



UNIVERSIDADE CATÓLICA PORTUGUESA

(Over)performance in 13F filings

Extracting investment managers' alpha
generating ideas

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Católica Porto Business School
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Resumo

A dissertação avalia o desempenho de uma carteira construída utilizando uma estratégia “piggyback”, alavancando divulgações de um subconjunto de empresas de investimento selecionadas com base nas suas ações e quantidade de ativos sob gestão.

Para responder à questão de investigação foi construído um portfólio composto por vinte ações, selecionando ações “vencedoras” identificadas no conjunto de dados global. Essas seleções foram feitas de acordo com três critérios principais: consenso, convicção e “momento”.

As conclusões indicam que a estratégia delineada na dissertação não conseguiu produzir um desempenho superior entre maio de 2018 e novembro de 2023, apesar de ter alcançado um desempenho semelhante ao índice S&P500 (antes de despesas). Esta conclusão é retirada da análise tanto do alfa CAPM (que é considerado significativo, mas próximo de zero) como do modelo de 4 fatores de Fama e French (que mostra um alfa negativo significativo, mas próximo de zero).

Palavras-chave: “piggyback” portfólio, ficheiros 13F, simulação de portfólio

Número de palavras: 7119

Abstract

The dissertation assesses the performance of a portfolio constructed using a piggyback strategy, leveraging disclosures from a subset of investment companies selected based on their holdings and assets under management.

To address the research question, a portfolio comprising twenty securities was assembled by selecting "winning" stocks identified within the overall dataset. These selections were made according to three primary criteria: consensus, conviction, and momentum.

The findings indicate that the strategy outlined in the dissertation failed to yield outperformance between May 2018 and November 2023 despite achieving a similar performance of the S&P500 index (before expenses). This conclusion is drawn from the analysis of both the CAPM alpha (which is found to be significant but close to zero) and the Fama and French 4-factor model (which shows a significant but small negative alpha).

Keywords: piggyback portfolio, 13F filings, portfolio simulation

Number of words: 7119

Table of Contents

Acknowledgements.....	vi
Resumo.....	viii
Abstract.....	x
List of figures.....	xiv
List of tables.....	xvi
Chapter 1 - Introduction.....	1
Chapter 2 - Literature review.....	6
2.1. Introduction to the literature review.....	6
2.2. Copycat portfolios performance.....	6
2.3. Determinants of mutual fund performance.....	9
2.4. Do funds outperform the market?.....	13
Chapter 3 – Data and Methodology.....	19
3.1. Data source.....	19
3.2. Summary statistics.....	20
3.3. Choosing the investment managers.....	23
3.4. Selecting the portfolios' holdings.....	26
3.5. Determining the results.....	31
Chapter 4 - Results and discussion.....	32
Chapter 5 - Conclusions.....	35
Bibliography.....	37

List of figures

Figure 1: Overall holdings value	21
Figure 2: Average value and number of holdings	22
Figure 3: Frequency of percentage of the total portfolio.....	23
Figure 4: Consensus points by the number of investment companies	27
Figure 5: Number of conviction points.....	28
Figure 6: Number of points attributed to the most bought (sold) stocks	29
Figure 7: Portfolio distribution	30
Figure 8: Performance of the Portfolio vs S&P500 index	32

List of tables

Table 1: Performance metrics of the portfolio vs the S&P500 index.....	33
Table 2: CAPM and Carhart 4 factor model analysis.....	34

Chapter 1 - Introduction

Since 1985, the Securities and Exchange Commission (SEC) mandated that investment companies with assets under management exceeding a certain threshold disclose their holdings semi-annually. However, in 2004, this requirement shifted to quarterly disclosures, with the rationale that more frequent reporting would enhance investors' ability to monitor portfolios, make informed asset allocation decisions (Verbeek & Wang, 2013) and make it harder to funds indulge in window dressing practices (Frank et al., 2004).

Following this regulatory change, numerous studies have delved into these disclosures, aiming to evaluate performance (Grinblatt & Titman, 1989, Brown & Schwarz, 2020), investment strategies (Angelini et al., 2019), the impact of 13F filings¹ on investment firms (Frank et al., 2004), or comparing returns between investment managers and mimicked portfolios formed from 13F filings (Verbeek & Wang, 2013). Nevertheless, little attention has been paid to assessing the effectiveness of constructing portfolios based on these disclosures that can outperform standard benchmarks.

In this dissertation, I aim to address this gap and answer several questions. Firstly, I will try to assess if it is feasible to develop a piggyback strategy, leveraging information from the 13F filings, that outperforms the market (adjusting for risk). Secondly, I will investigate if a portfolio strategy based on

¹ 13F filings is the form filled by institutional investment managers (for example, banks, insurance companies, brokers, corporations, pension funds or investment advisors that manage private accounts and mutual funds' assets) in the United States that exercise investment discretion over \$100 million. The filings only disclose equity long positions in the United States, and do not disclose any movements within the quarter they correspond to.

conviction, consensus, and the top stocks bought and sold each quarter can beat the market, as represented by the S&P 500. Finally, I will test if there is valuable information that can be extracted from a subset of investment managers, selected specifically based on the number of holdings and assets under management they have.

The decision to explore this topic stems from several reasons. Firstly, I seek to investigate whether investors can obtain insights from 13F filings to make better investment decisions, particularly considering the prevalent narrative of retail investors struggling in the investment realm. Retail investors often face biases (Barber & Odean, 2013) and lack the resources and expertise of institutional investors, placing them at a disadvantage in what may be perceived as a zero-sum game for generating alpha (Fama & French, 2010). Secondly, the literature suggests that even when professional investors do achieve alpha, they often translate this success into higher fees (Grinblatt & Titman, 1989), thereby nullifying any potential benefit to investors. Despite the limitations surrounding 13F filings, the question of whether valuable information can still be extracted from them remains.

The objectives of this dissertation are to select a portfolio based on 13F filings and assess its performance, and construct this portfolio straightforwardly for practical implementation.

A methodology was employed to achieve these goals, wherein a group of investment companies filing 13F disclosures was selected. From these filings, stock picks were extracted based on consensus (the number of investment companies holding the stock), conviction (the proportion of portfolio allocated to the stock), and momentum (the most bought or sold stocks).

This dissertation contributes to existing literature by filling gaps and proposing a straightforward and replicable approach for not only retail, but also professional investors. While some research exists in this domain, it remains

limited and lacks practical implementation strategies. Moreover, this work raises new avenues for future research.

Moreover, the dissertation has strong implications for investors. I highlight here what I believe to be the most important, stemming from the fact that one cannot just simply mimic portfolio holdings disclosures and expect strong outperformance relative to a benchmark, based on the dissertation's conclusions.

The dissertation is structured as follows: chapter two reviews the literature, chapter three outlines data sources and provides statistical summaries, chapter four explains the methodology, chapter five evaluates the results, and chapter six concludes.

Chapter 2 - Literature review

2.1. Introduction to the literature review

It is clear that retail investors suffer from biases that hurt the chance of having long-term success in the stock market, such as the “disposition effect”, the significant influence of past return performance on stock selection, or simply the holding of undiversified portfolios (Barber & Odean, 2013). For this reason, one must wonder if professional investors can overcome these problems and biases and outperform the market. If they can, the question arises of whether there is some valuable information that can be obtained from the holdings of these investors.

In this section, I start by assessing the literature about the performance of copycat portfolios, then I analyse the determinants of mutual fund performance and finally, see what the literature states about the funds’ capabilities to consistently outperform the market.

2.2. Copycat portfolios performance

Angelini et al. (2019) find that it is possible to outperform the S&P500 by using information from the 13F filings to identify a group of managers who have a more long-term view on their investments and who hold their positions for more time,

the so-called piggyback strategy. The strategy the authors develop is based on conviction – the percentage of the portfolio allocated to a given security – and consensus – how many asset managers have that security.

To construct these portfolios, Angelini et al. (2019) use a private database provided by Novus, which keeps track of the investments of different investment managers. The opaqueness of this proprietary sample makes it impossible to replicate the strategy and the results.

