakthrough discovery. One of the most relevant studies of whether mutual funds performance is primarily driven by luck or skill is Fama & French (2010). They consider a large sample of actively managed mutual funds in the USA for their analysis. The main objective of this study is the analysis of the performance persistence of the considered funds over time, assessing whether funds that performed well or poorly in one period continued to do so also in subsequent periods, showing if past performance could predict future performance. The main insight is the distinction between luck and skill: skillful fund managers are those who can consistently generate positive alpha (returns in excess of what would be expected based on risk), while luck-driven performance occurs when a fund's returns are essentially random. It highlights the difficulty of consistently identifying skillful fund managers, suggesting that luck plays a significant role in the performance of mutual funds. Confronting my results with the main insights from this study, I ended up finding that the number of funds that have been able to significantly beat the benchmark is not that relevant, since it is always lower than the 2% out of the total sample of the specific Group. For this reason, I strongly believe that these results are actually in line with Fama & French (2010), Carhart (1997), and Titman S., and Wermers R., (1997), according to which mutual fund managers do not demonstrate a statistically significant level of skill in generating positive alpha. In other words, the typical fund manager's performance is not consistently better than what could be achieved by random chance. This suggests that some funds may appear to outperform due to random chance rather than expertise. So, even if some funds exhibit positive alpha, it can be challenging to distinguish skillful funds from those that have been lucky in generating excess returns.

Even though the results of the study do not show evidence of skill of the fund managers because of a consistent and relevant outperformance of the benchmark, I do not believe that all the existent funds with a positive alpha are able to beat the benchmark as a consequence of randomness and casually favorable market conditions, confirming the results reached by applying a T-test. For this reason, it is particularly interesting the more recent study by Berk, J., & Van Binsbergen, J. H. (2015). As previously introduced, this last study wants to distinguish between skillful and unskilled mutual fund managers and assess the impact of their skill on fund performance. Even though the way of numerical computation of the results is different, the authors find that the majority of mutual fund managers do not exhibit statistically significant skills in generating returns that consistently surpass random chance. This suggests that for many funds, their performance may be attributed more to luck than skill. However, the study does identify a subset of fund managers who demonstrate skill, as indicated by their consistent outperformance relative to random portfolios. These skillful managers tend to have positive ACI (Alpha Consistency Index) scores. Even though I did not compute the ACI score for my sample of mutual funds, I am going to present in the following part of the study that it is possible to reach the same conclusion of Berk, J., & Van Binsbergen, J. H. (2015), by comparing the results of a sample of mutual funds with the performance of one single strong benchmark index (MSCI World Index). It means that, while many mutual funds may not exhibit skill in consistently outperforming random chance, there is evidence of skillful fund managers who consistently generate positive alpha. For this reason, the next part of the study will be focused on the analysis of a possible pattern or common behavior among specifically identified top performing funds.

Chapter 4

Systematic Behavior Identification

As presented, the results of the first analysis, considering the sample of 5148 equity global mutual funds, are the same of the classic studies, since the mutual funds did not show a significant variation of their performances over the analyzed time horizons. Hence, the positive performances of these funds are attributable to pure luck, without being able to confirm the existence of superior skills of the fund managers. Pushed by the findings of more recent studies, I decided to go further deep in the study, trying to identify if a relevant portion of equity global mutual funds have been able to perform better than one single specific benchmark (MSCI World TR Index), in order to compare once more these results with the classic literature, finding a different and significant result. For this reason, I decided to change the previous sample of mutual funds, keeping only the 812 funds of Group 4 because the time horizon will be extended to the last 15 years, 10 and 5 years in the following analysis, (excluding the very short-term time intervals such as 1 year and 3 years); so, the only funds of the total sample that can be considered belong to Group 4.

Then, after introducing the characteristics of the new group, I delve into the final analysis by comparing the Return performances of the selected funds with the return performances of a strong benchmark, the MSCI World Index, in order to overcome the problem of the benchmark manipulation phenomenon, discovering a systematic positive behavior of a portion of the sample.

4.1 Introduction to the second Analysis

The objective of this study is the individuation of a systematic behavior of a considerable sample of global equity mutual funds; that means understanding and explaining whether there is a relevant group of mutual funds that are able to constantly "beat" the benchmark over a long-term time horizon. To pursue this goal, I decided to conduct a survivorship bias-free analysis presenting a direct comparison between the performances (in terms of percentage growth of NAV)[30] of a sample of mutual funds and the percentage growth of the MSCI World TR index[31]; both computed taking into account the same time horizon. According to MSCI World Index report (2023) directly provided by the MSCI company, this index captures large and mid-cap representation across 23 developed Markets countries, covering approximately the 85% of the free float-adjusted market capitalization in each country, representing then an indicator of the overall health and direction of the global economy. This index is typically considered as a refence point when designing investment portfolios, because of the high level of diversification. Therefore, it is used for evaluating the performances of mutual funds, comparing them to the returns of the index.

First of all, the considered sample is not only given by the 812 funds of the previously introduced Group 4[32], but I decided to extend the observations by considering additional equity mutual funds born right after 31/12/1999, for a total of 2086 funds, to

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[30] The percentage growth of a mutual fund measures the change in the fund's NAV over a specific period, typically expressed as a percentage. It is a way to quantify how an investment in the mutual fund has performed over that period. it can be positive or negative, reflecting the net change in fund's value, taking into account factors like capital gains, income distributions and expenses.

[31] It is relevant to consider that the MSCI World Index represents a broad global equity market, and it's a passive benchmark. Mutual funds, on the other hand, are actively managed, so they may aim to achieve better returns but often come with higher fees and risks associated with active management.

