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Master Thesis **Financial Economics**

Active investment: skill or luck? The case of Equity Mutual Funds in the US that are bought either directly by investors or through brokerage apps.

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Abstract:

This paper investigated if active managers of US equity mutual funds have the financial skill to overcome the returns of the passive investment. As the method of research was used the added dollar value mechanism computed by Berk and van Binsbergen (2015). Also, the paper studied if there exists any difference in the added dollar value of the US equity funds that are financed through different approaches; first, being sold directly to investors and second, bought through a mobile phone brokerage application. The period covered was January 2010 until December 2020. The total amount of mutual funds was 1203, from which 295 were sold through the Fidelity brokerage app, the proxy for the brokerage question, and 908 were sold directly to investors. Based on the main results, the active managers possess enough financial skill to persistently create a significant added dollar value on the financial markets. However, there is no statistical difference between the two groups investigated.

Keywords: US equity mutual funds, active investment, managerial skill, added dollar value, brokerage app

Table of Contents

Introduction

Since the beginning of the financial markets, there have always been questions on how can more money be integrated into the market, and how can more investors be integrated into financial deals. Considering that most of the people in the 20^{th} century did not have a high level of financial education, a new industry was developed in the economic sectors, asset management. By a simple search in the Cambridge dictionary, asset management represents the action through which a person manages someone else's money, stock, or shares ("Asset Management", 2021). Throughout the years, this industry grew exponentially, so, in 2017 it was estimated that the world's largest 500 managers have under their management $93.8 trillion, which represented a considerable rise of 15% compared with the previous year ("Assets of world's largest fund managers jump by over 15% to nearly $94 trillion", 2018).

So, why is it important to understand what assets under management represent? Because, the newest crises that the world is facing, changed multiple domains, including the financial one. Even though we are in a crisis, the financial markets are booming. This is happening, because, ironically, the Covid-19 crisis made it possible for households to achieve the highest saving rates in a very long time (Dossche & Zlatanos, 2020). This created a new precedent of how people can use their savings. Due to the fact of high saving rates, high interaction between people through social media platforms where the information about financial markets is more open than ever, more people started to be intrigued and invest in financial markets.

This paper investigated this domain by exploring the equity mutual funds industry in the US financial markets, more precisely the active investments, to understand if someone can get lucky and achieve high value in the financial markets, or some financial skills are needed. In the main conclusion of this paper, the analysis showed that to achieve value, managers have to possess the financial skill. Moreover, it was studied if there is a difference between funds that are funded through trading apps or directly by investors, to be able to understand if managers perceive this difference. Even though this model worked on some unrealistic assumptions, discussed in later sections, the paper could not find any statistically significant difference between the two groups described.

To put these findings into a clear perspective, a thorough analysis and motivation about the most important choices that an investor has to consider will be provided. Firstly, in order to invest in the financial markets, investors have to choose how they want to buy their assets, by buying and selling directly on the financial markets, or through intermediaries. In the last decade of the 20th century, with the Dotcom bubble, a lot of companies started to deliver services as online brokerages. From the brick-and-store era to the online platforms which only need an account, and people can start investing. As the technology industry developed and became more complex, the next “jackpot” in terms of investing is in our phones. The smartphones created a unique means for investing, the brokerage apps, in which people just connect a credit or debit card, get their ID checked, and can start investing. The top five brokerage apps for investing in mutual funds in the present are eToro, Robinhood, Fidelity, Fineco Bank, and Plus500 ("Best Mutual Fund Apps 2021 - Top App Revealed - StockApps", 2021). However, not much research was done to understand the influence of this accessibility over the risks an investor or manager takes.

Next, it is important to choose the style of investing. Investors can choose passive investments, in which they invest in index funds; or they can choose active investments as investing through mutual funds, exchange-traded funds, or active stock-picking by themselves. According to Willis Towers Watson’s Thinking Ahead Institute in 2017, 25% of the assets were passive managed, and 75% were active managed (“Assets of world’s largest fund managers jump by over 15% to nearly $94 trillion”, 2018).

The style choice leads us to one of the most debated dilemmas in the financial literature. Investors have always two choices; first, to invest in an active mutual fund that will manage their financial assets on their behalf, or, second, to simply follow the market by investing into an index fund – which is the passive type of investment. In most of the literature, a unique answer could not be found, about which option is better. Over the last years, active management showed that they can outperform the market. However, here, a new question appears, if indeed managers can outperform the market, is it due to luck or possessing a financial skill? The most used measure in the literature to assess this is the gross alpha of the mutual funds. In this paper, I will try to investigate this question through a different method that is implied by the literature, I am going to use the value-added measure used by Berk and Van Binsbergen (2015). Through this measure, the authors want to evaluate the value that the managers of active mutual funds are able to bring out from the financial markets.

Besides the style of investment, an investor needs to know in which country/region, he or she wants to invest, as the financial markets differ across the globe. By looking at the asset management industry, the largest shared of management investments are in North America, with 58.1%, then Europe with 31.8%, and Asia with around 10% (“Assets of world’s largest fund managers jump by over 15% to nearly $94 trillion", 2018). Because of this, and the large, publicly available datasets, this paper will look into the equity mutual funds that are based in the US and invest exclusively into the US market.

Taking into consideration the above paragraphs in which are described the importance of investment style, dimension measure of active investment, and region of investment, this paper presents the main research question: "*Are the equity mutual funds in the US able to deliver added dollar value because of the active management of the financial assets?*" Moreover, to bring something new into this dilemma, I am going to extend my research with a sub-research question that will look into the brokerage online environment. As discussed before, due to the easy access that a smartphone can give nowadays to different investment opportunities, and the lack of literature on this topic, it is important to discover if the facility of these apps influences somehow the behavior of the active management of the mutual funds. So, the sub-research question is: "*Are managers of active equity mutual funds that are funded through brokerage apps better at delivering added value?*"

Through these two questions, the paper aims to have two important objectives; the analysis of the added dollar value that active managers can extract from financial markets and if there exists a difference in the added dollar value brought out by managers considering two types of fundings. This paper has the following structure. In the next section, there will be presented the literature review which will look closer into mutual funds, their advantages and disadvantages, what are the main tools to measure performance in the industry, and how differently the industry behaves in different regions over the world. Following, the data section will be presented in which the datasets used will be described. In the fourth section, the methodology will be detailed. In the fifth section, the main results of the paper will be shown and interpreted. Lastly, the paper will come to a conclusion in which will also be present recommendations for investors, limitations of this work, and future research into the topic.

Literature Review

a. *Mutual funds: advantages and disadvantages*

Even though there is an increase in investing with mutual funds in the last years, the concept of mutual funds is well known, from the beginning of the economic theories. Rouwenhorst (2004) describes in his work the origins of mutual funds. In his paper, he shows that the first mutual fund ever created was a Dutch trust named *Eendragt Maakt Magt* at the end of the 18th century. The founder of the trust had in mind a form of a platform that will allow small investors to diversify away their risk and increase their wealth.

According to King (2002), one of the main advantages of mutual funds is that an individual is able to hold a pool of well-diversified assets. Through this pool, investors can invest even a small amount of money and still benefit from economies of scale in lowering their risks. Another advantage described in the same paper is the liquidity that mutual funds represent for investors. This is due to two important characteristics of a fund: the shares of the mutual funds that are always sold at the fund's net asset and the fact that mutual funds investors do not pay any fees for the redemption of the shares. Indeed, there are some fees that can affect liquidity, for example, the transaction costs, but in the case of this paper, they will not be considered. The last advantage discussed by King (2002) is that mutual investors are guided by professional asset management teams, which invest on their behalf, with a very thorough analysis, which small investors are not able to do it by themselves since it can be very time consuming or more resources are needed to find out some information.

However, as with any other financial product, there are some crucial disadvantages of mutual funds that also need to be discussed. According to King (2002), mutual funds are not taxed efficiently as shareholders receive taxable income and capital gain even though they did not engage in any investment activity during a specific period. Another disadvantage discussed is regarding the portion of cash a fund needs to keep at hand. Because of this, in different scenarios, the cash affects negatively the returns of the portfolios. Lastly, the shares of a mutual fund are only sold once a day, at a specific hour when the net asset value of the fund is assessed.

In the US, according to Elton and Gruber (2013), the mutual fund industry affects the US economy through 3 different channels. The first one, the mutual fund is one of the two largest financial intermediaries. The second channel is the individual investors, as almost 50% of the families own a mutual fund. And lastly, the channel of the institutional investors, as almost 50% of the pension's funds invest through mutual funds.

After understanding a bit more, the concepts, main characteristics, advantages, and disadvantages of mutual funds, we can move in understanding the way mutual funds perform. Throughout the years, the mutual funds' performance has been investigated at large (Jensen, 1968; Carhart, 1997; Friend et al.,1962; Redman et al., 2000). Curiously, the literature never reached a unique conclusion in regards to mutual funds. The discrepancy is about the managers of the mutual funds. The dilemma is whether the managers are financially skilled or they just get lucky. Consequently, this affects how a mutual fund performs. Moreover, this investigation into performance showed another puzzle, namely, "Why do investors still buy active managed mutual funds if they tend to underperform the passive ones?"

