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**"DO ACTIVE MUTUAL FUND MANAGERS DESERVE THEIR FEES?
A RETURN-BASED STYLE ANALYSIS ON THEIR PERFORMANCE"**

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Firma dello studente

Andrea Zambolin

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Introduction

In the present thesis we discuss one of the most famous topics in the literature on mutual funds performances: do fund managers really deserve their fees? Our focus is exclusively on the top performing funds which invested in S&P 500 stocks in the period from March 31st 1999 to December 31st 2019. Our goal is to determine if at least the most successful managers, belonging to the 1% highest percentile of the distribution of 5001 different funds, have measurable skills that can benefit the investors after adjusting the performance for the risk and the operational expenses. In order to perform our analysis, we employed a technique called Return-Based Style Analysis that helped us in the determination of the portfolio style of each manager. Afterwards, we reported the Alpha returns that they achieve, calculated as the difference between their performance and the reference benchmark and representative of the manager's contribution to the results. In conclusion, we estimate if the Alphas, also known as active returns, are driven by the exposure to factors or should be reconducted to the skills of the managers.

Our study is part of the line of research that follows the findings of Fama and French (2010), who show that the largest majority of mutual fund managers have a negative or statistically not significant impact on returns. Only a small subgroup of managers, belonging to the high tail of the distribution of returns, is deemed able to achieve positive extra returns over the benchmark and to transfer them to the investors.

The originality of our approach is to focus only on the top 1% of the universe of managers, discarding all the other managers who didn't perform as well as them. We use traditional tools, like factor investing and RBSA, blending them together to determine whether, at least the top 1% of the managers show actual skills. This small subset has not been deeply analyzed yet by other researchers, who instead focused on larger groups of managers without a-priori selection: conclusions have never been directly drawn to the top 1%, but only the majority of the managers.

We estimate this extra return at an average of 3.98% among the subset of skilled managers and our analysis aims at drawing a clearer and more detailed picture on this talented subgroup. The results of our research confirms that there is only a fraction among the high-performing managers with significant skills that should be compensated with appropriate fees. In our sample of 30 funds meeting all the selection constraints that we have imposed, the fraction of skilled managers is 60%, meaning that our estimation is that only 0.60% of the universe managers is able to generate significant extra returns. The remaining managers, instead, didn't achieve Alphas which were significantly different from zero, showing that these managers didn't add a relevant contribution to the performance and, based on our definition, are not skilled enough to deserve their compensation.

Another relevant aspect investigated in the thesis is linked to the investment style of the analyzed mutual fund managers, measured with the tools of factor investing. We discuss the persistence of the risk premiums connected to the exposure to the six factors (Size, Low Volatility, High Quality, Momentum, Dividend Yield and Value), especially in relation to the recent diffusion of Smart Beta funds.

The research is structured in five chapters and each of them is focused on a specific aspect of the analysis.

In the first chapter we describe the main framework of the paper and review the literature pertaining to our study. The focus is on the dichotomy between active and passive funds and the introduction of Smart Beta funds as an alternative with characteristics in common with both types of funds. We discuss previous models and research assessing the performance of mutual fund managers and the differences among them. We also introduce the setting and tools used in the following chapters.

We begin chapter 2 with an in-depth analysis of the six factors, their discovery and the explanation of their risk premiums. Furthermore, we describe the ongoing debate among academics and practitioners on the persistence of the factors, together with different theories suggesting the existence of other additional factors. The six factors represent the basis in the construction of the six indexes of chapter 3, which includes also a detailed assessment of their performance in relation to the S&P 500 benchmark.

Additionally, in chapter 3 we explain the rules in the selection of the stocks in the construction of our customized indexes, the weighting criteria and the rebalancing constraints. Furthermore, we compare and comment on the performance of the indexes, both relative to the S&P 500 and among themselves. The results reported are consistent with the major studies on factor premiums and factor investing.