[32] The real Group 4 is composed by 812 funds but I excluded 139 funds (reaching a total of 673) because of the time horizon that I decided to consider for the performance analysis, as I will later explain.

be more coherent with the size of the sample of the first analysis. Second, it is important to notice that the focus of the first analysis of this study was related to the identification of a relevant group of mutual funds able to beat their own benchmark (not the MSCI World TR index) by looking at the variation of the main mutual funds parameters over time (1, 3, 5, 10 years to last month end). According to Cremers, K., Fulkerson, J., & Riley, T. (2022), mutual fund managers may be sometimes motivated to manipulate benchmarks ("benchmarking manipulation")[33] due to performance related incentives. If a fund outperforms its benchmark, the fund manager may receive higher fees, bonuses, or attract more investors. To illustrate the possible drawbacks of benchmark manipulation, the study makes use of a sizable mutual fund dataset to investigate the connection between fund performance and benchmark selection. Investors may be duped into choosing less-than-ideal investments when funds choose benchmarks that are not indicative of their investment methods.

For this reason, the goal of the second analysis I decided to present is to understand whether a relevant group of mutual funds has been able to constantly outperform the MSCI World TR, eliminating any possible bias of interpretation.

With the objective of presenting an exhaustive and complete result, I divided the calculations of the second analysis into five parts:

- In the first part I will compare the NAV percentage variation of 1178 funds[34] out of the total of 2086 equity mutual funds with the percentage variation of the Return of the MSCI World Index, considering a time horizon of 15 years (Starting Date: 31/12/2007; Ending Date: 31/12/2022).

[33] The practice of purposefully choosing or utilizing benchmarks that are not indicative of a fund's investing strategy, with the objective of deceiving investors or inflating the fund's performance, is known as the "benchmarking manipulation" phenomena. Fund managers may benefit financially from this manipulation by attracting more investors, giving the impression of better performance, and maybe receiving greater fees or incentives.

[34] I exclude those funds born after 31/12/2007.

- In the second part, I will consider a 10 years time horizon (Starting Date: 31/12/2012; Ending Date: 31/12/2022), and the sample is the total one of 2086 funds.
- In the third, the time horizon is 5 years (Starting Date: 31/12/2017; Ending Date: 31/12/2022) and the sample is the same of the second part.
- In the fourth part, I go further with the analysis trying to identify the "Top Performers" funds; a subgroup of funds that are able to consistently beat the benchmark over time. It means that, starting from the sample of 1178 funds, I want to understand how many of these funds outperform the benchmark in the last 15, 10, 5 years, in order to discover a systematic positive behavior.
- In the fifth and final part, the goal is to overcome one specific problem that is affecting this second analysis of the study. I want to use an example to explain what kind of problem I am considering. Let's take two generic mutual funds (Fund 1 and Fund 2), and both of them (imagining to use the exact same procedure applied in the first three parts of this analysis[35]) are outperforming the benchmark in the last 5 years. For this reason, they have both the potential to become "Top Performers". Looking then at the performances of each of the two considered funds in the last 5 years, some relevant differences can be identified. Fund 1 have been beating the benchmark in year 1, 2, 3, 4, 5; a result that may be achieved as a consequence of superior skill of the fund manager. Fund 2 have beaten the benchmark in year 1, than it has underperformed the benchmark in year 2,3,4 and again it has beaten the benchmark in year 5.[36] Such result is clearly the consequence of luck. A favorable change in the market

[35] Formulas and computations are going to be presented in the next paragraph.

[36] Another scenario: Fund 2 beats the benchmark in year 1, 3 and 5, while underperforming the benchmark in year 2 and 4. This result is affected by randomness, showing an even worst scenario; the fund is not under control at all.

conditions at year 5 has strongly improved the performances of Fund 2. It is clear that the two funds are not the same. Yet, following the procedure applied in the first three parts of the analysis, they are inserted in the same cluster. For this reason, to deal with this problem, the focus of the fifth part of the analysis consists in taking the 15 years time horizon, dividing each year in quarters[37] (60 quarters total), then comparing (for each quarter) the performances of the 1178 funds with the return of the MSCI World TR index on the same quarter. Doing so, it is going to be possible to check whether the previously identified "Top Performers" have been actually able to generate better results than the benchmark in each (or most) quarter, or there are other funds (that I did not consider in the previous part 4), that have been showing positive performances quarter after quarter, maybe better than the first "Top Performers".

Finally, after the identification of the best funds, I will introduce a new parameter, that is the probability that a fund that is able to overperform the index during a quarter, will repeat itself in the next one, two and three.

[37] Example: the quarters of year 1 (2007) are 31/12/2006 to 31/03/2007, 31/03/2007 to 30/06/2007, 30/06/2007 to 30/09/2007, 30/09/2007 to 31/12/2007. The same logic is applied for the following years.

4.2. Results Part 1, 2, 3

	15 Years (S_date: 31/12/2007; E_date:31/12/2022)	**10 Years (S_date: 31/12/2012; E_date:31/12/2022)**	**5 Years (S_date: 31/12/2017; E_date:31/12/2022)**
Return % Var MSCI World Index	**123.31%** **REFERENCE**	**139.72%** **REFERENCE**	**38.69%** **REFERENCE**
Total Sample	1178	2086	2086
#funds with a NAV % Var higher than the Reference	227	349	338
% out of the sample	**19.27%**	**16.73%**	**16.20%**
# Dead funds at E_date	150	212	115
New sample = Total Sample - # Dead funds	1028	1874	1971
% out of new sample	**22.08%**	**18.62%**	**17.15%**

Table 4.2.1: Identification of the number of funds of each sample that have been able to beat the benchmark in the considered time horizon (15 years, 10 years, 5 years).