Verbeek & Wang (2013) construct hypothetical copycat funds, based on 13F filings, to investigate the performance of free-riding strategies that duplicate asset holdings of actively managed mutual funds. The authors conclude that copycat strategies have more success than the vast majority of mutual funds after 2004 when the SEC imposed quarter portfolio holdings disclosures instead of semesterly disclosures. These copycat portfolios on past winning funds generate better returns (net of trading costs and expenses) and show evidence that free-riding on disclosed fund holdings can be an attractive strategy.

The main conclusion of Frank et al. (2004) regarding the topic under analysis is that, for a limited group of mutual funds with high expenses, copycats earn statistically indistinguishable (and possibly higher) returns than their actively managed counterparts after expenses.

On a different note, Frank et al. (2004) also examine how copycatting portfolios can impact the same funds that have their positions replicated. On the one hand, if other investors can copy the actively managed funds' investments without affecting asset values, the return on the manager's research is diminished. Also, if one can copy the funds' position and (net of expenses) obtain similar performances, then this will be a drawback for investment managers, given that they will have assets withdrawn from their funds. On the other hand, if buying drives up the prices of assets held by actively managed funds, then disclosing the funds' positions may benefit those funds.

Brown & Schwarz (2020) find no evidence of consistent outperformance, and little evidence of performance persistence in the return patterns of strategies based in the 13F filings, despite a short-term outperformance around the announcement date of the filings. Overall, the findings of the paper suggest that market participants do attempt to take advantage of hedge fund disclosures: 13F filings are downloaded frequently, and it is possible to observe abnormal trading volumes (and positive returns) for the respective filings' holdings, immediately after the documents are released.

Phillips et al. (2014) present an analysis of copycats between investment managers. The paper states that investment managers select funds with high prior performance and investment inflows when developing copycat portfolios. The study also concludes that very few managers actually do this, and when they do, they "do so out of desperation." The results suggest that the performance of the target fund reverses copying initiation, thus concluding that fund managers cannot detect superior skills in their own industry.

On the other hand, Wermers (2006) shows that publicly disclosed mutual fund portfolio holdings contain valuable information about stock fundamentals and future returns. The author developed a model to efficiently aggregate this information across actively managed funds with different skills to predict individual stock returns. This stock-level measure, which the author calls the "generalized inverse-alpha" selects portfolios of stocks that exhibit much better performance relative to a "copycat strategy" that simply mimics the stockholdings of funds.

They use the model to study the source of fund managers' stock selection ability and find that some managers have skills in uncovering information from fundamental research about the future earnings of stocks. The efficiency of the approach relies on the fact that the authors can distinguish stocks that are held

to generate alphas from the ones that have other goals unrelated to achieving performance (that are usually related to diversification purposes).

There are some important drawbacks regarding the 13F filings that should be made clear. As Schwarz & Potter (2016) show, the data on fund holdings from Thomson Reuters misses many reported holdings from mandated SEC filings, while including many voluntary filings that are not publicly available from the SEC.

“Window dressing” is also a major limitation of the 13F filings. As stated by Danthine & Moresi (1998), Morey & O’Neal (2006) and Agarwal et al. (2014), investment managers know that their positions will be publicly available and that this will have repercussions on the funds they run, having incentives to change the allocations of the portfolio by the end of each quarter, that does not represent what are their true investments most of the time.

2.3. Determinants of mutual fund performance

The main finding of Ferreira et al. (2013) is that mutual funds underperform the market overall. The authors also find differences in the determinants of performance of U.S. funds vis-à-vis non-U.S. funds. The most relevant for this dissertation is the size effect in mutual funds: while U.S. funds have diminishing returns to scale (funds with higher assets under management perform worse than funds with lower assets), non-U.S. funds do not suffer the same problem. Findings suggest that this is related to liquidity constraints faced by U.S. funds that, by virtue of their style, have to invest in small and domestic stocks.

Another key difference is that funds located in countries with liquid stock markets and strong legal institutions display better performance: funds perform better in countries with high trading activity and low trading costs.

Here is also considered the size of the fund family on fund performance: the authors find that, controlling for fund size, fund performance improves with the size of its fund family, as large fund families benefit from substantial economies in trading commissions and lending fees.

Finally, there is also evidence of short-term persistence in fund performance and the “smart money effect”, i.e. funds flow to funds with good performance from funds with poor performance (but only for non-U.S. funds).

Cohen et al. (2021) find that the stocks in which active mutual fund or hedge fund managers display the most conviction towards ex-ante, their “Best ideas,” outperform the market, as well as the other stocks in those managers’ portfolios, by approximately 2.8 to 4.5 per cent per year. The results of the paper also suggest that fund managers have, in fact, stock-picking abilities and that the overall poor performance of the portfolio compared to the benchmark is due to institutional factors that encourage to over-diversify and pick stocks that are beyond their alpha-generating ideas, consistent with the findings of R. Wermers (2006). The cross-sectional tests employed in the paper suggest that active managers’ best ideas are most effective in illiquid, growth, momentum stocks, or for funds that have outperformed in the past.

Still on this topic, Pomorski (2009) starts by finding the mutual funds’ “best ideas” are likely found by “centralized research of fund management companies”. According to the research, these trades account for about 30% of fund volume, and outperform benchmarks and other trades by as much as 47 basis points per month. The authors also state that this outperformance is not explained by herding, short-term liquidity pressures, changes in the index composition or funds’ reaction to analyst revisions. The abnormal returns also do not revert in the following six quarters, suggesting that transitory liquidity effects do not drive the results.

Furthermore, the remaining funds' trades fail to beat benchmarks (even before expenses). However, Pomorski (2009) approaches this problem from a different perspective than Cohen et al. (2021) and R. Wermers (2006), and speculates that these trades are idiosyncratic, meaning that they are made by individual managers within an investment firm. The author argues that, in spite of the fact that these trades fail to beat their benchmarks, it might be rational to engage in them even if there is no expectation of outperformance, since managers are required to manage flows to their funds, keep up with their peers and benchmarks, or perhaps window dress their portfolios to attract and retain investors using information other than fund returns.

Fulkerson & Riley (2019) state that mutual fund managers should choose to increase their portfolio concentration when their information set is valuable enough that the benefits of the expected increase in alpha more than offsets the costs of the expected increase in idiosyncratic volatility.

The authors find that fund performance improves after concentration increases, and that the concentration-performance relation is stronger for funds with less institutional ownership and when investor sentiment is low. The authors' argument to explain this relationship is the following: since retail investors are less sophisticated, if they see a high increase in portfolio concentration, they probably will react negatively and move their funds elsewhere. For this reason, for mutual funds to decide to increase concentration, they must have much more strong reasons to do it, meaning that the information they have needs to be much more valuable.

It is also stated that the optimal concentration for a fund is a function of the fund manager's information set, i.e.: if the manager has no information about security prices, then holding a completely diversified portfolio is preferable; on the other hand, if the manager has valuable information, then they would increase the portfolio concentration until the marginal gain of the expected

increase in alpha would be equal to the marginal costs of the expected increase in the idiosyncratic volatility.

Brown et al. (2017) assert the premise of the literature that most skilful managers are the ones that hold the most concentrated portfolios. The conclusions state that talented asset managers should, and actually do, hold more concentrated portfolios, and that the extent of this concentration decision is meaningfully related to forecasting skill, drawing a clear line between the two variables.

Pollet & Wilson (2008) argue that if actively managed mutual funds experience diminishing returns to scale, adjustments in investment behaviour should occur as assets under management increase. As funds grow larger, both large funds and small-cap funds tend to diversify their portfolios. This heightened diversification, particularly notable in small-cap funds, is often associated with improved performance.

On the other hand, the paper argues that the growth of fund families typically coincides with the introduction of new funds that hold different stocks compared to their existing counterparts. Interestingly, as funds within a family accumulate, they tend to diversify less rapidly, implying that the fund family may influence the portfolio strategy of individual funds.