The following chapter includes the main findings of the analysis and starts with a detailed explanation of the technique (RSBA) and the list of all the constraints in the selection of the pool of managers. We develop a step by step description of the model used in the multiple variable regression and determine the investment style of fund managers. We evaluate their skills by calculating the R^2 coefficient, whose complement to one represents the share of the variance of the performance not explained by the factors. We measure the performance of the managers by calculating their Alpha return over customized style portfolios and we conduct T-tests on the significance of the results. Our analysis shows that among the most successful managers a relevant portion of them - 18 out of 30 - deserve their compensation fees and are able to produce significant net returns for the investors. Furthermore, we make additional remarks on what could distort our analysis, such as statistical biases and luck component in the excess returns. In the end, we compare our results to those of other researchers.

The fifth and last chapter expands our focus on Smart Beta funds, highlighting the main concerns regarding the persistence of the risk premiums of factors and mentioning the new specific risks pertaining to factor investing. Furthermore, we review some studies attempting to identify skillful managers based on their personal background, without relying on their past performance. We include the description of two common statistical biases (the selection and the survivor biases), their effects and the relative corrections. Finally, we conclude remarking the relevance of the fee structure of the funds on the investors' investment decisions, showing that, based on the results of our paper, retail investors would be better off allocating most of their money to passive funds and a small share to Smart Beta strategies. On the other hand, institutional investors with appropriate resources and capable of determining if a manager is skillful or not, should include active funds in their holdings too.

In the last section we summarize the conclusions of our thesis and indicate some suggestions for further research, like an alternative managers' selection process and the inclusion of other factors in the style analysis of mutual funds.

Chapter 1 - The Main Framework

1.1 Introduction

In this chapter we introduce the main concepts and framework that will be developed in the thesis. We review the most relevant literature on our topics and discuss the implications for our work. We begin from the characteristics and the main distinctions between the two management styles that can be observed in most mutual funds in the world: active or passive management. We consider the benefits and drawbacks for the investors of both types of funds, setting the framework for the principal question of the paper: do the most successful active managers deserve their fees?

We briefly introduce the methodology in the selection of the mutual fund managers, who are chosen among the best of their category[1], and how the analysis will be developed in the determination of their skills. The approach, called Returns-Based Style Analysis (RBSA) is concisely outlined with its advantages and inner limitations.

In the description of RBSA, we pose great attention on the construction of factor style indexes to create the appropriate benchmark for each one of the 30 mutual funds under examination. We review the literature and previous researches on performance measurement, Total Alpha Return, style factors and factor investing, presenting the six most famous factors and describing how we employ them in the analysis. In conclusion, we recall the recent growth of funds whose strategies are based on factor investing, the so called "Smart Beta Funds."

1.2 Active Versus Passive Management

When it comes to deciding where to invest their money, investors have to make a choice between two main categories of funds: active or passive portfolio managed funds. There are many differences between the two, highlighting two completely opposite views on the markets and their functioning. In our paper we do not include bond funds or funds investing both in stocks and bonds, both just mutual funds with stocks and cash as holdings.

First of all, active managers try to outperform a reference benchmark by taking active positions in the market and expressing their views, selling or buying securities based on their forecasts. On the other hand, passive managed portfolios have the goal to replicate the performance of the selected benchmark

[1] Identified in the "high tail of the distribution of managers' returns", as analyzed by Fama and French (2010).

as closely as possible, without assigning different weights to the securities in the portfolio construction with respect to the benchmark allocation[2]. No active position is taken by the passive managers, implying that their portfolio composition mimics the weights assigned to the securities of the reference index. Passive portfolios are, for example, index portfolios, as well as most Exchange Traded Funds (ETFs). Their goal is to replicate the performance of the market, of another reference index or of a set of indexes. Passive equity mutual funds were less common than active equity mutual funds, but their share in the market has increased during the past years to the point that the assets under management are the same as active equity mutual funds.[3] In our entire work we are always considering US mutual funds, since the US market is the most developed in the world and investors have the chance to invest in a wide set of companies.