As it is presented in Table 4.2.1, the starting value of each the three parts of the analysis is the "Reference", that is the percentage variation of the return of the MSCI World Index computed considering the following equation 4.2.1:

$$Return\ \%\ Var\ MSCI\ World\ Index = \frac{Return\ MSCI\ at\ E_{date} - Return\ MSCI\ at\ S_{date}}{Return\ S_{date}} \tag{4.2.1}$$

Where S_{date} and E_{date} are the Starting and Ending dates respectively of the considered time horizon. This measure serves as a benchmark for the mutual funds of this analysis. The following relevant measure (not reported in Table 6.2.1) is the NAV percentage variation of each one of the total sample's funds, computed as following (equation 4.2.2):

$$NAV\%Var = \frac{NAV\ E_{date} - NAV\ S_{date}}{NAV\ S_{date}} \tag{4.2.2}$$

Having these values, it is possible to understand that the "#funds with a NAV % Var higher than the Reference" is computed by counting how many funds of the considered sample have been able to outperform the Index in the analyzed interval of time.[38] Then the first result presented in the table is the percentage of best funds out of the overall sample, simply computed following the equation 4.2.3:

$$\%\ out\ of\ the\ \text{sample} = \frac{\text{\#funds with a NAV \% Var higher than the Reference}}{\text{Total Sample}} \tag{4.2.3}$$

At this point, since the analysis is survivorship bias-free, it is relevant to check how the result may change excluding from the total sample those funds that "died" before the ending date of the considered time horizon, to provide a clear and broader picture. So, first of the "# Dead funds at E_date" is the number of dead funds, computed by counting all those funds for which it is not possible to compute the NAV percentage variation[39], then the final result is computed using the last introduced formula, but the Total Sample at the denominator is not anymore the starting one, but is given by the difference between the Total Sample and the number of dead funds (New Sample).
Carrying out this analysis, it is possible to notice that the final result ranges between 19.27% in the last 15 years, and 16.20% in the last 5 years. As expected, (and in line with previously mentioned studies)[40], a significant portion of the considered mutual funds

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[38] Considering the 15 years analysis with a total sample of 1178 funds, it is reported that 227 out of 1178 funds have been able to generate a NAV percentage variation higher than 123.31% (value of the reference).
[39] It means that the NAV at the ending date is not available.
[40] Fama & French (2010) and more recently Berk, J., & Van Binsbergen, J. H. (2015).

did not outperform the MSCI World Index over the analyzed time horizons, with the highest percentage of outperforming funds observed in the long-term period (15 years), but considering a smaller sample. This could imply that, over a longer time horizon, with a lower overall number of funds, the share of them that have been able to consistently outperform the benchmark is higher.

Excluding from the total sample those funds that "died" before the ending date, it is reported a slight increase of the final percentage result, going above 20% in case of the 15 years analysis. These updated percentages imply that the evaluation of fund performance may be significantly impacted by survivorship bias. The percentage of outperforming funds rises when only those funds that made it through the entire time horizon are taken into account. This leads to more optimistic conclusions about the performance of the funds and gives the impression that the remaining funds have done better than they might have in a more thorough analysis that takes into account all of the funds, including the ones that closed. These findings may have an impact on investors' mutual fund selection selections. While some investors may seek out more aggressive, high-risk funds, keeping in mind that not all of them will survive, others may select less risky funds whose probability to close is still relevant if their investment strategies are too riskless and conservative.

Even though the majority of the funds of the sample is not able to beat the benchmark, the fact that more or less the 20% is overperforming the considered Index can be still considered as a relevant result, according to the previous mentioned study by Berk, J., & Van Binsbergen, J. H. (2015). It is true that most of the overall sample of funds underperform the benchmark[41], but I strongly believe it is worth to further analyze the smaller portion of better performing funds, since some funds' ability to endure and outperform their benchmark over time may be a sign of their flexibility in responding

[41] Fama & French (2010).

to shifting market conditions, staying true to their investment philosophy, superior ability of the fund manager and possibly even delivering value to investors who stuck with them.

4.3 Results Part 4: Initial “Top performers”

Total Sample	1178	Total Sample	1178
# Funds with better performance than MSCI World at 15y and 10 y	157	# Funds with better performance than MSCI World at 15y, 10 y and 5y	120
% out of the Total Sample	**13.33%**	**% out of the Total Sample**	**10.19%**

Table 4.3.1: Identification of the “Top Performers” looking at how many funds out of the Total Sample have been able to constantly beat the benchmark over time.

The previous paragraph showed that between 16.20% and 19.27% of the considered funds have a better return than the benchmark. Now the questions are: is their performance random? How many of them have been actually able to surpass the MSCI World TR Index over time? The Table 4.3.1 shows that, out of the considered sample of 1178[42] equity global mutual funds, over a time horizon of 15 years (Starting date: 31/12/2007; Ending date: 31/12/2022), divided into last 15 years, last 10 years, last 5 years, a subset of funds that have demonstrated resilience and superior performance in beating the MSCI World Index can be identified. In particular, 13.33% (157) funds did overperform the index in the last 15 years and 10 years, but the most noteworthy finding is that the number slightly decreases to 10.19% (120) considering the funds that did beat the benchmark in the last 5 years as well. Hence, due to their highest level of consistency in outperforming the benchmark across different time frames, these last 120 funds can be considered as the “top performers” of the analysis.

[42] I am analyzing 1178 funds and not the overall 2086 because there are some funds that were born after 31/12/2007, for which the 15 years performance does not exist.