The authors conclude that fund managers primarily increase their ownership shares in companies already held in their portfolios, the expansion of the number of stocks in the portfolio occurs at a gradual pace in response to inflows and that there is a positive correlation between diversification and subsequent performance, even after controlling for factors such as fund size and fund family size.

Chen et al. (2002) find that fund performance declines with fund size, even after adjusting performance by different benchmarks and controlling for other fund characteristics such as turnover and age. Furthermore, this effect is more

noticeable for funds that play small-cap stocks. Other conclusions of the paper state that performance does not decrease with the increase in family size, and that small funds are better than large ones at investing in local companies.

Griffin & Xu (2009) try to find out if hedge fund managers are better at picking stocks and sectors than their counterparts (mutual funds) in the hedge fund industry. The paper raises serious questions about the perceived superior skill of hedge fund managers.

Kosowski et al. (2006) apply a bootstrap statistical technique to test the performance of U.S. equity mutual funds for the 1975 to 2002 period. The main finding suggest that a sizable minority of managers pick stocks well enough to more than cover their costs, and that the superior alphas of these managers persist over several periods of time.

The tests indicate that the large positive alphas of the top 10% of funds, net of costs, are extremely unlikely to arise solely due to sampling variability (luck). Further results indicate that superior after-cost performance holds mainly for growth-oriented funds. On the other hand, the average manager of an income-oriented fund cannot deliver persistent alpha, and the occasional outperformance of some income fund managers can be attributed to luck.

2.4. Do funds outperform the market?

On probably what is one of the most influential paper regarding the topic, Fama & French (2010) find that the aggregate portfolio of actively managed U.S. equity mutual funds is close to the market portfolio, but the high costs of active management show up intact as lower returns to investors. Bootstrap simulations suggest that few funds produce benchmark-adjusted expected returns sufficient to cover their costs.

Sharpe (1991) and Carhart (1997) also reinforce the idea that mutual funds are not capable of delivering outperformance relative to the market portfolio. Carhart (1997) also states that past performance is not a good indicator of future performance.

Grinblatt & Titman (1989) examine mutual fund performance mutual fund performance by analysing quarterly portfolio holdings from 1975 to 1984. The authors analyse the gross returns from these portfolio holdings, arguing that this approach is essential because it allows for observing abnormal performance. The underlying rationale is that if mutual fund managers possess superior investment talent, they may be able to capture the benefits of this talent through higher fees.

The authors find that abnormal performance, based on gross returns, displayed an inverse correlation with fund size. However, since transaction costs also showed an inverse relationship with fund size, the actual net returns did not correlate with funds' net asset values. Other findings suggest that, on average, actual returns did not exhibit positive abnormal performance across any fund category.

Berk & van Binsbergen (2015) measure skill in a different way than the literature has done to this point, using the value that mutual fund extracts from capital markets as the go-to measure. The authors find that the average mutual fund has used this skill to generate about 3.2 million per year and that this skill persists for as long as ten years. Furthermore, investors recognize this skill and reward it by investing more capital with better funds.

The authors argue that the cross-sectional distribution of managerial skill is predominantly reflected in the cross-sectional distribution of fund size, not gross alpha.

On the other hand, Grinblatt & Titman (1992) analyse how mutual fund performance relates to past performance. Findings suggest that differences in

performance between funds persist over time and that this persistence is consistent with the ability of fund managers to earn abnormal returns. This means that fund performance information is useful for investors, who can allocate their funds according to funds past performance.

An important note in this paper is that the authors consider that traditional benchmarks used to evaluate performance exhibit persistent biases related to firm size, dividend yield, past returns, skewness, interest rate sensitivity or CAPM bet, and for this reason, they introduce a new benchmark that is free from these biases.

Hendricks et al. (1993) find that the relative performance of no-load, growth-oriented mutual funds persists in the near term, with the most substantial evidence for a one-year evaluation horizon. The analysis was made for the 1974-1988 period.

The authors also find that portfolios of recent poor performers do significantly worse than the benchmark, and that recent top performers do better (although not significantly so). Furthermore, in this period, the authors find that the difference in risk-adjusted performance between the top and bottom octile portfolios is six to eight per cent per year.

The central finding of Wermers (2003) is that mutual fund returns strongly persist over multi-year periods. Consumer and fund manager behaviour plays a significant role in explaining these long-term continuation patterns: consumers invest heavily in last year's winning funds, and managers of these winners invest inflows in momentum stocks to continue to outperform other funds for at least two years following the ranking year. By contrast, managers of losing funds appear reluctant to sell their losing stocks to finance the purchase of new momentum stocks, perhaps due to a disposition effect (holding on to stocks that lose value).

However, authors findings indicate that these abnormal returns are strongly related to fund inflows, but not to the past performance of the funds, casting some doubt on prior findings of persistent manager talent in picking stocks.

Nonetheless, the most important finding for this dissertation is that a copycat strategy of winning funds stock trades appears to be a wise strategy that can produce outperformance relative to a benchmark, by taking advantage of flow-related returns.

Chen et al. (2000) find that stocks widely held by funds do not outperform other stocks. Nevertheless, the authors also find that stocks purchased by funds have significantly higher returns than stocks they sell, and this holds true whether one is assessing large, small, value or growth stocks.

Baker et al. (2010) assess the nature of this stock-picking ability and find that the average fund's recent buys significantly outperform its recent sells around the following earnings announcement, and that this accounts for a disproportionate fraction of the total abnormal returns. The main conclusion is that mutual fund managers are able to trade profitably due to their ability to forecast earnings-related fundamentals.

Consistent with the findings of Kosowski et al. (2006), Chen et al. (2000) also state that growth-oriented funds exhibit better stock selection skills than income-oriented funds.

Opposite to the conclusions reached by Grinblatt & Titman (1992), Chen et al. (2000) find only weak evidence that funds with the best past performance have better stock-picking skills than funds with worst past performance.

Diving deep into the factors that explain these differences in past performance, the authors address the stocks passively held and newly bought stocks. They conclude that the stock-holdings passively carried by winning funds outperform passively carried holdings by losing funds. However, stocks that are newly bought by winning funds only marginally outperform stocks newly bought by

losing funds. Therefore, the results indicate that the superior performance of these passive holdings is primarily attributable to the general tendency of past winners to outperform past losers (momentum effect) rather than persistent stock selection skills.

Bodnaruk & Simonov (2015) offer direct insights into the impact of financial expertise on investment outcomes through an analysis of private portfolios managed by mutual fund managers. The authors' findings do not support the notion that financial experts consistently make superior investment decisions compared to their peers. They neither outperform in terms of returns, nor demonstrate better risk diversification, nor exhibit reduced behavioural biases.

However, managers excel in stocks where they possess an information advantage over other investors Fulkerson & Riley (2019), particularly those also held by their respective mutual funds. Additionally, managers appear aware of limitations in their investment abilities, as evidenced by their increased holdings of mutual fund-related stocks following periods of poor portfolio performance.

Grinblatt et al. (1995) analyse the extent to which mutual funds purchase stocks based on their past returns as well as their tendency to exhibit "herding" behaviour. The authors find that 77% of the mutual funds were "momentum investors". However, this momentum is only related with winning stocks and not losing ones, i.e., mutual funds tend to buy past winners but they do not sell past losers.

Finally, I highlight the main conclusions one can possibly take from the literature review, bearing in mind that the topics approached are still very much debatable to this day, and one cannot take definite positions but rather be receptive to new and convincing arguments.

Regarding copycat portfolios, there is valuable information to take from the companies' files, and one can create portfolios that present similar performances to the original ones (after subtracting fees and expenses).

In terms of the determinants of fund performance there are two main conclusions: a) more assets under management seem to result in worst fund performance (diseconomies of investment); and b) more portfolio concentration suggests more skill, and investment managers should increase this concentration according to the information they possess on that investment.

Lastly, in terms of funds' performance there is literature that proves both that funds can outperform and are persistent in this performance, and that funds do not outperform, and investors are better simply allocating funds to the market portfolio. However, the main goal of this dissertation is about finding if it is possible to create a portfolio that outperforms, and not reach any conclusions about the capability of funds to outperform.