Passive investors usually face low fees and expenses, because the managers are not requested to beat the market and achieve an extra-return, but they only need to follow the market performance as closely as possible. The expected return of a passive mutual fund is reflected by the performance of the market, less the small costs that the managers face, such as rebalancing and transaction costs. The net return adjusted for fees will then decrease a bit more depending on the annual management fees[4].

Active investors, instead, set their goal at outperforming the reference benchmark. Their holdings differ from the index because they look for higher returns, buying and selling securities that they deem as undervalued or overvalued. The performance of these funds depends on how they allocate their endowment among the asset classes and how they implement the security selection. Their ability is reflected into the returns that they achieve.

In our paper we try to determine if active managers have substantial skills and if they are the true determinant in achieving superior returns, or if their results can be simply explained by the historical premiums recorded by the so-called "style factors," which will be introduced in chapter 2. Active managed funds usually have higher turnover ratios[5] than passive funds, since the managers need to adjust their position more often, depending on their expectations of the market. Subsequently, active funds incur in higher transaction and rebalancing costs due to the larger number of trades with respect to passive investing. The costs connected to active mutual funds management are higher, in a range between 0.5% and 1%, occasionally up to 3% (Morningstar, 2019). Furthermore, an additional cost which, in general,

[2] Passive managers have the mandate to track the benchmark, maintaining the portfolio allocation as close as possible to the index and reducing deviations from it.
[3] The growth of passive funds has been particularly fast after the Financial Crisis. (Bloomberg, September 2019)
[4] Management fees vary among funds, but the average in 2019 for passive mutual funds is about 0.2%.
[5] Defined as the percentage of portfolio's holdings replaced in a fiscal year.

is not taken into consideration is the taxation of capital gains when a trade is closed. On the other hand, passive investors, who buy and hold securities for a long time, can benefit from lower taxation costs and, sometimes can benefit from tax reductions too if they satisfy country-specific regulations on holding periods.

Our goal is to determine if the skills that the managers use in their activity in the market are backed by statistically significant returns, after accounting for the risk that they undertake. The risk is measured by the volatility of the returns and, in order to compare the results of different managers, we calculate the Sharpe Ratio, also known as risk-to-reward ratio. The prevailing literature is pretty much aligned: active fund managers have traditionally underperformed passive indexes, excluding short periods. In particular, Fama and French (2010) prove in their analysis that only "few active managers can cover their costs" and can guarantee an extra return above the market to their investors. In order to address this specific and small subgroup of managers in our analysis, we set strict criteria to select only the managers that have performed far better than their peers and also with respect to their reference index (S&P 500 Index) from March 31st 1999 to December 31st 2019.

Active portfolio managers try to maximize the value that they add to their clients by using their skills in discerning how to undertake risk in order to achieve a higher return. The risk that they focus on is called "active risk," which is the risk measured outside the benchmark. In fact, the performance of the benchmark is not under the managers' control, who can instead show their skills deviating from the returns of S&P 500.

Managers can then make a difference in two ways: timing the benchmark[6] and selecting the best securities[7]. The first strategy is followed by managers who assign different weight allocations to the index sectors with respect to the benchmark, while the second entails the identification and selection of single stocks that outperform or underperform the market. We measure the aggregate ability of the managers in our analysis, after identifying the components that better reflect their investment style.

The past literature on active portfolio management offers many approaches to the implementation of the managers' strategies, such as Black and Litterman (1992) who suggest that the managers add value by expressing their views on the market and by optimizing the asset classes weights following their expectations. Grinold and Kahn (1995), instead, determine that the managers add value to the portfolio

[6] This strategy goes under the name of "Active Beta" in finance.
[7] Traditionally referred to as stock picking.

by forecasting Alphas of the available securities, which are defined as the extra returns over the market return.