According to classic literature such as Jensen (1968), Fama & French (1965,1970, 2010), Carhart (1997) active mutual fund managers always lack skill, explaining how, as a group, investors in active mutual funds underperform the market, as a result of an unpredictable mutual fund performance. Even though the classic literature presents the idea that mutual fund returns show no evidence of outperformance, it is not possible to attribute to pure luck the ability of a subgroup of mutual funds to constantly outperform a strong index such as the MSCI World. There are several characteristics that may explain this superior performance:

- Effective risk management strategies to navigate market downturns with lower drawdowns.
- Outperformance on a regular basis could be a sign of competent and responsible management according to their methods for making decisions, and to how they put together their portfolios, and how to adjust to shifting market conditions, being able to select stocks that consistently outperform the benchmark index, examining different elements including industry developments, competitive positioning, growth potential, and financial health.
- Investment strategies of the funds, according to their ability to navigate global economic trends. Since they are global equity funds, their ability to identify opportunities and manage risks in different regions and sectors becomes crucial.
- Willingness to maintain a long-term investment perspective, rather than reacting to short-term market fluctuations.

The following Table 4.3.2 shows the average performances of the 120 top performers in terms of Beta and Sharpe Ratio[43]:

[43] Those parameters that are not computed in relation to a certain benchmark.

	Beta 15y to last month end	Beta 10y to last month end	Beta 5y to last month end	Sharpe Ratio 15y to last month end	Sharpe Ratio 10y to last month end	Sharpe Ratio 5y to last month end
Average	0.906681808	0.893078476	0.883681237	0.177165314	0.164617585	0.209746204

Table 4.3.2: Average values of the considered parameters (Beta, Sharpe Ratio) over three-time horizons (last 15 years, last 10 years, last 5 years) for the 120 "Top Performers".

These results show that both Beta and Sharpe Ratio are quite consistent across time[44] without significative variations, suggesting a high level of stability in the risk and return characteristics of these funds. Anyway, even if it is a small reduction, the average Beta has decreased over the past 15 years, meaning that, on average, these top performing funds have become less volatile than the MSCI World TR Index during this period. On the other hand, the Sharpe Ratio (that is a measure of the risk adjusted return) has firstly decreased from the last 15 years to the last 10 years, in order to increase again in the last 5 years reaching a value of more or less 20.97%, indicating that, on average, these funds have improved their risk adjusted performance in the more recent period, with a better balance between risk and return.

Moreover, even if it is a small variation, the decreasing Beta and the increasing Sharpe Ratio indicate that these funds have been successful in minimizing risk and optimizing returns. This is encouraging for investors looking for a steady and well-rounded approach to investing.

[44] 15, 10, 5 years to last month end refer to the last 15, 10, 5 years to the end of 2022, according to the time horizon at the base of this second part of the study.

Going then in details analyzing the structure of each of the 120 top performer funds, the following Table 4.3.3 is then built:

	JP funds	EUR funds	USD funds	GBp funds
#	42	26	22	13
Total Sample	120	120	120	120
%out of the Total Sample	**35.00%**	**21.67%**	**18.33%**	**10.83%**

Table 4.3.3: The 120 funds are divided per country of origin.

It is worth noticing that the share of Japanese funds accounts for 35% of the overall group for a total of 42 funds; the second largest share is then represented by European funds (21.67%), followed by the US funds (18.33%), ending with the smallest share given by UK funds (10.83%)[45]. The fact that Japanese funds make up 35.00% of the best-performing funds indicates that Japanese funds are well-known and successful in the international market, reflecting the expertise of Japanese fund managers in navigating the global market. At the same time, it is also true that all the Japanese funds have the largest portion of their portfolio of investments in United States[46], showing how certain sectors or industries that align with the investment strategies of Japanese funds might be more prevalent in the US. It is interesting that among the top performing funds, the largest share is given by Japanese ones that invest mostly on the American market, than American funds investing on the American market.

Another relevant factor is represented by the different types of issuers. The 42 Japanese funds are all issued by the same organizations (Sumitomo Mitsui Trust Asset Management Co Ltd, Mitsubishi UFJ Asset Management Co Ltd, Nikko Asset

[45] For sake of simplicity only the most "relevant" shares are considered. In order to be as much precise as possible, the following are the remaining "not relevant" shares: NOK (2.50%), DKK (1.67%), CAD (2.50%), SGD (0.83%), HKD (1.67%), SEK (0.83%), AUD (0.83%), CHF (0.83%), THB (1.67%), NZD (0.83%).

[46] More than 60% on average.

Management Co. Ltd, Nomura Asset Management Co Ltd, UBS Asset Management (Japan) Ltd), while the issuers of European, American and UK funds are always different for each one of them. This result suggests that the Japanese companies have developed strategies or practices that consistently lead to top-performing funds. According to McGuire, J., Dow, S. (2009) the Keiretsu system is the pillar of the Japanese investment ideology, according to which a network of companies with interlocking business relationships has contributed to a culture where investors, including institutional investors, often take a long-term view.[47] These aspects have definitely contributed to the superior performances of Japanese mutual funds over time.

However, some common characteristics among these funds can be clearly identified looking at their investment strategies. Such as Japanese funds, also the European, American and UK funds tend to invest the largest part of their resources on the American market (more or less 50% on average), mostly in Tech and Software industries. Many different reasons may be considered:

- The U.S. stock market is one of the largest and most liquid in the world, offering a broad spectrum of investment opportunities, and the presence of globally influential companies.
- The U.S. dollar is often considered as a global reserve currency, and funds might choose to invest U.S. assets because of currency stability and appreciation.

These results are consistent with that part of literature in financial economics that does find evidence of skill. According to Kacperczyk et al. (2005), portfolios of actively managed equity mutual funds frequently show a high degree of industry concentration. Factors like industry familiarity and geographic proximity are what

[47] Most of the times member companies of the Keiretsu system hold shares in each other, creating stability and collaboration, working together to achieve common goals and weather economic challenges collectively.

motivate this concentration. In the same way, the analyzed top performer funds have large part of their portfolios allocated to a specific sector (tech sector) and to a specific geographical allocation (USA). On the other side, my results are not consistent with other studies such as Coval and Moskowitz (2001) according to which geography is important; funds that invest a greater portion of their assets locally do better. It is true that the analyzed top performers funds invest a large part of their assets in USA, but all of them are global funds, that invest the remaining part in several countries.