Chapter 3 – Data and Methodology

3.1. Data source

The stock price data is from Yahoo Finance, downloaded via RStudio. Moreover, the prices correspond to the Adjusted Close Prices, given that these take into consideration (as the name indicates they are “Adjusted”) any stock splits and dividends paid.

The investment managers data regarding the number of stock holdings and the dollar amount of assets under management was consulted on the website <https://13f.info/>. For this dissertation, I selected 52 investment managers, with an average of holdings of 26.7 stocks, and an average of assets under management of around \$2.7 billion (data corresponding to the fourth quarter of 2017). The list of managers, as well as the corresponding number of holdings and AUM can be found in Table 3 and Table 4.

Finally, the company portfolio ownership data was downloaded from Refinitiv Eikon, which is built from data gathered from the 13F filings. The period analysed in this dissertation starts with the files submitted on the 31st of December 2017, and ends with the filings corresponding to the 3rd quarter of 2023.

There are problems with the data from Refinitiv Eikon besides the ones mentioned by Schwarz & Potter (2016), Danthine & Moresi (1998), Morey & O’Neal (2006) and Agarwal et al. (2014). The sum of the percentages of all stock holdings for each investment manager does not add up to 100%, meaning that, as stated in the previous sentence, there are some positions that are not disclosed. As mentioned in the introduction, this is partly due to the fact that the 13F filings only disclose long equity positions held in the United States.

Finally, investment managers oftentimes do not comply with the deadline corresponding to the 45 days after the quarter end to disclose their 13F filings. Institutional investors also make amendments to their 13F filings much further in time, changing the holdings of previous periods. Naturally, this affects the results of the research since the portfolio is rebalanced each quarter according to that periods' disclosures.

The data for the CAPM Fama & French analysis (4 factors) was downloaded from French's website and includes daily data until 15-nov-2023.

3.2. Summary statistics

Figure 1 shows that the assets under management of the 52 institutional investment managers that are integrated in the analysis increased in the analysed interval, and were around \$170 billion by the end of the third quarter of 2023.

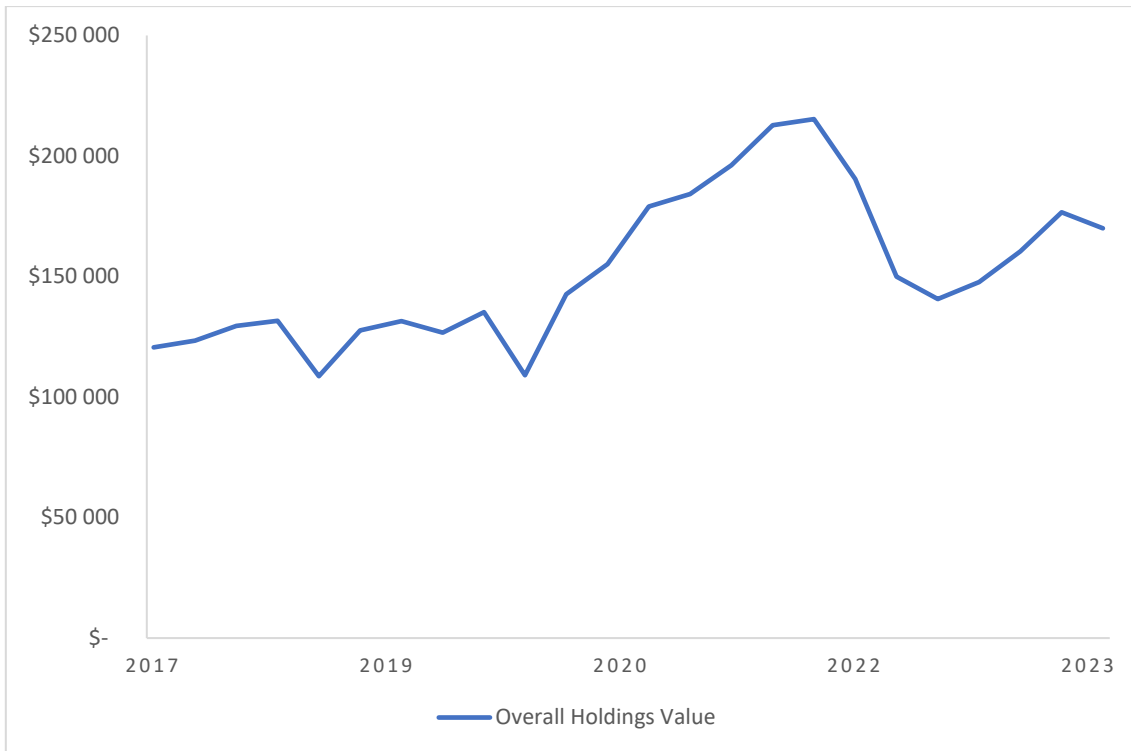


Figure 1: Overall holdings value

Source: Refinitiv Eikon

On the other hand, the average value of the holdings (i.e. the dollar amount allocated to each stock held in the portfolio) in the sample data is around 130 million dollars, with the lowest from 2021 to mid-2022. The average number of holdings increases by 8 (from 23 to 31) stocks between the sample data, suggesting that investment managers are diversifying more and more throughout the years.

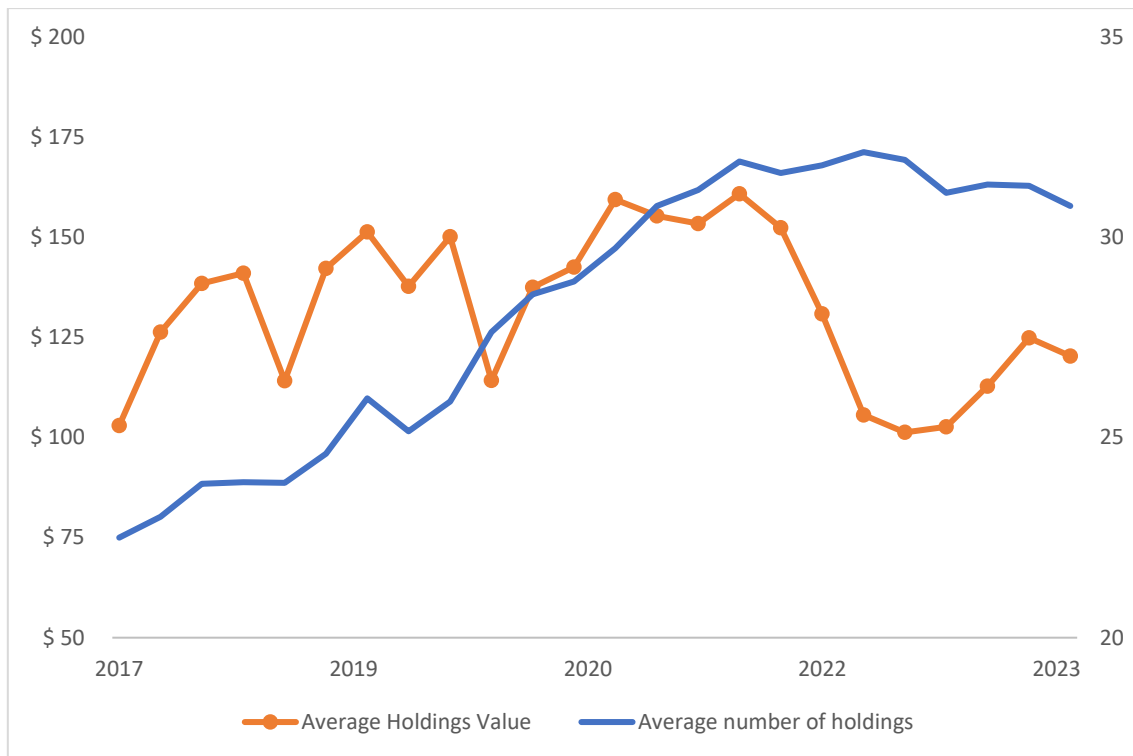


Figure 2: Average value and number of holdings

Figure 3 shows the number of times that the interval of percentages of portfolio appears in the overall data between 31-Dec-2017 to 30-Sep-2023. To illustrate this point, we quickly observe that almost half of the 34,973 data points available are between 0% and 2%. Furthermore, only 5% of the data points (referring to the percentage of the portfolio allocated to a specific stock) are higher than 10%, reinforcing the point made before regarding the high diversification of investment manager’s portfolios. We can also observe that 84% of the data points are less than 6%. Due to the drawbacks related to the data that were mentioned before, more specifically the one associated with the sum of the percentages of the portfolio holdings being less than 100%, I believe that this value can be even higher, assuming the very reasonable assumption that small positions are neglected in favour of larger ones.