Summing up, investors face the alternative choice between active and passive management when they decide where to invest their money and, in both cases, they have advantages and drawbacks. The biggest advantage of active investing is that the managers can express their views without being forced to allocate their assets like in the reference index. On the other side, active managers can make bad decisions and the returns might be poor or even below the market, in addition to the higher operational expenses and management fees.

Our focus is to determine if at least the most successful active managers have skills significant enough to be rightfully compensated with the fees that they collect. As a consequence, it would be also worthwhile for an investor to assign her money to active managers instead of depositing her savings in the alternative represented by passive mutual funds.

In the next paragraph we review some research on this topic, showing how, on average, active managers have underperformed their reference indexes.

1.3 Active Managers and Total Alpha Returns

As previously mentioned, our main reference is Fama and French's paper (2010). In their work, the two economists evaluate whether, after subtracting the management costs, the returns achieved by mutual fund managers add value to their clients at a significant degree of confidence.

Their findings are that "few funds produce benchmark-adjusted expected returns sufficient to cover their costs" and that "evidence of inferior and superior performance (nonzero true alpha)" is observed only "in the extreme tails of the cross-section of mutual fund alpha estimates" (Fama and French, 2010). This implies that only a small subgroup of the mutual fund managers that the authors analyze show results consistent with the hypothesis that managers can generate superior returns with their abilities. Furthermore, there is a small group of managers who significantly underperform the benchmark. The researchers calculate Alpha, known as abnormal expected return, to determine the outperformance of the managers over their benchmark.

These are the main similarities between our analysis and the work of Fama and French (2010), which provides us with the overall conceptual framework to set up our analysis. However, our focus is more specific and we target only managers belonging to the high tail of the distribution, where the two researchers suggest that "some managers do have sufficient skill to cover costs," instead of choosing the average manager as standard reference.

Fama and French (2010) employ both the Three Factor Model that they developed in 1992 and the Four Factor Model implemented by Carhart (1997). The variables of the time-series regression are the following: the market return, adjusted for the risk-free rate, the size and value factors, with the addition of the momentum factor adapted from Carhart's paper.

Our analysis, instead, implements six style factors and is based on the Returns-Based Style Analysis technique introduced by Sharpe (1988), generating fund-specific benchmarks to mirror the performance of mutual funds and to identify the relative Total Alpha Returns not captured by the style factors of the regressions.

Ang (2014) describes Alpha as a measurement tool of the skills of a manager that, with her abilities, generates a return higher than the benchmark. The author explains that, since Alpha represents the "average return in excess of a benchmark," also known as active return, "the benchmark is passive and can be produced without any particular investment knowledge or even human intervention." It is straightforward that, if a manager doesn't produce significant active returns, she would only be a net cost for the clients. The return adjusted for the fees would be lower than the return potentially achieved in a passive fund of comparable style, making the investors better off without the presence of the mutual fund manager.

Furthermore, Ang (2014) states that "Alpha by itself could be produced by a manager taking large amounts of risk," so it is not informative enough by itself. He suggests adjusting Alpha for its risk, dividing it by the tracking error, which is calculated as the standard deviation of the excess returns[8]. The ratio that he obtains is known as Information Ratio and it measures the performance of an investment with respect to the benchmark, after adjusting for its additional risk.

Ang (2014) reports that "Information ratios above one are not common - although many hedge funds trying to raise money claim to have them" and mentions that "since the financial crisis, information ratios on many funds and strategies have come down substantially." Grinold and Kahn (1995) estimate the average Information Ratio of the top 25% of fund managers at around one half. In our analysis, given that each benchmark is specifically tailored for each mutual fund on the basis of the results of the RBSA,

[8] It is also denominated "active risk", since it is the additional risk added by the manager's choices.

the most appropriate procedure to assess the manager's skills is to calculate the T-statistics, instead of other ratios that do not take into account the significance of the results, such as the Information Ratio[9].