4.4. Results Part 5

At this point, the objective is to deal with the problem introduced in the first paragraph of chapter 4. For this reason, I divided the analyzed 15 years into 60 quarters. I computed the percentage variation of the NAV of each fund for each quarter, in order to compare it with the percentage variation of the return of the MSCI World TR Index. I gave value "1" if the fund has beaten the benchmark in that quarter, while "0" otherwise. Doing so, I have been able to compute the number of Good Quarters[48] for each fund. This computation has been done for all the 1178 funds, with the objective of understanding whether the previously identified 120 "Top Performers" hold still even considering the quarterly performances. For this purpose, I applied the Tuckey Method[49] on the calculated Good Quarters, and the result is presented in the following Table 4.4.1:

[48] During a Good Quarter, the funds beats the benchmark.

[49] The same method that has been applied in the first part of the study (Empirical Analysis).

	Good Quarters
Total Sample	1178
Q1	24
Q2	**27**
Q3	**31**
Q4 (max)	49
Min	11
IQR	7
Outliers 1 Threshold	13.5
# **Outliers 1**	**8**
Outliers 2 Threshold	41.5
# **Outliers 2**	**18**

Table 4.4.1: Positive and Negative Outliers Identification for the 1178 funds.

According to these results, there are only a few Negative Outliers (type 1), while the number of Positive Outliers is slightly higher. This demonstrates that the majority (97.8%) of the sample has a performance that belongs to the median cluster (second quartile) beating the benchmark in a number of quarters between 27 and 31. There are only 18 Positive Outliers (type 2) that have beaten the benchmark in more than 41.5 quarters (type 2 threshold).

Now, in order to understand if the previously identified 120 Top Performers can still be considered as the best funds of the sample, I applied the same Tuckey Method on those 120 funds only. The analysis has been conducted following this logic: first of all, I have again computed the NAV percentage variation (and the MSCI World Index Return percentage variation) in each of the 60 quarters for each of the 120 funds. Then I computed the number of quarters during which each fund has (Good Quarters) and has not (Bad Quarters) beaten the benchmark.

So, first of all, I compute all the Quartiles (Q1, Q2, Q3, and Q4 is the maximum value), in order to find the Inter Quartile Range IQR. Starting from the IQR value, it is possible to calculate the left (negative) and the right (positive) threshold, according to which the two types of Outliers are then identified. The results are showed in the following Table 4.4.2:

	Good Quarters
Total Sample	120
Q1	32
Q2 (Median)	**35**
Q3	**40**
Q4 (Max)	49
IQR	8
Outliers 1 Threshold	20
# of Outliers 1	**1**
Outliers 2 Threshold	52
# of Outliers 2	**0**

Table 4.4.2: Positive and Negative Outliers Identification for the 120 funds.

The Outliers type 1 are the Negative Outliers, so those funds with a number of Good Quarters that is significantly lower than the number of Good Quarters of the median group[50]. On the other hand, the Positive Outliers (type 2) have a number of Good Quarters that is significantly higher than the average group. All the funds, except for one only Negative Outliers are inside the median group. It means that, on average, these 120 funds have similar performances, without having funds that have been performing better than the average. Anyway, I will exclude the only Outlier type 1 that has been identified, going further in the study considering 119 funds, rather than 120. This fund that is eliminated has the lowest number of Good Quarters, equal to 10.

This result is actually showing why these 119 funds con be confirmed to be the best funds, out of 1178. In order to explain why, I present the following Table 4.4.3 for the comparison between the results of the Tuckey Method, previously applied for the two groups:

[50] The median group is given by those funds with a number of Good Quarters that is higher than Q1 but lower than Q3.

Total Sample	1178	120
Q1	24	32
Q2	**27**	**35**
Q3	**31**	**40**
Q4 (max)	49	49
IQR	7	8
Outliers 1 Threshold	13.5	1
# Outliers 1	8	0
Outliers 2 Threshold	**41.5**	**41.5**
# Outliers 2	**18**	**18**

Table 4.4.3: Comparison between Tuckey method applied on 1178 funds and same method applied on 120 funds.

I applied the type 2 threshold that was previously identified at the moment of the usage of the Tuckey Method on the 1178 funds. Using the same threshold, it is possible to identify 18 Positive Outliers inside the 120 that I am considering, that is exactly the same number of Positive Outliers that was previously identified. It means that all the best funds among the 1178 funds are already inside the 120 Top Performers.

Moreover, another element that is confirming this last result is given by the difference in terms of median number of Good Quarters. In both cases, almost all the funds belong to median cluster, but looking at the 120 funds column, the number of Good quarters that is identifying the second quartile is way higher than the column for 1178 funds, indicating a superior performance of all the 120 funds over the total sample. The Top Performers have been able to beat the benchmark in a number of quarters between 35 and 40, that is sensibly higher than the average number of total quarters.

4.5. "Real" and "Fake" Top Performers

Now I will try to be stricter, trying to make a distinction between "Real" top performers and "Fake" top performers on the basis of a new parameter (the probability of beating the benchmark) checking if the result of the previous paragraph is still valid or not. The considered time horizon in this case is 15 years (S_Date: 31/12/2007; E_Date: 31/12/2022), divided into 60 quarters. First of all, I want to explain in details the meaning of this terminology:

- I consider a Real top performer, a mutual fund, among the initial 119, that have been able to constantly beat the benchmark[51] in terms of NAV percentage variation in each (or most) of the 60 quarters. Hence the probability of beating the benchmark in following quarters is significantly higher than the average value. It is important to explain that in the context of this quarters analysis, beating the benchmark also means performing less negatively than the benchmark (beating the benchmark in absolute value)[52]. Since I am considering very short time periods, the market fluctuations and the variation of the macroeconomics trends strongly affect the short-term performances of both funds and MSCI World Index, making them have a negative performance in some quarters. In this case the positive results of the funds are not results of luck, but it is representative of superior skills of the fund's managers and incredibly accurate investment and risk strategies, confirming the results found in the previous paragraph.