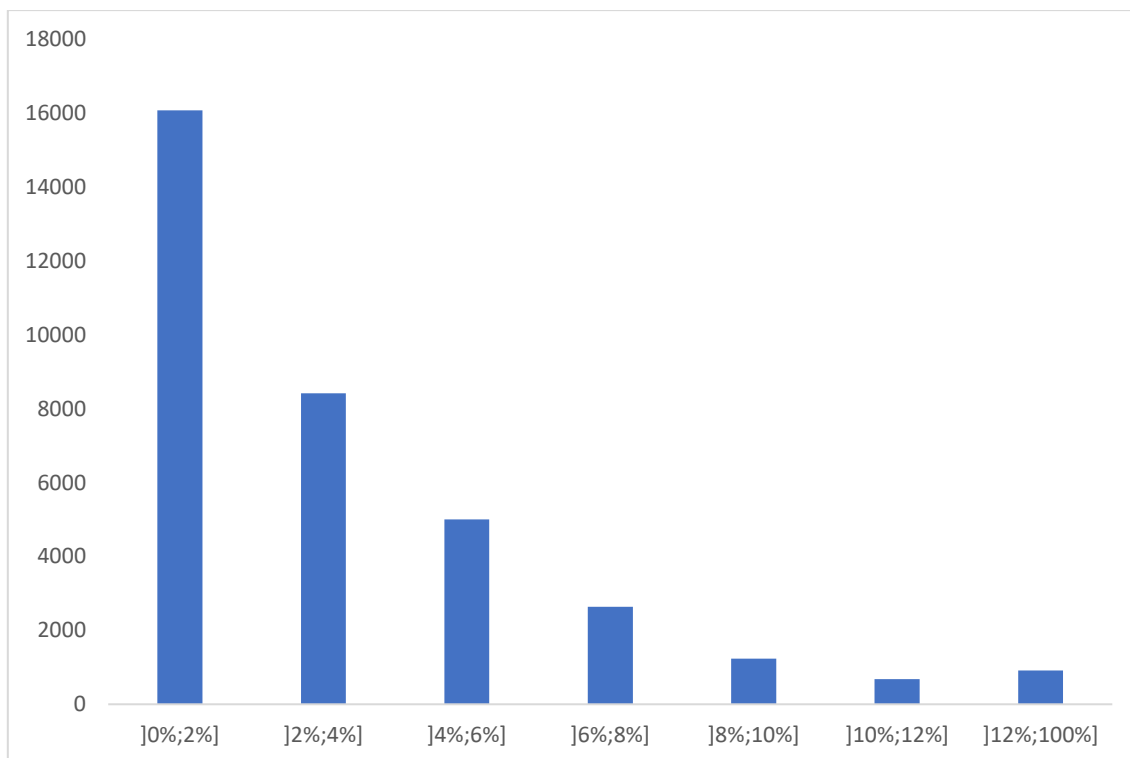


Figure 3: Frequency of percentage of the total portfolio allocated to a single position

3.3. Choosing the investment managers

The two criteria used to select this group of managers from which the portfolio would be drawn were 1) the amount of assets under management and 2) the number of holdings in the last quarter of 2017 (date from which the analysis begins).

In terms of the amount of assets under management, the selected interval was between \$1 and \$10 billion in the last quarter of 2017. These values were selected due to multiple reasons.

In the first place, since the 13F filings are filled by the whole company, and not by each fund within that company, it gets harder to capture the investment managers “best ideas” when analysing bigger companies. As funds get bigger and bigger, these “best ideas” get increasingly diluted, and it is harder to find real conviction in investment managers’ portfolios.

Even though a higher family of funds does not necessarily mean that a given fund will have worse performance, if that fund is included in a company with multiple funds, the percentage of the portfolio allocated to the investment companies' best ideas will be meagre.

Also, as the literature suggests, as funds increase their size, their performance decreases. However, if one were to choose companies with assets under management close to 100M USD, there would be a higher chance of these investment companies falling below this threshold, and for this reason, they would not be obliged to disclose the 13F filings anymore. To avoid this problem, which could eventually disrupt the rationale of the portfolio, only investment companies with assets under management higher than 1 billion USD were selected in the last quarter of 2017. Also, it is a reasonable assumption to assume that these investment managers with lower AUM have a lower quality in terms of data (especially in the Refinitiv Eikon platform), since they are probably less relevant and are not scrutinized as bigger investment managers are.

This lower performance for bigger funds can also be attributable to the fact that these funds are more constrained in terms of investments they can make and the assets that they can allocate to a given company, since they must comply with specific ratios and can only indulge in a controlled level of volatility (for example, if one were to allocate a lot of the portfolio assets to a specific company, this would increase by a fair amount the overall volatility of the portfolio).

Concerning the second filter for selecting the investment companies, the number of holdings in the last quarter of 2017, was selected a number higher than 10 and lower than 50.

The logic behind these values was similar to the previous point. In the first place, the main goal was to capture the best ideas: If a company has fewer securities in the portfolio, this means that the same portfolio will be more concentrated. As some of the literature suggests, alpha generating ideas come

from the “Best ideas” that are positions where investment managers allocate a lot of their portfolio funds.

On the other hand, the data quality was also an important point that made me select this interval of holdings. Companies with high numbers of holdings have less reliable data, since this means that companies from the period from 2017 to 2023 had hundreds and even thousands of different securities in their portfolios. For this reason, the data-gathering process is much heavier, and this has clear implications for the overall quality of the data. To illustrate this point, as this dissertation was being developed, it was noticed that the percentage of the portfolio allocated to securities was oftentimes well below 100%, and this problem was particularly noticeable (and also by a large amount) to companies with superior stock holdings.

The appendix provides information on the selected investment companies, including their number of holdings and assets under management in 2017.

On a different note, research shows that superstar investors can consistently outperform the market (Kosowski et al., 2006). By selecting this group of managers, one could probably extract more valuable information that could translate into higher returns on the portfolio developed.

However, to the best of my knowledge, historical data regarding performance of institutional investors is unavailable. The only data available are specific to funds, which does not necessarily reflect the overall performance of the whole investment company. Institutional investors usually have tens of funds available to their clients, each with very different strategies and goals.

Plus, if the point about the size and performance mentioned above holds true, it is expected that smaller funds perform better than larger ones. From this information, if we assume that inside any institutional investment company, the smaller funds within that company perform better than larger ones, it would be

hard to extract the ideas that resulted in the outperformance of the smaller funds, since these would be “diluted” by non-outperforming positions of larger funds.

Due to all these constraints, future work can be developed to assess how quarterly copycat portfolios, following specific institutional investors disclosures to the SEC via the 13F filings, performed in the past. Also, future work can be done to assess whether picking the copycats that outperformed in the past would yield better results for the portfolio that was later constructed, with the same rationale used in this research.

3.4. Selecting the portfolios’ holdings

I developed a point system to select the portfolio based on three criteria: consensus, conviction and top buys/ sells. This point system was developed based on the literature (e.g., Angelini et al., 2019 and Cohen et al., 2021) and aims at capturing the best stocks to hold in a given quarter according to a group of investment managers, and considering what were the factors that possibly made those stocks the best investments.