The key aspect of the analysis is that managers can only generate Alphas with their abilities in making bets that deviate their holdings from the weights assigned to the securities in the benchmarks. As Ang (2014) support of the results of the T-tests, we can determine whether the selected mutual fund managers have substantial skills and deserve their fees.

Reviewing other studies on the determination of managers' skills, the results are consistent with the findings of Fama and French (2010). The SPIVA US Study conducted by S&P (2014) establishes that, on average, the percentage of mutual funds unable to beat the benchmark[10] ranges between 61% and 89% based on 1, 5 and 10 year periods before 2014. The same conclusions are reached in research by Arthveda Capital (2015) in which the amount of funds underperforming the benchmark is around 80% for the same period. Also Sebastian and Attaluri (2016) show that, referring to strategies focused on the traditional factors of rules-based investing, no statistically significant Alpha is found when confronted with a T-statistic of 2.0[11] and accounting for the Value and Size factors.

In our analysis we account for the style strategies implemented by the managers, isolating the Total Alpha Return with the statistical methodology that is introduced in the next paragraph.

1.4 The Main Framework

After reviewing the most relevant literature pertaining to our paper, we develop the main framework that is implemented in the next chapters. We follow the methodology introduced by Sharpe (1988), analyzing the 30 mutual funds that we select among the 5001 reported by Bloomberg.

First of all, we build six indexes based on the following six factors: Size, High Quality, Low Volatility, Value, Dividend Yield and Momentum. These six factors have been recognized by most researchers as the drivers of historical premiums in the explanation of market returns. Given our goal in determining the effective skills of mutual fund managers, we need to distinguish if the returns achieved can be explained just by the six factors premiums or if a component of skills is significantly present. The indexes are built following what academia has considered as the key identifiers for each factor, discussed in chapter 3. We decide to build customized indexes and not to rely on those available in the financial

[9] Furthermore, we would have to consider the same benchmark across the funds to make proper comparisons.
[10] In this study the common benchmark is the S&P 500.
[11] Approximately equivalent to a 95% confidence interval.

markets, such as MSCI Factor Indexes[12], because the most tailored they are, the more precise and accurate the regression would be.

The Returns-Based Style Analysis provides all the necessary information for a first snapshot of the manager's skills, which are further investigated to fully understand what are the true determinants and if there can be any statistical inaccuracy or luck component that might be responsible for distortions in the results.

Crucial to our analysis is a proper a-priori selection of the managers. We impose strict criteria on the selection, in order to choose those few managers that are considered skillful by Fama and French (2010) and belong to the highest tail of the distribution of managers' returns. We include additional constraints on the analysis to create benchmark portfolios that are realistic and can appropriately determine what is the style that each manager adopts in her investment portfolio[13].

The main question of the paper is addressed by the calculation of the Total Alpha Return[14]: if the value is statistically significant, the manager deserves her fees and is able to grant her clients a superior return adjusted for her management expenses. Further details are discussed in the relative paragraphs.

1.5 Style Factors and Their Implementation

One of the key steps of our analysis is the identification and construction of style indexes based on factors. We now describe what factors are and review the most important literature on this topic.

Factors are defined as "investment styles that deliver high returns over the long run" by Ang (2014). The author states that each factor, since "risk premiums don't come for free, can underperform in the short run" and this "can occur especially in periods of economic recession." The traditional and first example of a factor is the exposure to market risk, which explains the extra returns of stocks over the risk-free rate: it was described for the first time by Sharpe (1964) in the introduction of the Capital Asset Pricing Model. This factor is defined as "static," since it is linked to simple long-only positions[15] and investors are rewarded for the exposure to the risks of the market.

Other factors, instead, are linked to different risk premiums, such as value, growth, momentum and volatility, which generally offered extra returns to investors exposed to the connected risks (Ang, 2014).

[12] MSCI Inc. is the global provider of many stock indexes and the leader in factor indexing.
[13] It is important to use indexes that can be potentially invested by managers, since the goal is to be close to reality and not just finding statistical relationships that are not realistic in the financial environment.
[14] Defined as the return over the customized benchmark.
[15] This is the factor typically rewarded in a buy-and-hold strategy.