[51] Again, the benchmark in this case is the MSCI World Index whose Return percentage variation in each quarter represents the Reference value that I compare with the fund's NAV percentage variation on the same quarters to understand if a fund is able to beat or not the Index.
[52] Example: if during a quarter the MSCI World has a Return Percentage variation of -10%, the fund with a NAV percentage variation of -9% and above is still beating the benchmark in absolute terms.

- A "Fake" top performer is a fund whose performance over the 60 quarters is random, sometimes positive and sometimes negative (or mostly negative for several consecutive quarters), showing a fund that is not under control and well managed. It means that the probability of beating the benchmark in following quarters is significantly lower compared to the other funds. This result means that they have been previously added to the list of top performing funds purely as a consequence of luck; because initially, the NAV percentage variation of the funds has been computed by taking only the NAV value at the beginning and at the end of the period of observation, and those funds that have beaten the benchmark only in these two instant of time and never (or sometimes) in the middle quarters, have been included as well.

The objective is the computation of three different types of probabilities:

- P1, that is the probability that a fund that beats the benchmark in one quarter, will be able to repeat itself in the following one (two quarters total).
- P2, that is the probability that a fund that is beating the benchmark in one quarter, will beat the benchmark in the following two quarters (three quarters total).
- P3, that is the probability of overperforming the benchmark in the following 3 quarters (four quarters total).

Considering 119 funds over 60 quarters, I converted into a binary value the performances of the funds in each quarter[53]. With this structure, I computed for each fund the number of times that the value "1" is repeated in two following quarters (for P1), in three following quarters (for P2) and in four following quarters (for P3). At the end the final P1, P2 and P3 for each fund has been computed as the ratio between the

[53] "1" if the fund does beat the benchmark, "0" if it does not.

previously computed number of times that "1" is repeating and the overall number of Good Quarters of that fund.

At this point, I applied the Tuckey Method on the probabilities to identify the Fake (Outliers type 1) and Real (Outliers type 2) Top Performers. The results are presented in Table 4.5.1:

	P1	**P2**	**P3**
Total Sample	119	119	119
Q1	48.48%	22.23%	9.45%
Q2 (Median)	**56.25%**	**30.56%**	**17.65%**
Q3	**65.00%**	**40.27%**	**25.00%**
Q4 (Max)	76.74%	58.14%	44.19%
Min	30.00%	4.76%	0.00%
IQR	16.52%	18.04%	15.55%
Outliers 1 Threshold	23.71%	-4.84%	-13.88%
#of Outliers 1	**0**	**0**	**0**
Outliers 2 Threshold	89.77%	67.33%	48.33%
#of Outliers 2	**0**	**0**	**0**

Table 4.5.1: Tuckey Method results.

In this case the Outliers type 1 should be those funds of the sample with a performance in terms of probabilities that is significantly negative than the median group (the average group), so the Fake Top Performers with a value of probabilities that is much lower than the Threshold type 1[54]. While the Outliers type 2 represent the opposite, so the Real Top Performers whose results are significantly better than the median group, whit a value of probabilities that is higher than the Threshold type 2[55] across the three cases. Looking at the results, there are no Outliers of both types, nor type 1, nor type 2. It does not mean that the 119 analyzed funds do not show superior performances, but it means that there are no funds in the sample that are performing significantly

[54] Threshold type 1 represents the limit below which the funds are performing very negatively.
[55] Threshold type 2 represents the limit that should be surpassed by the Real Top performers.

better or worse than the median group; all of them are performing inside the second quartile in terms of all the three probabilities. The median group for P1 has a significantly high probability, since the funds inside this cluster have a P1 value between 56.25% and 65%, so they have a very high probability to beat the benchmark in two subsequent quarters. The value goes down a bit considering the following probability P2, but still it can be considered as a significant result since it means that the probability that these funds can beat the benchmark in three quarters is between 30.56% and 40.57%. Finally, the median group for P3 has a value between 17.65% and 25%, that is the lowest compared to the others. This last result makes sense because P3 is the probability that a fund beats the benchmark in a total of four quarters, so one entire year (considering the first quarter as well). So, with a probability between 82.35% and 75%, these funds do not outperform the benchmark for four following quarters, that is a quite high value, showing a certain degree of chance rather than of skills, in this last case, at least. In the very short term, various external factors can affect the performances of the funds. By lowering the Threshold for both the types of Outliers using 1 as coefficient rather than 1.5, the results do not change. Hence, it is possible to affirm that the performances of these funds are very similar.

Finally, the performances of the lastly analyzed 119 funds are very similar one with the other. Hence, it is not possible to clearly identified significant Outliers in the group, making less meaningful the distinction between Fake and Real Top Performers, since all of them can be considered as Real Top Performers. This finding is showing that their performances are not merely the result of luck, because starting from the overall sample of 2086 funds, these funds are significantly and consistently making better, suggesting anyway strong evidence of skills of their managers. The aim of this study is not the identification of "perfect" funds with a probability of 100% of beating the benchmark in every quarter, but it aims at understanding how the market for mutual funds nowadays is able to create equity global mutual funds that, compared to the past (classic literature), can perform better than the benchmark for a longer period of time, characterized by a high probability of repeating their results.