In the next subsection, the papers presented will focus on the traditional analysis of the mutual fund industry, the usage of "Jensen's Alpha" in understanding the performance of the industry. All the papers from this section achieve the ultimate conclusion that active managers underperform. Later, two subchapters will be presented, in which new methods and strategies were implemented and different conclusions are reached. Next, one subsection will describe the previous literature regarding investing behavior through brokerage apps. The last part of this whole chapter will describe a more global perspective regarding active managers' behavior is shown.

b. Mutual funds: traditional view - underperformance

In most of the papers that conclude that the active managers underperform, one unique measure is used, the gross alpha or "Jensen's Alpha". Through this measure, researchers want to estimate how much can a manager forecast the returns of a specific fund (Jensen, 1968). This measure is based on the basic theories of asset pricing which were developed by Sharpe (1964) and Lintner (1965).

Jensen (1968) investigated the performance of mutual funds in the US from 1945 through 1964. He used two different types of mutual funds, the ones that were doing active stock picking and funds that were randomly choosing their investments. In his work, he reached two important conclusions. First, active managers are not able to predict future returns. Second, there is little statistical evidence that the funds that engage in active stock picking are better than the ones that engage in randomness. Moreover, Jensen (1968) found that active investment funds are not able to achieve enough capital to even pay their expenses.

Bogle (1992) investigated the equity mutual fund in the US during 1980-1990 on a yearly basis to understand why the "winner stocks" are "hard to pick, yet so easy" by the funds (p.94). In his paper he argues that equity funds could not achieve high performance, mainly choosing the right stocks to invest in, based on the past performances. Furthermore, another conclusion of the author is that for investors to choose the right fund, an easy choice would be to invest in a passive index fund.

Another paper by Day, Wang, and Xu (2000) investigated what are the main causes of the underperformance that is seen in the industry. As most of the papers in this subsection looked at the underperformance of the managers due to the lack of skills, these authors show another explanation – the inefficient weights attributed to the portfolios. In other words, even though the managers have enough financial skills to choose the right stocks, they do not have the skill to allocate the right percentage of allocation within a portfolio.

Last, but not least, the last paper of this subsection is one of the most famous works in regarding mutual funds, the work of Carhart (1997). In his research, using the momentum strategies, he analyzed why mutual funds cannot access the same high level of returns after following the momentum strategies. Momentum strategies are investment strategies in which different types of investors buy the stocks that achieve high performance in the past and sell stocks that perform poorly, to achieve high returns (Jegadeesh & Titman, 1993). Carhart (1997) was interested in why cannot funds achieve persistence in the financial markets with these strategies. Based on the model developed in the paper, the author's main conclusion is that there is no such thing as skilled or better-informed managers of mutual funds.

Based on the literature discussed above, the first hypotheses of the paper follow the "traditional view" of the market, which considers actively managed funds underperformers. The hypotheses are:

Hypothesis 1: Active investment (equity mutual funds) underperforms passive investment (index funds).

Hypothesis 2: Active managers of equity mutual funds do not possess the financial skills to overpass the benchmark of their mutual funds.

c. Mutual funds and momentum strategies

Through the work of Carhart (1997) and Jegadeesh and Titman (1993), more and more scholars started to be interested in mutual funds and different momentum strategies that can be implemented in order to achieve higher returns, even though Carhart (1997) demonstrated that the managers of active mutual funds to not seize this opportunity right.

Grinblatt, Titman, and Wermers (1995) looked into the behavior of the mutual funds and if they present a "herding behavior", which represents "predominantly selling and buying of the same stocks at the same time" (p.1089). In their work, they found that almost 80% of the investors use momentum strategies, however not all of them make it in the right way. Grinblatt, Titman, and Wermers (1995) extensively found that managers take care to buy the best-performing stocks, yet, they lose sight to sell the loser stocks. Even with this, the mutual funds performing momentum strategies are able to overpass the market and obtain abnormal returns. In terms of the "herding behavior", the authors do not find any evidence to support their hypothesis.

O'Neal (2000) investigated a specific type of momentum strategy – the industry momentum. As described by Vanstone, Hahn, and Earea (2020), "industry momentum is a strategy in which the abnormal return that an investor can obtain is due to buying stocks that are part of the past winner industries and sell stocks from the past loser industries" (p.2). O'Neal (2000) investigated this concept based on the US stock market participants, over 10 years, through the rolling portfolios strategy with lag periods of 3, 6, and 12 months. The author was able to find significant evidence that shows that industry momentum is a winning strategy for mutual funds. Almost all strategies were able to outperform their benchmark and the S&P500 Index, in the case, the two measures were different. Moreover, O'Neal (2000) was able to find a significant relationship between industry momentum and default risk premiums.

Gorman (2003) investigated the momentum strategies for the small-cap mutual funds of the US. In her work, she investigated the mutual funds between 1986 till 2000, and how well 165 actively small-cap mutual funds performed in the US financial markets. Over the period investigated, the author has been able to assess the abnormal returns of the mutual funds at 2% per year, through a conditional model. As Gorman (2003) presents in her conclusions, the active managed small-cap mutual funds continue to outperform for a period close to 12 months, and then a performance reversal is taking place.

Breloer, Scholz, and Wilkens (2014) investigated if global and international funds that integrate into their risk-adjusted model the country and sector momentum tend to outperform the market. In their research, they had three main focuses, the performance of the funds, the persistence of outperforming, and the luck or skill dilemma. In their main results, they show that during January 1996 and December 2009 the country and sector momentum affects the performance of the portfolios by more than 50%. This significant exposure taken into consideration leads to lower alphas for all international and global funds. Furthermore, the two momentum strategies also influence the persistence of funds being “the best” and the relationship of understanding the luck and skills of managers.

Besides the momentum strategies, there are some other examples of outperformance on the part of active managers in the financial literature. For example, Junarsin and Libert (2015) found that investing in an active socially responsible mutual fund gives higher returns to an investor than randomly investing in a mutual fund that is not respecting social responsibility regulations.

Overall, the main conclusion of this subsection is that for actively managed mutual funds is very important the right choice of investing strategy, for the fund to achieve high returns. In this case, by investing in the right momentum strategy, managers should be able to deliver more value to the mutual funds.

d. *Mutual funds: new models of analyzing performance*

Moving further with the discussion, some important studies showed that the “Jensen Alpha” is not a good measure for the equity mutual funds’ performance, because it can be influenced easily by the choice of the benchmark (Elton & Gruber, 2020). The authors developed the models and conclusions first reached by Sensoy (2009). In his paper, he demonstrated that mutual funds tend to choose a “bad” benchmark or not right, according to their fund’s characteristics. This mismatching is important because on it depends how much cash inflow will a fund achieve in the next years. Sensoy (2009) found that small value funds with high fees and a high number of assets under management are most likely the ones to choose a “wrong” benchmark. The same results were later confirmed by Cremers, Petajisto, and Zitzewitz (2012).

Besides the works described above, another paper regarding active mutual funds is the work of Choi and Murthi (2001) which looked into the performance of the mutual funds through a different approach. Their approach takes into consideration how good funds are at economies of scale and if they can efficiently integrate this in their portfolios and make them more cost-efficient. With this measure, the benchmark problem, which is the mismatch - can be avoided, but the manager is still examined regarding his success or failure. In conclusion, most of the funds are performing well, besides the income funds, which struggle in achieving good returns to scale scores.

An interesting work of Petajisto (2013) looked into the performance of mutual funds. As the author describes in her work, active management is divided into different types. These four types are diversified stock picks, concentrated stock picks, closed indexing, and factor bets. Through a model that takes into consideration active share picking and tracking error, the author found that most active stock-picking managers of mutual funds show an outperformance of their benchmark. Moreover, these patterns were investigated during the financial crises, where the paper comes to the same conclusion mentioned before.

Last, but not least, the most important paper of this subsection is the work of Berk and van Binsbergen (2015). As Berk and van Binsbergen (2015) argue in their paper, the gross alpha does not represent the true value of the managerial skill because it is a proxy for the mispricing that the managers can find in the market. This is why they measure the skills of the managers through a formula that calculates the added dollar value of a fund over a benchmark. In this way, they found that active managers possess skills and are able to use these skills, so the fund persists up to 10 years in achieving high returns. Moreover, due to this, investors are willing to send more capital to these funds and the authors were able to establish a positive correlation between funds capital inflow and future performance.

As the last paper analyzed shows an interesting result, which was not seen in other papers before and after, this paper will try to replicate the results and also include an extra insight if there exists a difference in the added dollar value between buying a mutual fund directly by investors or through a brokerage app.

e. *Mutual funds: investing through a brokerage app*

As expressed in the Introduction section, there is not much research particularly on the topic of brokerage apps being used as intermediate for funding a mutual fund, however, some important conclusions can be drawn from more broad works covering investing through different channels.