Factors with characteristics similar to those of the latter group are defined as “dynamic,” since they are often implemented with long-short strategies by investors, who try to identify and buy the most promising stocks while they open short positions on poor-performing assets.[16]

Every factor premium is, in fact, connected to the exposure to a specific kind of risk that investors face by following factor-based strategies (Ang, 2014). Assets are inherently made of different types of factors and, based on the investors’ security selection, they create the style of the investment portfolio.

The determination of the investment style of each manager is fundamental in the decomposition of the returns, since it allows us to define the proper benchmark in the calculation of the Total Alpha Return[17]. This is also the best approach to track the exposure to factors of each manager, which relies upon the determination of their style and the identification of an appropriate reference benchmark.

Furthermore, the traditional measures of volatility are based on the standard deviation of the total returns but, in performance measurement, it is more accurate to use the active risk only, which is the volatility of Alpha over the reference period. Active risk and active return are the two key measures in the calculation of the value added by the manager’s abilities and views in the market.

Other researchers implemented similar analysis, focusing on specific funds or on a pool of funds, finding concordant results: Brinson (1986) determined that in his pool of funds almost 90% of the variance of the returns was explained by style factors, leaving very small room for the managers’ skills.

There are many ways to invest in the dynamic factors that we consider, including long-only and long-short positions, with the investor buying, for example, Value stocks and selling Growth stocks. Each fund has a specific benchmark and activity, based on its clients’ mandate, and its performance must be tracked by an appropriate benchmark.

Other models, like the Arbitrage Portfolio Theory (APT), do not focus on style factors, but on macroeconomic determinants such as inflation, GDP growth, investors’ confidence and the yield curve.[18] APT was introduced by the economist Stephen Ross (1976) as an asset pricing theory that could explain the return of assets depending on factors coming from macroeconomics and depending on the sensitivity of each asset to the aforementioned factors.

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[16] Most funds can only open limited short positions, resulting in a final exposure that is almost always on the long side of the market.

[17] In the paper when we mention Alpha, we always refer to the Total Alpha Return, except when we define the variables of the regression.

[18] The distinction with style factors lies in the aggregate view of macro factors.

Another model, named Barra Risk Factor Model after the firm which developed its framework in 1998, employs over 40 different metrics, ranging from earnings data to debt quality, to determine the factor risk exposure of a certain security and consequently assessing its potential return and risk. This last model, like all the others, is based on the risk-return tradeoff and uses the concept of factors in the determination of the peculiar characteristics of the investments.

Additional improvements in the determination of the style factors come from S. Thomas (2010), who "extends RBSA to form style groups using cluster analysis," resulting in a closer monitoring of the changes in the portfolio style throughout the life of mutual funds. In his analysis he also invents an index, named "Best Fit Index," to evaluate which style mix can better replicate and explain the performance of mutual fund managers. His results confirm the relevance of RBSA by "explaining a significant proportion of the cross section of out of sample returns." (Thomas, 2010)

On the other hand, some critics address the results reported in these studies by indicating inconsistencies in the approach and in its principles, citing the Efficient Market Hypothesis. In its strong form, it states that "current stock prices fully reflect available information about the value of the firm, and there is no way to earn excess profits by using this information" (Fama, 1964). This means that, if the strong form of the Efficient Market Hypothesis Most is valid, beating the market is impossible and there is no room for managers' skills. On the other hand, if the hypothesis doesn't hold in the strong form, there are chances for managers to make an impact and add significant value with their activity.