Referring to the previously presented Table 4.1.1, all of the 119 funds can be inserted inside the median group, meaning that all of them are beating the benchmark between 35 and 40 times (out of 60 quarters in total). In my opinion, this result shows the existence of a relevant group of equity mutual funds that are able to constantly generate a positive performance, with a high probability.

In the same way of Cogneau, P. and Hübner, G. (2017), according to which performance persistence is contingent upon the performance measure selected, I believe that structural factors of the funds as well instead may have an impact on their probabilities of beating the benchmark.

Conclusions

This thesis makes a substantial contribution to the general understanding of the modern performance persistence of mutual funds by carefully examining both traditional literature and more recent research, in order to find and explain similarities and differences with their results, confirming at the end the existence of equity mutual funds with superior performances as a consequence of both skills of their managers and specific structural factors of the funds, explaining the impact on performance persistence of the funds, generated by benchmark selection and manipulation problems. The initial discovery of the presented empirical analysis according to which it is not possible to detect a significant variation of the performances of the analyzed mutual funds across time is in line with the classic multifactorial model of Fama & French and Carhart. Even though a small subgroup (less than 2% of the sample) can be clustered as Positive Outliers, more than 98% of the sample shows an Alpha value that is significantly lower than zero (according to the results of the T-test), making that positive subset less impactful and relevant, showing a possible prevalence of chance in their positive performances. Because of this result, I believe that the findings obtained from the last part of the study are even more important. Investors are attracted by the promises of fund’s managers of generating abnormal returns compared to their benchmark (positive Alpha), leading sometimes to the “benchmark manipulation” phenomena, and consequently to a benchmark selection problem. According to Hougaard, J., L., & Tvede, M. (2002) inaccurate evaluations of mutual fund's performances may result from improper benchmark selection. An inaccurate representation of mutual fund's strengths and weaknesses may result from selecting a

benchmark that is neither fair nor representative. Moreover, wrong performance reviews resulting from a not correct benchmark selection can affect how decisions are made inside the management of a mutual fund. Decisions made by managers could impede the development and advancement of the fund if they are based on inaccurate assessments. Since the performances of the mutual funds that have been analyzed in the empirical analysis chapter are evaluated in comparison with the results of their own benchmark (resulting into a constant underperformance across time), I believe that this kind of discovery may be related to a wrong benchmark selection, that leads to the misconception of absolute prevalence of luck and randomness over any other factor. There are early evidences of this problem as well, coming from Fama & French (1990); they raised the possibility that the CAPM may not be the best model for calculating risk-adjusted returns. The benchmark used to measure fund performance in the persistence analysis is a contentious decision. As a benchmark, a number of other market indexes can often be utilized, which may produce somewhat varied outcome.
For these reasons, and because I do not believe that all the modern existing funds with a positive performance are able to beat their benchmark as a consequence of casually favorable market conditions, I decided first of all to extend the time horizon to 15 years, and then to compare the results of the considered equity mutual funds, with one single and strong benchmark, the MSCI World TR Index. I ended up finding that 120 funds (10.19% of the sample) have been showing consistent positive performances over the three time intervals (15 years, 10 years and 5 years). Compared to a percentage that was lower than 2% in the first analysis, I consider this one as a more significant and relevant result. These “Top Performers” are characterized by a decreasing Beta and an increasing Sharpe Ratio over the last considered 15 years, indicating that these funds have been able to optimize returns, while decreasing the overall level of risk. This constant improvement leads to a superior performance compared to the benchmark,

signaling the presence of a high-quality management. Then, with the objective of dealing with the "short term performance problem" I delved into the evaluation of the results of the considered funds for each quarter of the analyzed 15 years (60 quarters). Showing how the 120 funds, identified as Top Perfomers, are actually the best funds out of the total 1178 funds, as a result of the Tuckey method applied on the number of Good Quarters, for both the sample, I ended up excluding only one fund that was doing significantly worse than the others, presenting how the remaining 119 funds have been able to beat the MSCI World TR Index in more than the half of the quarters (between 35 and 40). Thus, these funds have similar and positive performances over time, being all of them inside the median cluster (second Quartile), and both Negative nor Positive Outliers can be found, eliminating any possible evidence of randomness and chance. Finally, trying to make an even stricter filtering, I computed the Probability of beating the benchmark in two, three, four consecutive quarters, showing that the probability that a fund that beats the benchmark in one quarter can beat the same benchmark in the following quarter is quite high (between 56.25% and 65%), slightly decreasing for the following two (between 30.56% and 40.27%) and three quarters (between 17.65% and 25%). In this last situation as well, it is not possible to identify both Positive nor Negative Outliers, since all the funds shows probabilities that fall inside the median cluster (second Quartile). This result is then confirming the previous finding, hence all the 119 funds are Top Performers, and "Fake" top performers do not exist. I consider normal the progressive decrease of the Probabilities, since in the very short term, various external factors such as macroeconomic factors (e.g., rising income, inflation) can affect the performances of the funds, and this is something that goes beyond the abilities of the managers.

Therefore, the answer to the question in the introduction of this study is that: it is possible to identify some funds that, due to their structural characteristics in terms of investment strategy and quality of their management, are able to generate positive performances across time, increasing the probability of constantly beating the opportunely and carefully selected benchmark, minimizing the effects of adverse market conditions. If, on one hand, the EMH theory states that passive strategies are more effective than active management of portfolios because you do not actively choose individual stocks (you just track the market index), on the other hand, there are evidences of constant outperformances of the market index, making active management even more effective.

At the same time, it is not even correct to totally eliminate the "luck factor", since the skills of the managers cannot always be enough against a sudden change in the financial market conditions, and variation of macroeconomic factors, that can impact on the returns of various asset classes on which the fund is investing. But, if the results of mutual funds are considered as the consequences of pure luck only, investors would prefer to invest by themselves; as a consequence, the market for mutual funds would have not been growing that much in the last 50 years.