In the first place, consensus consists of the number of investment companies that hold a particular stock in portfolio each quarter. The amount of points a given stock earns each quarter is the following:

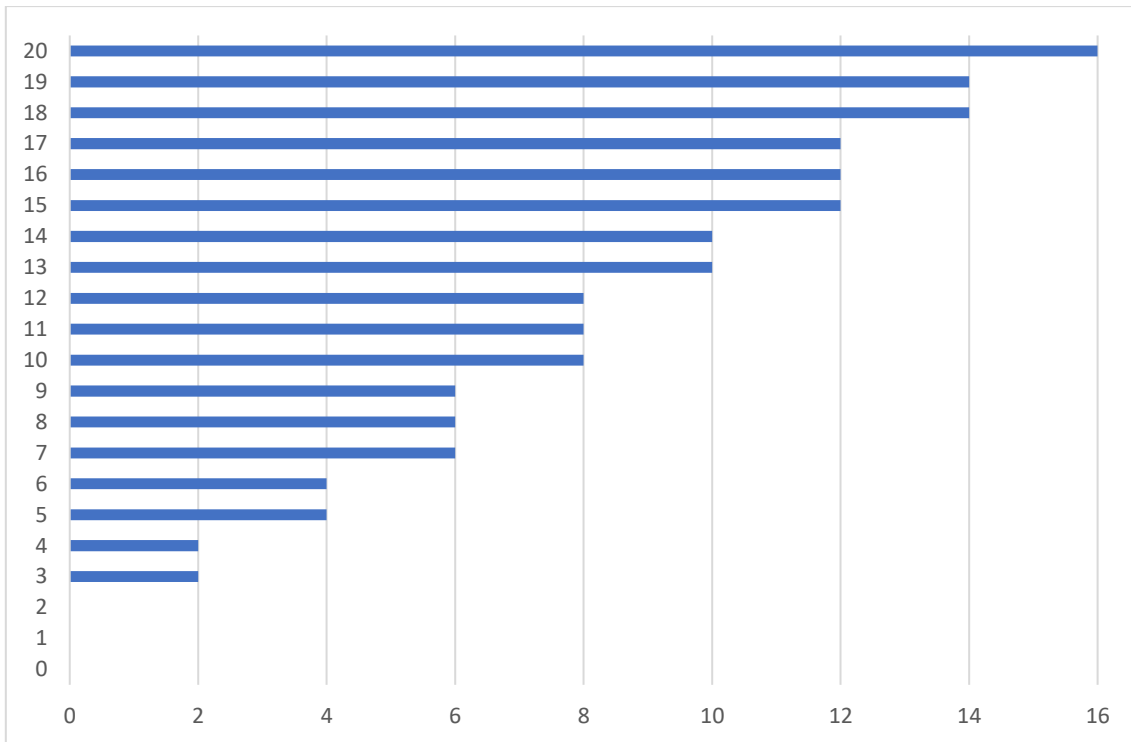


Figure 4: Consensus points by the number of investment companies that hold the portfolio

Regarding the conviction factor, the focus is on the percentage that a given asset has on the portfolio. However, if different investment managers have the same stock with a good percentage of their portfolio, there is also a consensus that enters in the equation. For example, if two investment managers hold more than 10% of a stock, this stock will have 28 points (14 + 14). The core of the portfolio relies on this criterion, since most of the points attributed to the stocks come from the conviction factor. The amount of points a given stock earns each quarter is the following:

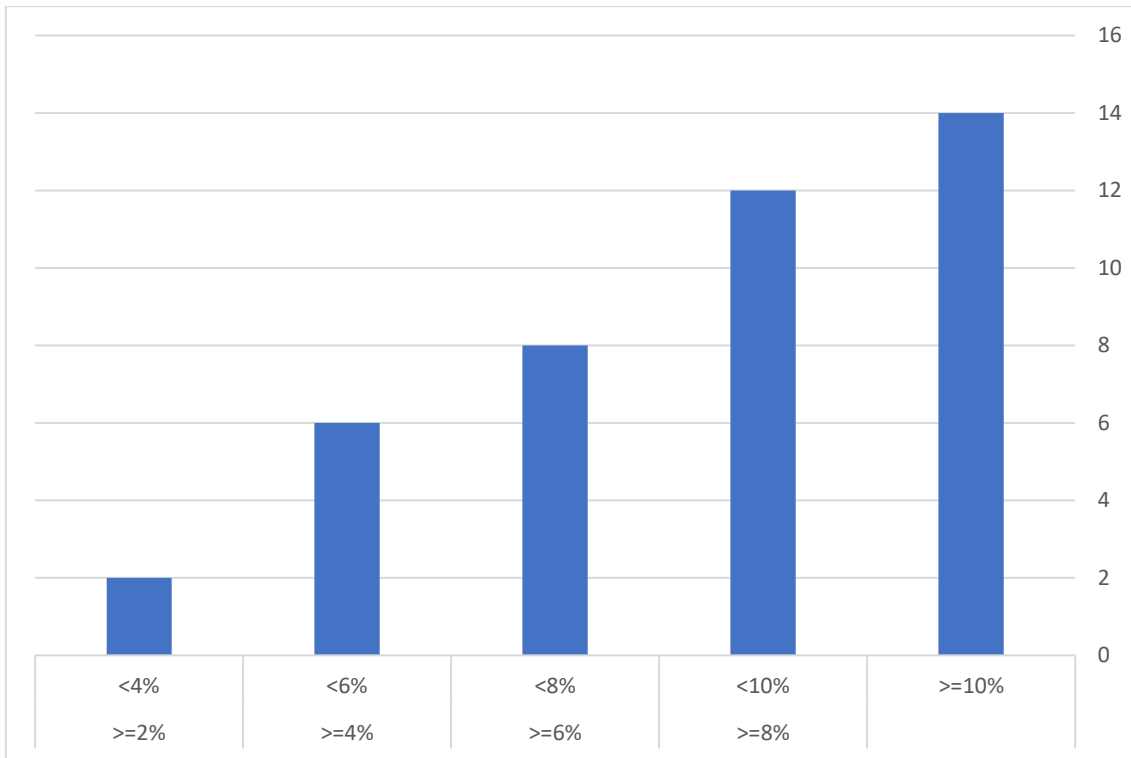


Figure 5: Number of conviction points based on percentage of the stock holds on the portfolio

The top buys/ sells criterion was selected because, as was addressed in the literature review, investment managers tend to buy outperforming stocks and dispose of underperforming stocks. To address the top buys and sells, it was calculated the value of the holdings of each stock every quarter and subtracted the same value for the previous period. If the value is positive, it means that the stock is being bought from one semester to the other, and the opposite is also true. Then it was extracted the ten highest and lowest values from this calculation and attributed the following points:

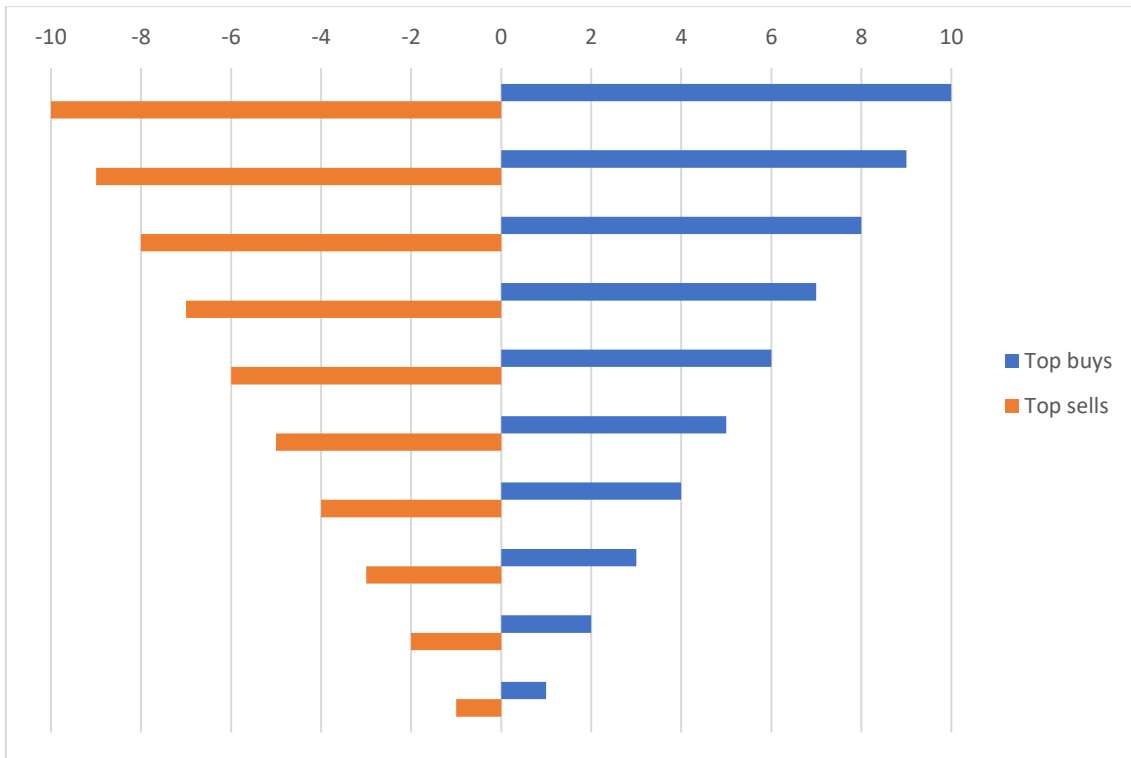


Figure 6: Number of points attributed to the most bought (sold) stocks each quarter

Finally, I summed the points that resulted from these different criteria and selected the top 20 stocks in terms of points each quarter. The positions are adjusted every quarter, when the new 13F filings are released (45 days after the end of each quarter). According to the number of points of each stock each quarter, it was created a portfolio with the following distributions of each stock:

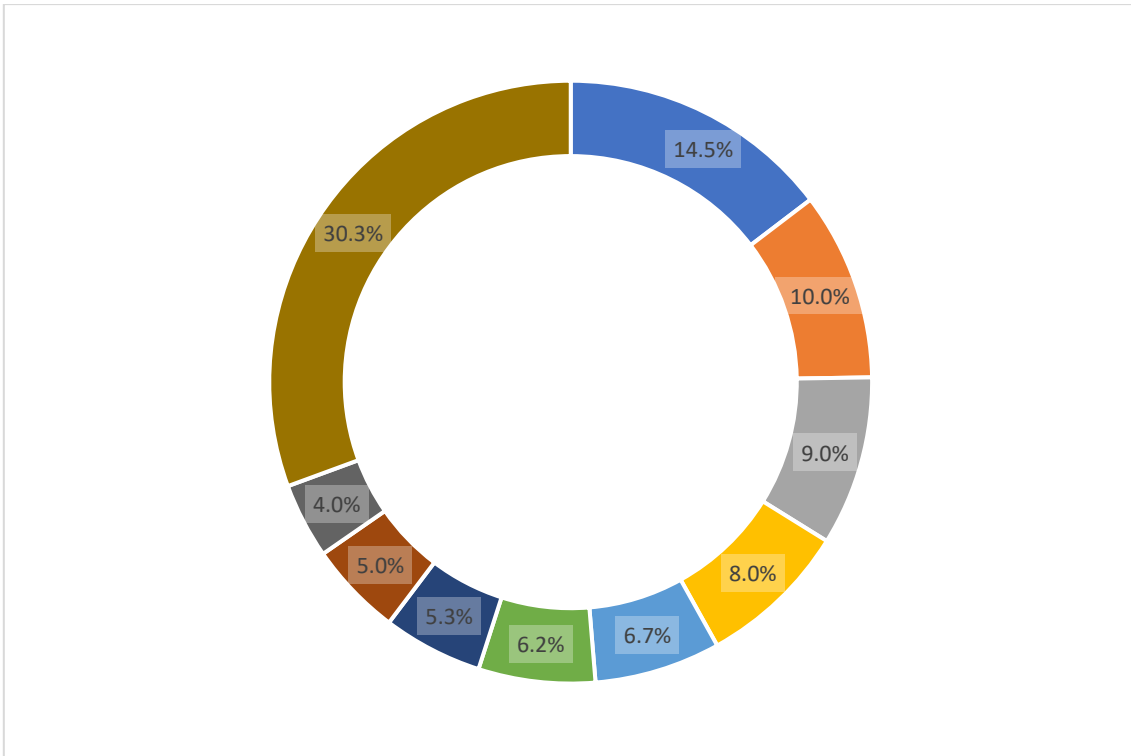


Figure 7: Portfolio distribution

This distribution of the portfolio was built taking into account the absolute number of points attributable to the stocks in the first quarter of the portfolio constitution. For example, considering a hypothetical portfolio of 2 stocks where the first stock has 100 points and the second has 50 points, the percentage of the portfolio allocated to the first stock would be 66% ($100/100+50$) and 33% to the second ($50/100+50$). This distribution is then maintained throughout the next quarters because constant adjustments would increase the overall cost of the portfolio if this was to be replicated in real life.

3.5. Determining the results

First, using modified closing prices, the logarithmic returns of each stock throughout the studied time were calculated. The annual returns and standard deviations for every stock were then computed from these returns.

Then, each stock's excess returns were calculated by subtracting the market excess returns from each stock's logarithmic returns. The goal of this action was to separate the performance of the individual stock from market movements.

Following this, the Beta of each stock was calculated by conducting a regression analysis. The regression model utilized the excess returns of each stock as the dependent variable (y) and the excess returns of the market (represented by the excess returns of the S&P500 index) as the independent variable (x). The coefficient of the resulting slope provided the Beta value for each stock, indicating its sensitivity to market movements.

To evaluate the portfolio's performance over the entire period, the average weight of each stock in the portfolio was computed from May 15, 2018, to November 15, 2023.

To assess the results of the portfolio and the ability to generate alpha, it was used both the Fama-French Three-Factor Model and the Capital Asset Pricing Model (CAPM). These well-known models are crucial for assessing how well investment portfolios perform and to shed light on the efficacy of portfolio management techniques, i.e., evaluating where the portfolio is investing.

Chapter 4 - Results and discussion

Figure 8 shows the main result of the research. The portfolio performed better than the S&P500 index, mostly after the Covid-19 outbreak, but overall, the returns have been relatively similar throughout the period from May 2018 until November 2023.

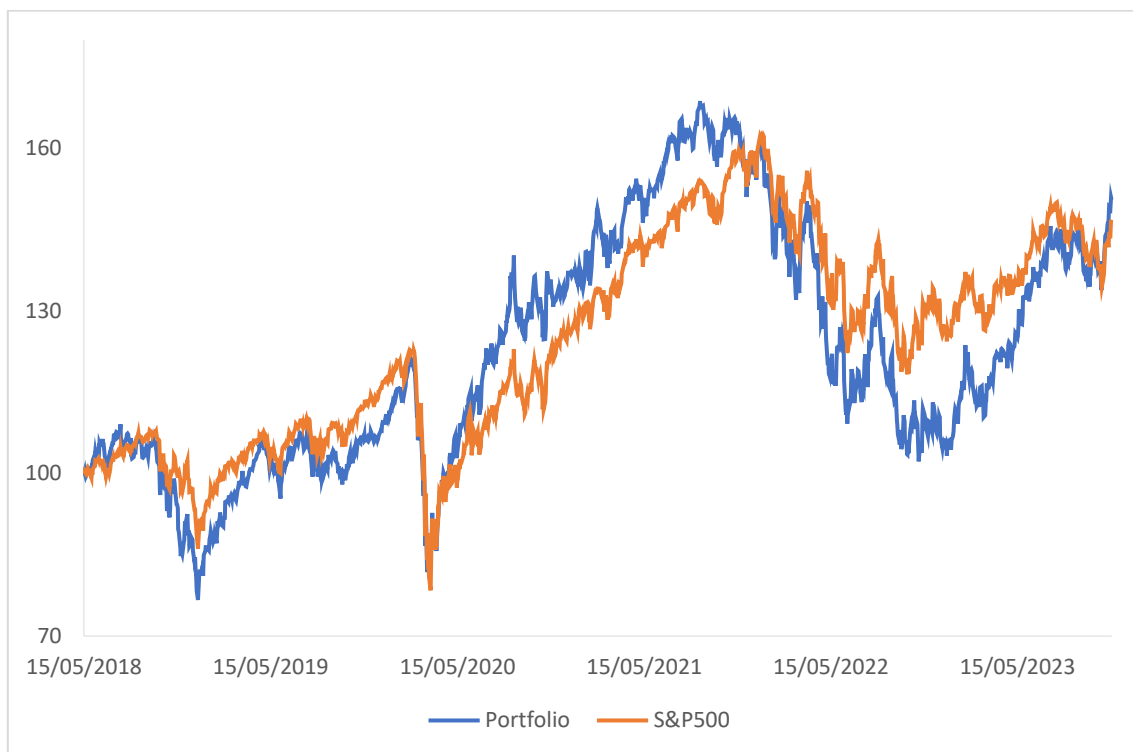


Figure 8: Performance of the Portfolio vs S&P500 index (rebased to 100 as of 15/05/2018)