First, Bergstresser, Chalmers, and Tufano (2008) investigated if investing through a broker as an intermediate channel gives some benefits to the investors. In their work, they looked at the trade-off between costs, which are the high fees that investors have to pay to the brokers, and the benefits which were measured through five different dimensions. These five dimensions included the assistance of the broker, two measures of accessibility to funds, asset allocation, and lower investment behavior biases. As in the case of this paper, the focus of the work was on the US financial market. The authors, Bergstresser, Chalmers, and Tufano (2008), found that even though investors were exposed to mutual funds that are not that visible in the eyes of the media or investors, any other benefits could not be found. Moreover, the brokers are not better at allocating assets, which, generally, is believed to be an advantage for the intermediate's channels. This is why, the authors conclude that the benefits expressed by the brokers could not be tangible, in their case.

From the perspective of the investors or users that use brokerage apps to invest, Kalda et al. (2021) investigated the effect of smartphone investing on the behavior of German users. They found that investors that start to use these types of apps tend to make riskier investments and look out for "lottery-type" assets by analyzing the past performance of all types of financial instruments. Moreover, Kalda et al. (2021) found that after investors have changed their investments to more risky ones, they start trading in such a manner always, so the behavior change is impactful. The same conclusions were also found in the study of Chaudhry and Kulkarni (2021) which showed that investing through brokerage apps leads to a very "unhealthy" trading behavior. The authors referring to the unnecessary risks that investors take and the idea of making money in a very short period.

From the perspective of managers, the literature is quite lacking in terms of giving a precise answer on how this affects their ability to allocate financial assets. First, Röder and Walter (2019) discovered that managers that are active on the brokerage platform through commenting or posting different charts about their progress are able to attract more cash inflow for their funds. In other words, managers that are transparent and establish a connection in the online environment are seen as more trustworthy and this in the end, benefits the mutual fund. Another important conclusion of Röder and Walter (2019) is that active funds that are in the top lists in the brokerage apps tend to receive more cash inflow in their funds. Overall, an important recommendation of the authors is that in the online environment, how visible you are, through being active or being at the top of the list, will help managers to receive more financial capital in the fund.

Due to the fact that funds that are present in the brokerage apps have the opportunity to receive more cash inflows, and because they need to be visible and stay at the top, the managers have to be able to allocate the financial assets in a very good manner to be always first. Namely, a higher cash inflow will make managers responsible to achieve higher returns, or added dollar value to keep the constant inflow of capital. Taking this into consideration, the next hypothesis was formed:

Hypothesis 3: The active managed mutual funds present on the brokerage apps have a higher dollar value than the actively managed mutual funds that are sold directly to investors.

f. *Mutual funds: global perspective*

As the world progressed and the financial markets developed, the equity mutual funds industry extended, as well. Moving away from the US, which is the geographic focus in this paper, this section will provide some insights regarding the literature from the global perspective, and if the same phenomena seen in the US, can be seen in other countries.

Redman et al. (2000) researched the performance of the global and international funds during three periods that include 1985 till 1994. To compare the results, the mutual funds were checked using Sharpe's index, Treynor's index, and Jensen's alpha. They found that from 1985 till 1989, the international mutual funds outperform the US and global markets. Then from 1990 till 1994, both, international and domestic mutual funds' returns declined in comparison with the market.

Quareshi et al. (2019) investigated how the stock markets and mutual funds perform in the Asian developing countries. Their study extended over more than 15 years, period of 2001 – 2017, to understand how the dynamics in the financial markets developed regarding the mutual fund industry. The main conclusions of the paper showed that the bond mutual funds in the Asian developing countries tend to outperform their benchmark, however, the equity mutual funds, tend to underperform most of the time. Another interesting conclusion of the paper looked into the effect of past performance on the mutual funds, regarding the type of asset that is focused on. Quareshi et al. (2019) showed that equity mutual funds react positively to past performance, however, the bond funds react negatively.

Regarding the underperformance of equity mutual funds in emerging markets, Ahmed et al. (2001) showed that mutual funds always perform better during periods of restrictive monetary policy in the world. As an example, they provide that during the times of high discount rates proposed by the Federal Reserve of the US, the equity mutual funds from emerging markets can outperform their benchmark. As well, this paper demonstrated that the US has conditional financial power over the emerging markets.

Lastly, Otten and Bams (2002) investigated the European market of mutual funds. During their research, they found that in the European industry, small-cap funds can always outperform the market. Moreover, in case the management fees are considered into the model, most of the mutual funds from the most important European countries are able to outperform the market. These results were later expanded by the work of Vidal-Garcia (2013) which looked into the persistence of European mutual funds over the market. He found that the "bottom" and "tops" of the mutual funds tend to keep their position for a longer period than in the US. Because of this, European mutual funds' past performance has higher explanatory power for future performance than what we are used to seeing in the US.

The works presented above present an interesting picture of the global markets. I wanted to show this perspective, to understand if the same behavior of active mutual funds can be observed at a global scale. On one hand, the global market as a whole and the European market of mutual funds tend to overpass their benchmark if they are actively managed. On the other hand, the Asian market shows patterns like the US market, where active managers most of the time underperform.

This important difference in markets can impact how investors or scholars approach the idea of financial integration from the perspective of active mutual funds. An insightful academic work that would look into these two different behaviors of active mutual funds, by comparing them, would give more perception for the investors that consider the active investing into a more integrated mutual funds market. However, this is beyond the scope of this paper.

Data

As with any project is very important to choose the right data to receive the best results out of it. As the main theme of this research is about equity mutual funds in the US, the most used data for this type of project is the Survivor-Bias-Free US Mutual Funds database provided by the Center of Research in Security Prices (CRSP). In order to be able to access this dataset the Wharton Research Data Service (WRDS) platform was used. The platform is well known as it provides a wide variety of products, data sets, subscriptions that make it easier for different types of scholars to access this information.

The Survivor-Bias-Free US Mutual Fund data set has been used since 1962. In the most important works of Carhart (1997) and Jegadeesh and Titman (1993), also, this database was used. As the decades passed, the database became more complex, upgraded with more information about mutual funds; containing information such as the fund summary, dividend policies of the funds, and the daily and monthly return.

As stated in the Introduction section, the asset management industry grew exponentially over time, so the choice of the period of investigation is crucial. In this paper, for both, main research question and sub-research question, the analysis of the performance of equity mutual funds will cover the period January 2010 till December 2020. In total a period of 11 years, or 132 months per mutual fund. This period was chosen, as it is the most recent one, and is possible to find observation for each mutual fund. Moreover, this period includes the post-financial crises time until the first months of the Covid-19 crisis; so, it makes it curiously to see the development of the movement of the mutual funds' industry in between crises.

a. Equity Mutual Funds data

The Survivor-Bias-Free US Mutual Fund data set is a very large body of data, so in order to get to the final data set some extra steps needed to be taken, to obtain only the information of the US active equity mutual funds.

Firstly, an important characteristic of mutual funds is the Committee on Uniform Securities Identification Procedures number, or shortly, the CUSIP number. The CUSIP number is an identification for each financial instrument, that is created by the combination of nine characters which can include letters and numbers ("CUSIP Number” | “Investor.gov”). Through this number, investors or scholars all over the world can find easier information about most financial instruments that are registered in the US and Canada. ("CUSIP Number” | “Investor.gov”). Based on the style of the CUSIP, all the fixed income mutual funds were deleted, mainly, the

CUSIPs that included letters. The next step of cleaning the data was to make sure that all the mutual funds that are part of the future dataset include all monthly observations over the period January 2010 – December 2020. In total, a period of 11 years, or 132 months. The mutual funds that have fewer observations due to the inactivity or because they stop existing during this period were taken out. The next step of cleaning was to remove the funds that identify as index funds, which are passive investment examples.

Another important step in the cleaning of the data was to follow some of the same steps as Berk and van Binsbergen (2015). All the funds that had less than $5 million as Total net asset value and funds that had less than two years prior data to the period that is investigated in this paper have been removed. The total net asset value represents the value of the total assets a financial institution has after taking out the value of its total liabilities ("Net Assets", 2021). This was done to avoid some biases in the case the funds are too small or too new in the market and are subject to a large inflow of cash and growth in the first years.

The last step of the cleaning data was to filter out all the funds that invest foreign or in real estate or are institutional or hedged. This has been able to be done by the filter imposed on the Lipper Objective codes that were introduced in the Survivor-Bias-Free US Mutual Fund data set after 1998. The Lipper Objective code is a specific type of classification that shows how financial instruments will invest their money (“Lipper Objective and Classification Codes” | “CRSP - The Center for Research in Security Prices”). In total, after all the steps mentioned above, the dataset consists of 1203 US active equity mutual funds.