At the same time, there are some other studies that have been conducted before 2000, such as the mentioned Hendricks, Patel, and Zeckhauser (1990) and Grinblatt and Titman (1992), that have showed evidence of superior performances in both short and long term. According to them, mutual funds that did well the year before are still better in the short term (four months to two years). Moreover, they demonstrate the fund managers' capacity to generate abnormal returns that last for five to ten years. The main point is that, these results were then taken by Carhart (1997) and disproved, determining every element that conceivably permits performance persistence, coming to the conclusion that skills and strategies are not among them, in favor of other factors such as momentum and luck.

Because I have been studying the mutual funds market in order to work at this thesis, I would like to introduce another personal observation, related to the following question: could it be that the results discovered by the classic literature were somehow affected by the fact that the market for mutual funds was in its early expansion? For obvious reasons, they took into account mutual funds that were born way before 2000 (during 70s, 80s, 90s), that were years of strong expansion of the mutual funds market. On the other hand, more and more recent studies after 2000 (mostly after 2010), have been able to show that a lot of funds are able to generate positive performances across time, as a function of their peculiar structural characteristics, performance measures and abilities of the fund's managers.

This is demonstrating the existence of a breakthrough change in the approach followed to build mutual funds across time (last two decades in particular), that has pushed fund's companies to put much more attention in the definition of dedicated investment strategies for specific clusters of potential investors and in the choice of the fund managers. According to Hall, R. E. (2016), investors have become, on average, more risk adverse than risk takers, as a consequence of the several financial crises of the last decades. For this reason, investors have been incentivized in the selection of "safer" financial instruments, such as mutual funds and ETFs, generating, as presented in the first chapter, an exponential increase in the size of the market for mutual funds and ETFs. Even though the financial education has been increasing in the last years, more people would rather prefer to trust expert and professional investors rather than invest by themselves, in order to reduce their risk.

Hence, financial instruments that are classified as "low risk" (mutual funds indeed), are generally preferred. Instead, the classic studies are conducted during a period of initial expansion of this sector, strongly impacting on the results that they have obtained, creating a series of bias that only nowadays are getting disproved.

What I want to demonstrate with my study is that: it is true that it is possible to find a huge number of equity mutual funds that are not able to be constant in their positive performances, as presented in the chapter about the Empirical Analysis. But, at the same time, nowadays it is not correct to attribute the positive performances of many other funds merely to pure luck, since more and more funds in the last decades have been showing a constant and consistent ability to outperform a strong index such as the MSCI World TR. Yet, the presented results may vary according to different structural factors of mutual funds that can be considered to conduct a performance persistence analysis. For this reason, the next step could be related to a possible extension of the sample of considered funds, taking into account not only equity global open-end, but local, closed-end as well, whose performances can be analyzed as a function of structural elements such as the size of the fund (in terms of Total Net Assets), fees and expense ratios, ESG factors, investment strategies (e.g., sector) and many other performance persistence measures (e.g., Sharpe Ratio, Beta).

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List of Tables

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List of Symbols

Variable	Description
$r_{p,t}$	realized return on mutual fund p observed in periods t = 1, · · · ,T
$q_{p,t}$	the price per share of mutual fund p at the conclusion of period t.
δ_1	persistence in the average performance of the n funds
#	Number of…
β_p	OLS estimate of the fund's beta, so the difference between the mean excess return on the fund
$^\wedge\alpha_p$	indicates whether the fund returns on average are larger (smaller) than the equilibrium value consistent with its amount of systematic risk; the fund is located above (below) the security market line
α_p	indicates whether the fund returns on average are larger (smaller) than the equilibrium value consistent with its

	amount of systematic risk; the fund is located above (below) the security market line
$\hat{}\beta_p$	OLS estimate of the fund's beta, so the difference between the mean excess return on the fund
$\hat{}\alpha_{p,1}$	estimated alpha of fund p over the first interval {1, 2, · · · ,T1}
$\hat{}\alpha_{p,2}$	corresponding alpha estimated over the second interval {T1 + 1,T1 + 2, · · · ,T}
R_{it}	return by fund i over quarter t
α_{it}	Jensen's alpha that measure the superiority of fund i in period t relative to the benchmark portfolio m in a mean-variance framework
β_i	β_i is 'beta' of fund, which is assumed to be time-invariant for convenience: measures systematic risk of fund i within the Capital Asset Pricing Model (CAPM).

ϵ_{it}	ex-post idiosyncratic component of the return, which would be unpredictable under a joint hypothesis of the CAPM and the EMH (Efficient Market Hypothesis).
μ_i	unconditional mean
$\dot{\rho}_j^2$	estimated residual autocorrelation at lag j
T	the number of observation
$\dot{\rho}_{(i)kk'}^2$	estimate of the k^{th} partial autocorrelation in the residuals of fund i
r	portfolio's expected rate of return
SMB	SMB stands for "Small [market capitalization] Minus Big
HML	HML for "High [book-to-market ratio] Minus Low".
VWRF	the excess return on the CRSP value-weighted portfolio of all NYSE, Amex, and Nasdaq stocks;
RMRF	excess return on a value-weighted aggregate market proxy
PRIYR	returns on value weighted, zero-investment, factor-mimicking portfolios for size, book-to-market equity, and one-year momentum in stock return

CR	Covariance of asset's return with market's return, that is used to calculate the correlation between the price changes of any two stocks.
R_p	return of the overall portfolio and R_f is the risk-free rate (return expected from an investment with no risk)
σ_p	standard deviation of the portfolio's excess return.

Appendix

https://drive.google.com/drive/folders/1Vzj18SxvAR8DSRGrAuS_Gfz3sHClZbv-?usp=sharing