Furthermore, the strategy does not deliver strong positive outperformance, as seen in Table 1. Despite the higher annual returns, the portfolio has much more volatility than the benchmark, resulting in the same Sharpe ratio for both instruments. Nonetheless, since tax and transaction costs are not considered in the computation of the returns of the portfolio, and due to the fact that there are now ETFs (Exchanged Traded Funds) that replicate the S&P500 index with little to no cost, investors would probably be better off investing in those same ETFs.

Metrics	Portfolio	S&P500
Annual Return	11.1%	9.1%
Standard Deviation	25.9%	20.9%
Sharpe ratio	0.403	0.403
Risk free	0.7%	

Table 1: Performance metrics of the portfolio vs the S&P500 index

The results yielded by the CAMP regression presented a high R-Squared (Table 2), suggesting that the returns of the portfolio are explained mainly by the returns of the market, which comes as no surprise, given that the holdings that have a higher share of the portfolio developed are some well-known names that drove a significant percentage of the returns of the S&P500 index. Although very close to 0, using the CAPM regression, the portfolio delivers a statistically significant alpha at the 5% level.

	CAPM	FF-4 Factor
Alpha	0.04%** (0.00)	-0.68* (0.00)
Mkt-Rf	1.506* (0.01)	0.011* (0.00)
SMB		-0.001* (0.00)
HML		-0.003* (0.00)
MOM		0.000 (0.00)
Adj.-R ²	0.859	0.757

Table 2: CAPM and Carhart 4 factor model analysis

*p<0.01, **p<0.05, ***p<0.1

On the other hand, the Carhart 4-factor model delivers a statistically significant negative alpha of 0.68%. All factors in the regression are significant except the momentum factor. As the CAPM did, the test also suggests that the portfolio is betting on a strategy that reflects the market, as this factor has the highest coefficient of all the variables used. The data is calculated using the daily returns.

The regressions estimated are:

a) CAPM regression: $r_{i,t} - r_{f,t} = \alpha_{i,t} + \beta_{Mkt}(SP500_t - R_{f,t})$;

b) Carhart 4-factor model: $r_{i,t} - r_{f,t} = \alpha_i + \beta_{Mkt}(SP500 - R_{f,t}) + \beta_{SMB}(SMB)_t + \beta_{HML}(HML)_t + \beta_{RMW}(RMW)_t + \beta_{Mom}(Mom)_t$

Chapter 5 - Conclusions

In conclusion, the main result of this dissertation shows that you cannot outperform the market, as represented by the S&P500 index, developing a portfolio with a methodology based on consensus, conviction and momentum. However, there are two critical points to take into consideration: 1) the methodology and the subset of investors used are very specific, and small changes would probably yield very different conclusions; and 2) regardless of the fact that the portfolio could not beat the benchmark, the results show that actually, the overall performance was very similar (albeit with a high-return and high-risk profile). For these two reasons, it is considered that valuable information can be extracted from the 13F filings.

In addition, one can conclude that valuable qualitative information can be extracted from the filings. The public nature of the data allows everyone to explore deeper into what institutional investors are doing and draw several conclusions. Besides the criteria used in the dissertation (consensus, conviction and momentum) there's much more intelligence that can be extracted from the filings that can support investment decisions.

Moreover, the dissertation raises essential questions and opens new doors for further investigation. Understanding the implications for institutional investors if copycat investments are implemented by a large group of (retail and other) investors and estimating the impact of transaction, tax and other costs in constructing a portfolio with this methodology can be examples of questions to answer in the future.

Additionally, it can also be interesting to study the same methodology with different inputs and nuances. For example, selecting a distinct group of investment managers (based on past performance or based on their media

coverage) or selecting different criteria to develop the portfolio can produce very different results.

The dissertation carries significant implications for investors, with a key takeaway being that merely replicating the portfolio holdings disclosed by institutional investment companies does not guarantee substantial outperformance compared to a passive index that follows the market.

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Appendices

Appendix 1. Institutional investors' list

Name	Q4 2017 # Holdings	Holdings value (M, \$)
Adelante Capital Management LLC	43	1800
Advent International, L.P.	18	4700
ADVENTIST HEALTH SYSTEM SUNBELT HEALTHCARE CORP	12	1500
AEW CAPITAL MANAGEMENT L P	45	3900
AKO CAPITAL LLP	19	1300
APPALOOSA LP	50	10000
Avoro Capital Advisors LLC	50	1500
Bares Capital Management, Inc.	17	2400
BAUPOST GROUP LLC/MA	34	10000
Black Creek Investment Management Inc.	27	2700
BloombergSen Inc.	13	1300
Brave Warrior Advisors, LLC	15	2400
CADIAN CAPITAL MANAGEMENT, LP	26	1600
Camber Capital Management LP	34	2000
CHAI TRUST CO LLC	23	1000
Contour Asset Management LLC	31	1800
Corvex Management LP	23	2000
Dorsal Capital Management, LP	26	2000
Duquesne Family Office LLC	30	2000
Focused Investors LLC	22	2500
Foxhaven Asset Management, LP	21	1400
FPR PARTNERS LLC	19	4700
Gates Capital Management, Inc.	33	4000
GREENHAVEN ASSOCIATES INC	23	6600
Hamlin Capital Management, LLC	40	2600
HS Management Partners, LLC	22	3200

Table 3: Institutional investors and respective number and value of holdings as of Q4 2017 (part 1/2)

Name	Q4 2017 # Holdings	Holdings value (M, \$)
KENSICO CAPITAL MANAGEMENT CORP	25	5000
LOCUST WOOD CAPITAL ADVISERS, LLC	36	1000
Long Pond Capital, LP	28	3500
Luxor Capital Group, LP	35	3500
Marshfield Associates	19	1500
Matrix Capital Management Company, LP	20	2800
MCDONALD CAPITAL INVESTORS INC/CA	21	1200
Meritage Group LP	18	6000
NEUMEIER POMA INVESTMENT COUNSEL LLC	40	1000
Palestra Capital Management LLC	21	1800
Palo Alto Investors LP	37	2300
Paradise Investment Management LLC	33	1300
PROVIDENT TRUST CO	32	2500
RGM Capital, LLC	18	1000
Saratoga Research & Investment Management	46	1400
Slate Path Capital LP	23	1016
Smead Capital Management, Inc.	29	2000
Sound Shore Management Inc /CT/	36	6500
SRS Investment Management, LLC	19	3800
Starboard Value LP	19	4100
Stockbridge Partners LLC	15	2000
TIMUCUAN ASSET MANAGEMENT INC/FL	23	1200
Two Creeks Capital Management, LP	26	1800
Valiant Capital Management, L.P.	14	1338
Westwood Global Investments, LLC	14	1330
Whale Rock Capital Management LLC	29	2158

Table 4: Institutional investors and respective number and value of holdings as of Q4 2017 (part 2/2)