Table 1. Descriptive statistics of 1203 US equity active mutual funds

Table 1 contains the main descriptive statistics of the 1203 US equity active mutual funds. The descriptive statistics cover the period January 2010 to December 2020. The variables included are Monthly return, Net asset value (NAV), total net asset value (TNA), the highest NAV of the last 52-weeks, the lowest NAV of the last 52-weeks, the amount invested in the Common stock, the amount invested in Cash. The monthly return is calculated monthly, the rest of the variables are calculated yearly. All these variables are measured in $millions. The other four variables: Monthly return, Management fee, Expense ratio, and Turnover ratio, are ratios.

The monthly return is calculated as the total return per share at the end of the month for each fund. The TNA is calculated as total assets minus the total liabilities of a fund. The NAV is the ratio between TNA and the number of outstanding shares. In other words, the NAV shows the share/unit price of the fund on a specific date. The next two variables show the highest and lowest NAV throughout the 52 weeks. The next two variables show how much a fund is investing in common stock and cash during a year. Management ratio is calculated as the division between the management fee and the average net assets of a fund during 12 months. Next, the Expense ratio is the ratio between the total investment of the shareholders and the operating expense of the fund. Lastly, the Turnover ratio is calculated as the minimum number of securities purchased divided by the average 12-months TNA.

Variable	Mean	SD	Min	Max
Monthly return	0.009	0.044	-0.47	0.44
TNA	1,902.75	6,889.39	5.1	125,807.90
NAV	27.74	45.99	2.1	1,683.17
Highest NAV 52	30.35	48.32	2.18	1,683.17
Lowest NAV 52	23.39	37.45	1.74	1,050.40
Invest. Common stock	81.27	22.30	-18.83	141.66
Invest Cash	2.35	6.98	-96.6	100.95
Management ratio	0.62	0.31	-4.898	1.97
Expense ratio	0.012	0.005	-0.0004	0.027
Turnover ratio	0.61	0.74	0	15.53

b. MSCI Benchmark and Fama French Carhart factors

Following the Berk and van Binsbergen (2015) approach, to be able to compute the added dollar value, the monthly returns of the mutual funds have to be compared to a benchmark. In this case, the paper follows two approaches, an alternative benchmark, and a traditional method. The alternative benchmark constitutes a portfolio made based on some specific passive investments, so indexes. The traditional approach is to follow a risk-adjusted model.

In the paper of Berk and van Binsbergen (2015), the alternative benchmark used was created by indexes from the Vanguard family. In this case, I decided to use another family of indexes. The benchmark in this case will be created based on different indexes that are part of the MSCI family. MSCI is a financial company that has invested all over the world in indexes in different countries, regions, with different styles. As expressed by the company itself, their indexes provide high returns, are accurate to the specific characteristics of the clients, and are able to efficiently construct complex benchmark portfolios ("Index Solutions"| “MSCI.com”). Also, next to the Vanguard family, MSCI family indexes are the next global players in this domain. In this paper, seven MSCI indexes that invest in the US financial markets are used. The prices of the MSCI indexes were downloaded from the MSCI website and the returns were calculated based on the prices.

The first three indexes are USA (All CAPS), USA (Standard), and USA (Small and Micro). These indexes only have as a characteristic the size of the indexes. In the case of All CAPS, the passive investment is in all types of size. The Standard index includes large and mid-caps; and the Small and Micro – small and micro-cap indexes. The other four indexes have two principles of investing: style and size. The styles refer to growth (G) and value (V).

Table 2. Descriptive statistics of the MSCI Benchmarks

Table 2 contains the main descriptive statistics of the return of the MSCI indexes that constitutes the alternative benchmark of this paper. The descriptive statistics cover the period January 2010 to December 2020, on a monthly basis. The indexes are all based on the US financial markets and include different types of styles of investing and different types of the size of the indexes. The letter G represents the style growth, and V – value. The USA (All CAPS) includes all types of sizes. The Standard index includes the sizes large and mid-cap. Last, but not least, Small and Micro refer to the sizes small and micro-cap.

Variable	Mean	SD	Min	Max
USA (All CAPS)	0.011	0.042	-0.14	0.132
USA (Standard)	0.011	0.054	-0.209	0.356
USA (Small + Micro)	0.011	0.054	-0.229	0.167
USA, G, Standard	0.014	0.047	-0.111	0.168
USA, G, Small	0.014	0.047	-0.111	0.168
USA, V, Standard	0.014	0.054	-0.19	0.157
USA, V, Small	0.007	0.04	-0.159	0.127

In the next graph below are shown the movements of the MSCI indexes over the period January 2010 – December 2020. The movements represent the yearly average of the monthly returns of these indexes. As mentioned in the table and text from above, the indexes were selected in such a way to cover the same styles and sizes as the equity mutual funds used in this research. Over this period, it can be observed that the indexes move in the same pattern. Over the last years, 2018-2020, an increase in the returns of almost all indexes is detected.

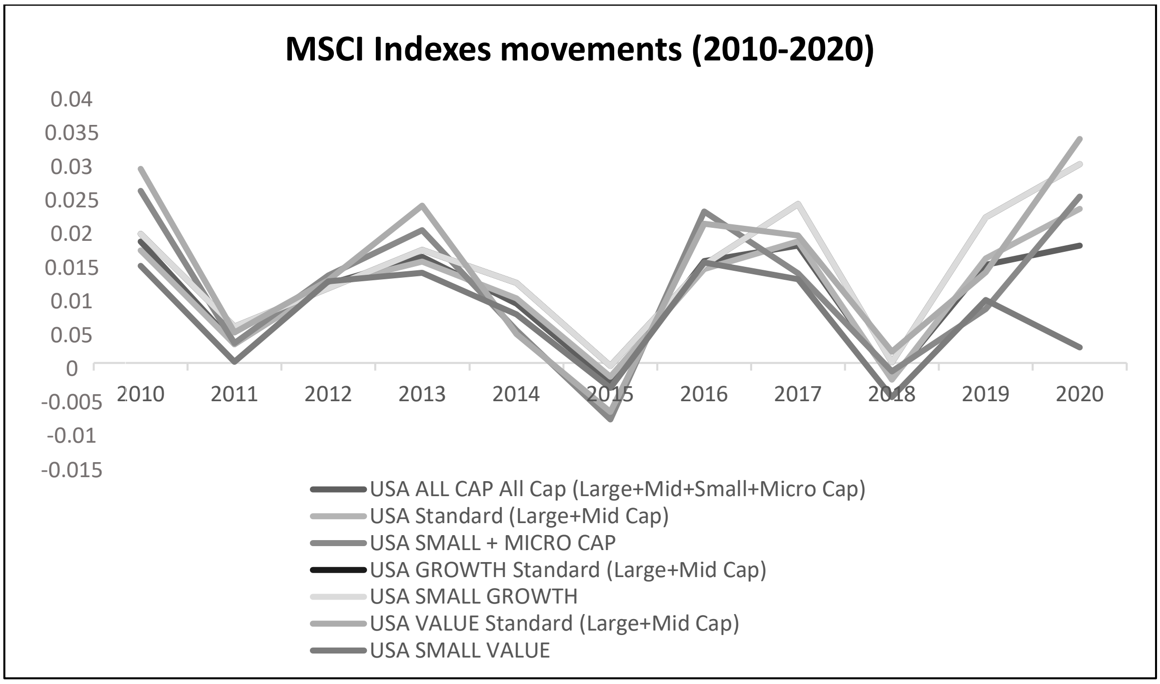

Figure 1. MSCI Index movements in the period 2010 - 2020

Figure 1 shows the movements of the MSCI Indexes over the period January 2010 until December 2020. The returns represent the average monthly returns per index fund. The indexes are all based on the US financial markets and include different types of styles of investing and different types of the size of the indexes. The letter G represents the style growth, and V – value. The USA (All CAPS) includes all types of sizes. The Standard index includes the sizes large and mid-cap. Last, but not least, Small and Micro refer to the sizes small and micro-cap.

The second way of testing the performance of the active mutual funds is going to constitute a benchmark created based on a risk-adjusted model which includes the Fama French factor model with the momentum developed by Carhart (1996), which will be shortly known in the paper as FFC model. The factors were downloaded from the same platform mentioned during this paper, WRDS, more precisely, the Fama French – Monthly Frequency dataset. Below, can be found the descriptive statistics of the factors.

Table 3. Descriptive statistics of the Fama French Carhart Factors

Table 3 contains the main descriptive statistics of the Fama French Carhart Factors. The descriptive statistics cover the period January 2010 to December 2020, on a monthly basis. The variables included are Risk-free rate (R_f), which is the rate of one month Treasury Bill, Excess Return on the Market (MKTRF), Small minus Big (SMB), High minus Low (HML), and Momentum (UMD).

Variable	Mean	SD	Min	Max
R_f	0	0.001	0	0.002
MKTRF	0.012	0.043	-0.134	0.137
SMB	0.001	0.024	-0.05	0.055
HML	-0.004	0.027	-0.14	0.082
UMD	0.003	0.035	-0.122	0.103

In the graph down below are shown the movements of the Fama French Carhart Factors over the period January 2010 – December 2020. The movements represent the yearly average of the monthly returns of the factors. Over this period, it can be observed that the factors move in different directions, and investing considering different factors in different positions, by taking a long or short position, could improve the portfolio of an investor. This situation is opposite to the MSCI indexes, which move most of the time in the same pattern. Over the last years 2018-2020, some noticeable extremes are detected. The HML (high minus low) factor has been declining, and the MKTRF (market premium), SMB (small minus big), and UMD (momentum) have kept rising.

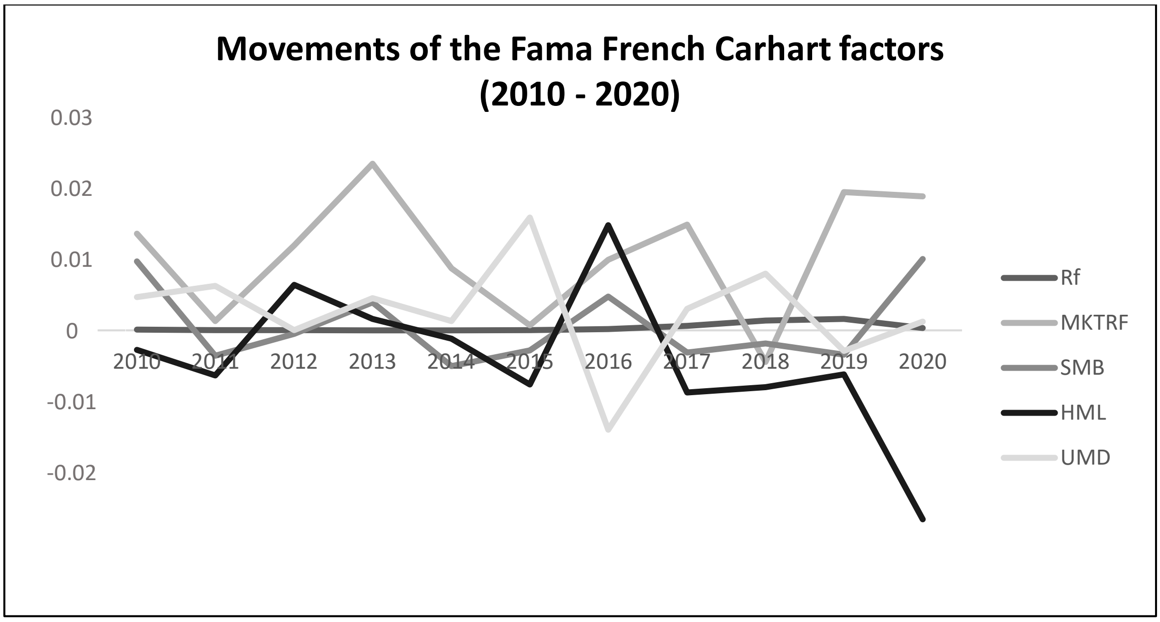

Figure 2. Fama French Carhart factors movements in the period 2010 - 2020

Figure 2 contains the movements of the Fama French Carhart factors over the period January 2010 until December 2020. The returns represent the yearly average of the monthly returns. The factors included are Risk-free rate (R_f), which is the rate of one month Treasury Bill, Excess Return on the Market (MKTRF), Small minus Big (SMB), High minus Low (HML), and Momentum (UMD).

c. Fidelity Brokerage app

The innovation of this paper is its investigation into the world of trading apps and if managers are influenced in any way by them to achieve higher added value from the market. Since it is a new question, there is no unique measure approved by the literature. In this case, I will answer the question by choosing a brokerage app as a proxy. It is necessary to find an online broker good enough as a proxy that would provide a public database with the mutual funds they offer to their clients. Moreover, this broker should have these mutual funds in their brokerage application for smartphones. After long research, based on what I found, one of the best online brokers is Fidelity ("Best Mutual Fund Apps 2021 - Top App Revealed - StockApps", 2021). Fidelity is an online broker that has been around the market for about 70 years and still goes strong with the introduction of its app for smartphones. One important distinction from the rest of the brokers is that Fidelity does not ask for any commission fees, just the expense ratio. Moreover, in the past year, they opened four types of index funds where even the expense ratio is not asked ("Best Mutual Fund Apps 2021 - Top App Revealed - StockApps", 2021).

It is very important to remember that the Fidelity brokerage app acts as a proxy in this paper, which tries to measure a unique question. This is why to be convinced that is a good proxy, I compared it to its closest competitors: Robinhood and eToro ("Best Mutual Fund Apps 2021 - Top App Revealed - StockApps", 2021). Robinhood is an app with over 10 million users and it is valued at approximately $7.6 billion (""Best" Stock Trading Apps - July 2021 (Quick Reviews)", 2021). The other competitor, eToro, has a pool of 20 million users ("Best Mutual Fund Apps 2021 - Top App Revealed - StockApps", 2021) and it is valued at approximately $10 billion ("What eToro's investors' presentation and $10B valuation tells us about Robinhood", 2021). Lastly, Fidelity has the advantage that is not only a brokerage app but a mature financial company with a pool of 35 million clients ("About Fidelity - Our Company" | "Fidelity.com") and its total worth is valued at $109 billion (Eule, 2018). Furthermore, the company covers more than 25 countries and has access to more than 10,000 financial assets ("Best Mutual Fund Apps 2021 - Top App Revealed - StockApps", 2021). Consequently, the mutual funds present on the Fidelity trading app could be thought of as a benchmark. Namely, is it very likely that the mutual funds are also present on the apps of its competitors. In this way, Fidelity becomes a good proxy.

Based on different remarks, the Fidelity database included 977 US equity mutual funds. Taking into consideration the same criteria from *Subsection (a)* of this chapter, out of them only 295 US equity mutual funds could be found with full information on the WRDS platform, in the Survivor-Bias-Free US Mutual Fund. In the database used for this research, the funds can be differenced if it is sold through a brokerage app or sold directly to investors through a dummy variable.

Table 4. Descriptive statistics of 295 US equity active mutual funds that are sold through the Fidelity brokerage apps

Table 4 contains the main descriptive statistics of the 295 US equity active mutual funds that can be bought through the Fidelity brokerage app. The same descriptive statistics over the period January 2010 to December 2020. The variables included are the same as in the case of Table 1: Monthly return, NAV, TNA, the highest NAV of the last 52-weeks, the lowest NAV of the last 52-weeks, the amount invested in the Common stock, the amount invested in Cash. All these variables are measured in $ millions. The other four variables: Monthly return, Management fee, Expense ratio, and Turnover ratio, are ratios.

Variable	Mean	SD	Min	Max
Monthly return	0.011	0.047	-0.33	0.24
TNA	2037.32	5900.25	5.1	113144
NAV	27.38	18.54	2.41	163.08
Highest NAV 52	30.06	20.06	2.69	166.76
Lowest NAV 52	22.80	14.88	1.99	110.88
Invest. Common stock	92.71	7.316929	16.25	108.93
Invest Cash	2.51	4.61	-15.67	74.29
Management ratio	0.74	0.25	-2.47	1.962
Expense ratio	0.011	0.003	0	0.027
Turnover ratio	0.55	0.49	0	9.22

Methodology

To find the added dollar value that the funds can obtain from the financial market, I will use two approaches; the first one will have a focus on the MSCI indexes, and the second one, the Fama-French Carhart Factors. Besides this important distinction, in order to get to the added dollar value number, both approaches follow the same formulas and logic flow. Both, research question and the sub-research question will go under test through these two approaches and this will make it possible to see if as research, I can reach the same conclusion.

a. MSCI Benchmark

The first approach focuses on obtaining the added dollar value that a mutual fund can obtain extra over the alternative benchmark. In order to create this benchmark, the MSCI indexes will be diversified into a portfolio. The usage of MSCI various indexes makes it easier to understand the development of the movements of passive investing in the US financial markets. As explained in the Data section, because we have active funds that vary in size and style of investing, the MSCI benchmark will combine different characteristics, as well. Following Berk and van Binsbergen (2015), the R_t^j represents the excess return that an investor can earn by investing in the *j*th MSCI index fund at the time *t*, then to calculate the return of the benchmark of particular fund *i*, the paper will use the next formula

$$R_{it}^B = \sum_{j=1}^{n(t)} \beta_i^j R_t^j, \tag{1}$$

in which *n(t)* is the number of the MSCI index funds and β_i^j represents the approximates of the *i*th active equity mutual funds regressed on the MSCI indexes (Berk & van Binsbergen, 2015).

Next, to achieve the added dollar value, there is a need for a formula to measure the amount of money an active fund can extract over. In this way, we multiply the excess that an active mutual fund has, its gross return, measured by $R_{it}^g - R_{it}^B$, with the size of a fund at the end of the previous period, its monthly total net asset value, measured by $q_{i,t-1}$ (Berk & van Binsbergen, 2015). Consequently, the measure has the next form

$$V_{it} \equiv q_{i,t-1}\left(R_{it}^g - R_{it}^B\right). \tag{2}$$

To be able to measure the skill over time, the estimated value will be transformed into the time series expectation of Equation *(2)*

$$S_i \equiv E[V_{it}]. \tag{3}$$

As a result, for all the funds, the estimated added dollar value will be calculated for every period T_i by the next calculation

$$\hat{S}_i = \sum_{t=1}^{T_i} \frac{V_{it}}{T_i}. \tag{4}$$

Lastly, the final step is to find the average dollar value that the funds can obtain from the financial markets. As all active mutual funds were selected in such a way that they have all the entries for over 132 months or 11 years, the cross-sectional mean will be calculated as

$$\bar{S}_i = \frac{1}{N}\sum_{i=1}^{N} \hat{S}_i, \tag{5}$$

where the N is the number of the mutual funds in our database. The N will equal the 1203 US active equity mutual funds that can be found in the dataset.

b. Fama French Carhart Factors

The case of the second approach, as a benchmark will be used a risk-adjusted model which includes the Fama French Factors and the Carhart momentum, the FFC model. As expressed by the literature, this is a traditional approach that has quite some controversies. Mainly as explained by Fama and French (2010) through the risk-adjusted measures it is quite hard to measure the systematic risk of a financial market. This, however, is crucial to understand the difference between active and passive investment. As in this case, the factors can just create a passive portfolio investment by themselves.

Expressly, in order to calculate the added dollar value, the process even in the case of Fama French Carhart Factors will follow Equations *(2)* to Equation *(5)*. However, the formula *(1)* will change a bit its form. In this case, was used

$$R_{it}^{B} = \beta_i^{MKT} MKT_t + \beta_i^{SML} SML_t + \beta_i^{HML} HML_t + \beta_i^{UMD} UMD_t, \tag{6}$$

in which $MKT_t, SML_t, HML_t, UMD_t$, represent the realizations of the well know factors (market premium, small minus big, high minus low, and momentum), and $\beta_i$are the exposure of the *i*th active mutual fund regressed on these factors (Berk & van Binsbergen, 2015).

c. Unskilled vs Skilled managers

To be able to answer the main question, and to be able to find evidence that supports or contradicts the first two hypotheses, again, will be followed the mechanism of Berk and van

Binsbergen (2015), and the hypothesis developed by Fama and French (2010). The last-mentioned work of Fama and French (2010) discusses the “no skill” assumption, in which they affirm that the average manager of an active mutual fund does not have the necessary financial skill to provide value to his or her fund. Following the same logic in this paper and the first two hypotheses, this implies that the average manager of the dataset should have an average added dollar value equal to 0. In other words,

$$\bar{S_i} = \frac{1}{N}\sum_{i=1}^{N}\hat{S_i} = 0, \tag{7}$$

for every *i*. In this case, the data will provide enough evidence that the active managers of equity mutual funds in the US are underperforming and do not possess the necessary financial skill to overpass their benchmark.

However, there is a possibility of another outcome. If the average added dollar value of the managers proves to be positive and persistent in the data set, the paper will have enough evidence to reject its hypotheses and arrive at the conclusion that managers are not only lucky but provide insight and create value for their managed funds. To put it in another way, in the case

$$\bar{S_i} = \frac{1}{N}\sum_{i=1}^{N}\hat{S_i} > 0, \tag{8}$$

for every *i*, the first two hypotheses of the paper will be rejected.

d. *Mode of funding: brokerage vs direct*

Last, but not least, this part of the research will investigate if there exists any difference in the added dollar value that managers can create, knowing how the mutual fund is funded, either directly sold to the investors or through a brokerage app. In order to investigate this, the paper will consider in the process of testing, that the funds are exclusively funded only through the two options. It is an unrealistic assumption, that needs to be taken into consideration in regards to interpreting the result. Besides this, it is crucial to have this assumption since this study cannot find the real weights of how much each fund is funded through which approach because this is private information that only the closed management circle has access to.

In the case of this paper, the information was taken from the Fidelity brokerage app. Through this method, the paper aims to answer its sub-research question and find enough evidence to support or rejects its third hypothesis. As in the case of the main research question, this question will also be answered through the two approaches with different benchmarks.

1. MSCI benchmark

In the case of the MSCI benchmark, Equation *(1)* to Equation *(5)* will have the same forms, however, in this case, two conditions will be imposed per each equation. For example, the change in a formula will be only shown in the case of Equation *(1)* and the same logic will be applied to the other ones. First, the paper will calculate the return of the benchmark only considering the estimates of the mutual funds that are sold through the brokerage app

$$R_{bt}^{B} = \sum_{j=1}^{n(t)} \beta_b^j R_t^j, \tag{1a}$$

in which *n(t)* is the number of the MSCI index funds and β_b^j represents the approximates of the *b*th active equity mutual funds that are sold through a brokerage app regressed on the MSCI indexes. Then, following the order of the equations, the paper will get to Equation *(5a)* which will calculate the average added dollar value of the funds sold through the Fidelity brokerage app ($\bar{S}_b$)

$$\bar{S}_b = \frac{1}{N}\sum_{i=1}^{N} \hat{S}_b. \tag{5a}$$

The next step will be to calculate the dollar value of the funds that are sold directly to the investors. In this case, the paper will use the next formula

$$R_{dt}^{B} = \sum_{j=1}^{n(t)} \beta_d^i R_t^j, \tag{1b}$$

in which *n(t)* is the number of the MSCI index funds and β_d^j represents the approximates of the *d*th active equity mutual funds that are sold directly to investors regressed on the MSCI indexes. The average added dollar value of the funds sold directly to investors ($\bar{S}_d$) will have the next form

$$\bar{S}_d = \frac{1}{N}\sum_{i=1}^{N} \hat{S}_d. \tag{5b}$$

The last step in assessing and answering the research question will be to statistically test if there is any difference between the two-average added dollar value numbers. For this testing, there will be used a two-sample t-test with two distinct assumptions. In the first test, it will be supposed that the variances of the two samples are equal. The second test will have this assumption relaxed, so, it will presume that the variances of the two samples are unequal. In both cases, the t-test assets that the samples are unpaired.

Moreover, besides the two assumptions, this testing will have the next statistical hypotheses. The null hypothesis will imply that the two-average added dollar value are equal *(H_0: $\bar{S}_b = \bar{S}_d$)* or the alternative hypothesis that the two averages are different *(H_a: $\bar{S}_b \neq \bar{S}_d$)*. Consequently, if the statistical test will have enough evidence to reject the null hypothesis, then the paper will have enough evidence to support its third hypothesis. Namely, that managers that have their funds sold through the brokerage apps have a higher dollar value than the ones that have the funds sold directly to their investors.

2. Fama French Carhart factors

As the literature does not have a perfect method in assessing the benchmark of the mutual funds, for the third hypothesis, no unique benchmark was chosen. Naturally, the logical flow of investigating the brokerage hypothesis through the Fama French factors will follow the above section. As in the case of *Subsection (b)* of this chapter, the Equations used are *(6)* and then *(2)* to *(5)*. In the case of mutual funds that are sold on a brokerage app, Equation *(6)* will change its form to *(6a)*

$$R_{bt}^{B} = \beta_b^{MKT} MKT_t + \beta_b^{SML} SML_t + \beta_i^{HML} HML_t + \beta_b^{UMD} UMD_t, \tag{6a}$$

in which $MKT_t, SML_t, HML_t, UMD_t$, represent the realizations of the well know factors (market premium, small minus big, high minus low, and momentum), and β_b are the exposure of the *b*th active mutual funds that are sold by Fidelity brokerage app regressed on these factors.

In the case of mutual funds that are sold directly to investors, the next formula will be used

$$R_{dt}^{B} = \beta_d^{MKT} MKT_t + \beta_d^{SML} SML_t + \beta_d^{HML} HML_t + \beta_d^{UMD} UMD_t, \tag{6b}$$

in which $MKT_t, SML_t, HML_t, UMD_t$, represent the realizations of the well know factors (market premium, small minus big, high minus low, and momentum), and β_d are the exposure of the *d*th active mutual funds that are sold directly. Then, the added dollar value per case will be calculated and the results will be put under the two-sample statistical test, discussed in *Subsection (c.1)* to determine if the averages are statistically different or not.

Results

In this section, the main results are discussed along with the tables that present the main statistical results. At the moment of the discussion of the results, the support or rejection of the three main hypotheses of this paper will also be related. The first subsection will describe the research question which looks into the financial skill of the active managers of the US equity mutual funds. Then, the second subsection will look into the difference between the mutual funds that are sold directly to the investors, and the ones sold through an intermediate, the Fidelity brokerage smartphone application.

a. Unskilled vs Skilled managers

The main results of the main research question of the paper are presented in Table 5 which can be found at the end of this subsection. In the process of testing and answer the main research question, the whole dataset of 1203 US active equity mutual funds was used. The average cross-sectional added dollar value over the period January 2010 and December 2020, in the case of the MSCI indexes, is approximately $17.85 million; in the case of the FFC benchmark, a slightly lower number at $13.66 million. In the case of both approaches, these averages were tested against a t-test that had the aim to test if these numbers are equal to 0, the null hypothesis of the t-test. The t-statistics in both cases are 9.43 and 9.21 which means a p-value smaller than 0.01. In this case, there is enough evidence to reject the null hypothesis of the t-test.

In other words, this means, that the active managers of the US equity mutual funds are able to provide a positive added dollar value in the financial markets. In this way, the paper has been able to prove that Equation *(8)* exists in the financial markets. Based on everything discussed above, the paper rejects the two main hypotheses. Mainly, we can affirm that in the case of the first hypothesis, the active investment can outperform; and in the case of the second hypothesis, the managers possess enough financial skill to create statistically significant added dollar value.

Another important picture to analyze is how the percentile of both approaches changes from low to high values. In the case of the added value that is created above the MSCI index, in most of the percentiles can be seen higher values compared with the values obtained considering the benchmark created by FFC factors. As presented by Berk and van Binsbergen (2015) is that usually, the large families of indexes offer more diversification services, which in the end can be useful in achieving higher returns in the financial markets.

The last measure presented in Table 5 is the percentage of the negative added dollar value in the case of each benchmark. In other words, this measure relates to how many added dollar value estimations were negative after all the computations were finished. By comparing the two observations, it can be seen that approximately 35% of active mutual funds have a negative value. However, taking into considerations that the period investigated is quite large and multiple economic events happen during the time, it would have been strange to not find any negative estimations.

To conclude, through these results we can answer the research question of the paper and affirm that the active managers have the financial skill to allocate and extract value from the US financial markets. Moreover, these results complement the work of Berk and van Binsbergen (2015), by assessing exclusively the active domestic (US) equity mutual funds over a different period than the one investigated by the after-mentioned authors.

Table 5. Added dollar value extracted by active managers over period 2010 – 2020

Table 5 contains the main results of the research in regards to the average added dollar value of the funds, $\overline{S_i}$, calculated based on Equation *(5)*. In the table can be found the cross-sectional mean, the standard error, and the t-statistic. Next to them are shown the different levels of percentiles of the average added dollar value measure. The percentiles were calculated as the estimates of the added dollar value were divided into 20 quantiles. The last measure, the percentage of the negative added value was calculated as the percentage of mutual funds that have their estimated added dollar value negative. The mean, standard error, and percentiles are measured in $ million, and the negative value variable is in %. The table presents the result of both approaches, first taking into consideration the MSCI indexes as the benchmark, second – Fama French Carhart factors. The number of mutual funds used *(N)* was 1203.

	(1) MSCI index	(2) FFC factors
Cross-sectional mean	17.85	13.66
Standard error	1.89	1.48
t-statistic	**9.43*** **	**9.21*** **
5th percentile	-248.15	-272.87
10th percentile	-51.47	-56.49
25th percentile	-11.13	-12.43
50th percentile	1.11	0.56
75th percentile	15.47	14.32
90th percentile	53.51	50.29
95th percentile	100.40	94.53
Percentage of negative added value	35.06%	35.52%

*(significance levels: *** p<0.01, **p<0.05, *p<0.1)*

b. Mode of funding: brokerage vs direct

This section will answer the sub-research question of this study, which represents the innovation of this paper, and will provide a small step in closing the gap on how investing through smartphones changes the behavior of managers that have assets under management.

The first main step was to analyze if the added dollar value that managers extract from the financial markets is statistically significant taking into consideration the way the mutual funds are receiving their cash inflow. In this case, there were performed four tests in which two of them consider the MSCI index as a benchmark, and two of them – the FFC factors. Also, two of the tests assume a direct approach, meaning the funds are sold directly to investors, and two of them – sold through the Fidelity brokerage application. In the case of the direct approach, both benchmarks, the number of mutual funds represent 295 out of the 1203 US equity mutual funds investigated in the first part. The rest, 908 mutual funds are the ones sold directly to investors. The period investigated remains the same.

Overall, the average cross-sectional added dollar value differs from case to case, the largest being for the case of the MSCI index, sold through the brokerage app with $21.86 million; and the lowest for the FFC factors, sold directly, with $12.72 million. However, the important part is in understanding if the extracted value is significant. In all cases, these averages were tested against t-tests that had the aim to test if these numbers are equal to 0, the null hypothesis of the t-tests. The t-statistics are lower than the ones in Table 5, nevertheless, all of them are statistically significant. In the case of the MSCI index benchmark, the t-statistics for mutual funds sold through brokerage app is 5.40, and the ones sold directly – 7.76. In the case of the FFC factor benchmark, the next t-statistics were found: 5.19 for brokerage sold mutual funds and 7.60 for the ones sold directly. All these t-statistics mean a p-value smaller than 0.01. In this case, there is enough evidence to reject the null hypotheses of the t-tests.

Consequently, we have enough evidence, even in this case, to reject again the first two hypotheses of the paper. Moreover, by finding both funding approaches significantly, the paper can suppose that there is no change in the behavior of the managers, and there are not influenced in any way by how their fund is funded. However, this is beyond the investigation of this study.

As in the case of Table 5, the percentiles of all approaches are present in the paper. It can be observed that the values are close to one another, but some important patterns are noticed. Considering the benchmark, the higher added value are the ones taking into consideration the MSCI indexes. Looking at the method of funding, the ones sold directly to investors have lower values. One reason why this is happening could be the argument discussed during the Literature review section. To be more visible on the investing smartphones applications, the managers have to always be part of the top mutual funds and be more visible to investors, this is why they need to keep higher returns.

The last measure presented in Table 6 is the percentage of the negative added dollar value in the case of each benchmark. By comparing the fours columns, it can be seen that approximately 35% of active mutual funds have a negative value, as in the case of Table 5. The highest number of negative added dollar value estimates is in the case of the FFC factors benchmark for the funds that are sold directly to the investors; and the lowest – MSCI index benchmark sold through the Fidelity brokerage application.

Table 6. Added dollar value extracted by active managers over period 2010 - 2020, a comparison between the way the fund receive capital

Table 6 contains a part of the results for the sub-research question of this paper in regards to the average added dollar value of the funds, $\overline{S_b}, \bar{S}_d$, calculated based on Equation *(5a), (5b), (6a)* and *(6b)*. In the table can be found the cross-sectional mean, the standard error, and the t-statistic. Next to them are shown the different levels of percentiles of the average added dollar value measure. The percentiles were calculated as estimates of the added dollar value were divided into 20 quantiles. The last measure, the percentage of the negative added value was calculated as the percentage of mutual funds that have their estimated added dollar value negative. The mean, standard error, and percentiles are measured in $ million, and the negative value variable is in %. The table presents the result of both approaches, first taking into consideration the MSCI indexes as the benchmark, second – Fama French Carhart factors. Columns (1) and (3) look into the average added dollar value of the mutual funds that are sold through the Fidelity brokerage app, where *N* equals 295. Columns (2) and (4) show the results of the average added dollar value of the mutual funds that are sold directly to investors, where *N* equals 908.

	(1) MSCI index Brokerage	(2) MSCI index Direct	(3) FFC factors Brokerage	(4) FFC factors Direct
Cross-sectional mean	21.86	16.55	16.52	12.72
Standard error	4.05	2.13	3.17	1.67
t-statistic	**5.40*** **	**7.76*** **	**5.19*** **	**7.60*** **
5^{th} percentile	-232.31	-250.74	-255.65	-275.69
10^{th} percentile	-151.14	-43.19	-76.88	-47.46
25^{th} percentile	-20.93	-8.55	-23.55	-9.52
50^{th} percentile	0.65	0.85	1.23	0.43
75^{th} percentile	31.66	11.68	29.11	10.84
90^{th} percentile	72.47	40.73	79.49	38.36
95^{th} percentile	135.75	85.09	127.10	80.16
Percentage of negative added value	34.91%	35.10%	35.30%	35.59%
Number of funds	295	908	295	908

*(significance levels: *** p<0.01, **p<0.05, *p<0.1)*

The last step that will lead to another conclusion of the paper and find evidence for the rejection or support of the third hypothesis is to test the difference between the two estimates of the average added dollar value, per benchmark, to understand if the difference is significant or not. These results were divided into two tables, Table 7 and 8, by the choice of the benchmark. Also, as mentioned in the Methodology section, the two-sample t-test took into consideration two assumptions, equal and unequal variance. In all cases of testing the t-test used an unpaired setting, as the number of funds differs, 295 mutual funds sold through the brokerage app, and 908 sold directly to investors. The period investigated remains the same.

From table 7, the difference in the estimation of the cross average dollar value between brokerage and direct equals $5.31 million, in the case of using the MSCI indexes as the benchmark. As in the case of the main results, these averages were tested against a t-test that had the aim to test if the difference is equal to 0, the null hypothesis of the t-test. The t-statistics, however, are 1.20 in the case of equal variance assumption and 1.16 for unequal. Namely, this means that the p-value is larger than 0.1, which leads this research to the failure of rejecting the null hypothesis.

Investigating table 8, almost the same conclusions can be drawn as in the case of table 7. Considering the FFC factors as a benchmark, the difference between the average dollar value is $3.79 million, slightly lower than the one from table 7. Also, in this case, there are lower t-statistics, with only 1.10 in the case of equal variances and 1.05 – unequal variances. As in the paragraph mentioned above, these t-statistcs relate to high p-values, mainly larger than 0.1. In these cases, the paper fails to reject the null hypothesis of the two-sample t-tests.

Consequently, taking into consideration these results, the paper has enough evidence to reject its third hypothesis which assumed that the managers that receive funding through the brokerage apps have higher added dollar value than the ones that receive the financial capital directly from the investors. Based on the t-test, there is no significant difference between the two.

Table 7. Results of testing the difference between the average added dollar value obtained by either being sold on Fidelity brokerage app or directly to investors, MSCI benchmark.

Table 7 reports the results of testing the difference of the two-average added dollar value that can be obtained when considering two ways the mutual funds get their cash inflow, by either being sold through a brokerage app or directly to investors. The benchmark used in this case is the MSCI indexes. The first column assumes that the two samples have equal variance. In the case of the second column, this assumption is relaxed, so the two samples have unequal variance.

	(1) Difference, Equal assumption	(2) Difference Unequal assumption
Difference	5.31	5.31
Standard error	4.39	4.57
t-statistic	**1.20**	**1.16**

*(significance levels: *** p<0.01, **p<0.05, *p<0.1)*

Table 8. Results of testing the difference between the average added dollar value obtained by either being sold on Fidelity brokerage app or directly to investors, Fama French Carhart benchmark

Table 8 describes the results of testing the difference of the two-average added dollar value that can be obtained when considering two ways the mutual funds get their cash inflow, by either being sold through a brokerage app or sold directly to investors. The benchmark used in this case is the FFC factors. The first column assumes that the two samples have equal variance. In the case of the second column, this assumption is relaxed, so the two samples have unequal variance.

	(1) Difference, Equal assumption	(2) Difference Unequal assumption
Difference	3.79	3.79
Standard error	3.45	3.59
t-statistic	**1.10**	**1.05**

*(significance levels: *** p<0.01, **p<0.05, *p<0.1)*

To conclude, through these results the paper can answer the sub-research question of the paper and affirm that there is no significant difference between the added dollar value that the managers of mutual funds create if we impose a specific mode of funding them. Furthermore, this research follows the same lines as the of Bergstresser, Chalmers, and Tufano (2008) which found no benefits for the investors which invest through intermediates; just in the case of this paper, there is no difference found between the added dollar value per mutual funds. An interesting conclusion for the literature in terms of the implications of using more smartphone brokerage apps as investing tools.

Conclusion and discussion

This paper aimed to investigate the active management skills of managers through the case of equity mutual funds in the US. Also, closer attention was paid to the way the mutual funds were receiving their cash inflow, with two approaches, either directly sold to investors or through a brokerage application on a smartphone. The dataset created was downloaded from the WRDS platform, specifically the Survivor-Bias-Free US Mutual Fund dataset. The dataset was cleaned and prepared in such a way that only US equity mutual funds that invest domestically were part of it. The period investigated was January 2010 until December 2020, monthly, so 132 months/observations. In the end, the dataset constituted of 1203 US active equity mutual funds, of which 295 were sold on the Fidelity brokerage app and 908 directly to investors. Three important hypotheses were generated to test and find evidence for the research questions.

The first and second hypotheses underline under the research question and were designed after the traditional view, discussed in the Literature review section, about the active investment in the US. Mainly, the first hypothesis focused on active investment and how is it perceived as underperforming. The second hypothesis concentrated on the lack of financial skills of the active managers to achieve higher returns than their benchmarks. Lastly, the third hypothesis underlines under the sub-research question and assumed that the actively managed mutual funds that are present on the brokerage app can achieve a statistically different added value than the ones that are not present on them.

To investigate the research and sub-research question, this work followed Berk and van Binsbergen (2015) process, which uses the added dollar value measure to understand the skills of the managers. The added dollar value measures how much value can the active managers extract from the financial markets to create value for their investors. The estimates of the added dollar value were then tested through a t-test to find the statistical significance. As a result, the two hypotheses of the research were rejected based on the statistical tests. In this way, the research re-confirmed the conclusions to which Berk and van Binsbergen (2015) arrived. These conclusions can also be added next to the ones made by Choi and Murthi (2001) and Petajisto (2013) which also found evidence of financial skills of active managers of mutual funds.

The innovation of this paper was to go beyond the work of Berk and van Binsbergen (2015) and see if by imposing a condition on the mode of funding, managers differ in the added dollar value they bring out from the market. Namely, in terms of the third hypothesis, the statistical tests did not provide enough evidence to be able to conclude that the managers that receive money through brokerage apps are better at reallocating the financial capital and achieve higher added dollar value. These conclusions are very close to the ones showed in the work of Bergstresser, Chalmers, and Tufano (2008).

Even though the paper was able to provide statistically significant evidence in rejection of the traditional hypotheses that were based on the previous literature, some crucial limitations have to be discussed. The first limitation of the paper is the data itself. I created the dataset to be strongly balanced, which can create a survivorship bias. In other words, I only considered the active US equity mutual funds that had an observation for each timeslot over 11 years, so a total of 132 observations. I only considered these funds to be able to create a unique cross-sectional average added dollar value. In order to not have this bias in the data set, which can lead to false conclusions in some cases, a future study could investigate, a data set that includes all American equity mutual funds. In this way, a more appropriate reality average can be found.

Another important limitation was the assumptions for the sub-research question, the first being that the funds are exclusively funded either through a brokerage app or directly by investors. This assumption is unrealistic, unfortunately. To obtain the real weights of how a mutual fund receives the cash inflow from the investors, the researcher has to be one of the largest shareholders in the fund, which will give him or her access to this private information. The second assumption is the one that involves the proxy, namely the Fidelity app. In the paper is assumed that due to its large advantage over its competitors and large data set, the Fidelity app is a good measure for the sub-research question. However, if more variables are considered, there could be a possibility of a better proxy than the Fidelity trading app. This is why the results should be approached with caution.

Besides the two limitations mentioned above, two more important aspects can influence the results of this type of research, specifically, the benchmarks and transaction costs. As I followed the Berk and van Binsbergen (2015) process, I constructed the alternative benchmark from a family of indexes, as well, the only difference being the MSCI indexes as a choice, and not the Vanguard indexes. For the traditional benchmark, the only difference from the work of Berk and van Binsbergen (2015) is the period investigated for the FFC factors. So, for future research, the choice of passive investment (indexes) and which risk-adjusted model the researcher will use, can influence the results of the value that the managers obtain from the financial markets. In this paper, all transaction costs were not considered, however, as economists, we know that the transaction cost can be very impactful for the returns made by a mutual fund. One specific example is the momentum strategy, which can generate huge value, but it can be very costly to implement. So, future research that would consider the transaction costs could shed more light on the dilemma of skilled or lucky active managers.

Moreover, further research will be interesting to look into another geographic zone. In the case of this research, the US financial market was chosen because of how easily can the data be accessed through special platforms, as in this case, the WRDS platform. As a region, the European market could present some curious results. Already, it could be seen from the Literature Review section, that the European investing behavior is slightly different from the one practiced in the US.

Furthermore, digitalization, smartphones, and telephone applications grow larger in our lives in general, and in investments, as well, so, more research could be done into this gap. Asset management companies that possess more information about the weights of funding, could investigate this gap, to a final aim to understand how the managers' behavior changes when they know exactly how they are funded. Could there be a possibility that managers that know that they are funded through brokerage apps feel less accountable for the mistakes made in the financial markets? Or, could it be the other way around?

As discussed in the Result section, the implications of this paper are the re-confirmation of the significant added dollar value that active managers create; and the new addition to the literature is the investigation around how different approaches of cash inflow into a fund can affect how managers allocate resources into the mutual funds and get new added value. However, this paper cannot conclude in whose advantage is the added dollar value. This added value could be absorbed by the managers, in this case, investors will not receive anything. Or, it could be the case that the managers absorb a part of the excess value, and some value is divided between investors, as well. Unfortunately, this is beyond the scope of this paper. Even so, one conclusion stands out, the active managers in the US financial markets are skilled.

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