One of the most famous supporters of the strong form of the Efficient Market Hypothesis, B. Malkiel, finds evidence in his studies that managers do not have substantial skills when they build their strategies on technical or fundamental analysis on public information (Malkiel, 2016). However, he also writes that "few mutual funds managers can be able to consistently outperform the market over the long term," but it is "statistically unlikely for an investor to select one of those few funds." (Malkiel, 2016)[19]

During the course of the years, however, most researchers suggest that there is some sort of market inefficiency which can be exploited by skillful investors (Rosenberg, 1985), leading the economists to define the factors explaining the extra returns. The relevant contributions will be discussed in the next chapter, together with a detailed explanation of the premiums of each factor and the relative explanation. Outside of the academic environment, a very relevant pattern has emerged during the last two decades, with the rise of factor investing in the form of open-ended mutual funds and ETFs[20], accessible to the

[19] The first edition of the Malkiel's research dates back to 1973, with the last update in 2016.
[20] Exchange Traded Funds. They are passive and low-cost funds traded on stock exchanges.

great majority of investors. Their strategy is based on a mix between a passive and an active strategy using factors, which is the topic of the next paragraph.

1.6 Factor Investing and the Rise of Smart Beta Funds

Factor investing is defined as an investment strategy which is based on the exposure to preselected factors and "typically focuses on capturing factor premiums that have been extensively documented in the literature, such as the value, momentum, and low volatility premiums." (Blitz, 2016). During the last years, "asset allocators increasingly consider factor premiums next to traditional asset class risk premiums" (Blitz, 2016) focusing mostly on long-only strategies. From a theoretical standpoint, the best way to capture the risk premiums connected to the factors is to pursue a long-short strategy in which the stocks are bought or sold depending on their factor exposure. This strategy captures a pure risk premium, isolating it from other influences[21] and generating a very low level of correlation with the market itself (Blitz, 2016). However, a long-short approach is not available to most mutual fund managers, given the constraints that they face in the management of their endowments.

Factor investing is a recent trend whose rise is a direct consequence of the introduction of Smart Beta Indexes, capable of reproducing the performance connected to the exposure to one or to multiple factors by following specific rules in the construction and rebalancing methodology[22]. Smart Beta Indexes employ "mechanical rules to deviate from capitalization-weighted market indexes, resulting in systematic tilts toward certain factors" (Blitz, 2016) and effectively capture "value that can be attributed entirely to exposures to established factor premiums." (Chow, 2011)

Smart Beta Indexes and portfolios can be considered a blend between passive and active investment styles, overcoming the traditional distinction between the two and offering a product that presents some of the peculiar traits of both strategies. They "offer the benefits of passive strategies combined with some of the advantages of active ones, placing it at the intersection of efficient-market hypothesis and factor investing." (Stewart, 2017) Smart Beta Indexes, also known as Factor Indexes, are in fact built based on the definition of the factor they are supposed to track, generating their exposure on the basis of financial indicators that identify the factors in the available stocks.

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[21] Such as the market return, for example.

[22] This is why they are called "Smart". "Beta", instead, traditionally represents the sensitiveness of an asset with respect to certain variables.

On the other hand, these indexes also have characteristics of passive indexes, which rely on the concept that asset prices already incorporate all public information, hence there are no arbitrage opportunities available for active investors as expressed by the Efficient Market Hypothesis[23].

Furthermore, most Smart Beta indexes are simple and transparent, without convoluted mechanism in the selection of the securities. Additionally, the low turnover, which measures how often the indexes change their composition, is typical of passive portfolios, while active managers are characterized by higher turnover ratios. Actively managed portfolios sometimes have turnover ratios exceeding 100%, while in the case of passive portfolios the ratio can be as low as 3% (Morningstar).

On the other hand, Smart Beta strategies have also characteristics traditionally attributed to active portfolios, such as the potential for outperformance. It is measured by the risk-reward ratio, expressing how investors can achieve higher returns or lower their risk without affecting the risk-adjusted performance. Alford (2016) shows that the superior return can be recorded by Smart Beta indexes because they are "tilt toward common equity factors attempting to exploit the inefficiencies of market cap-weighted portfolios," which instead "overweight stocks that are overvalued and underweight stocks that are undervalued." Subsequently, cap-weighted portfolios "may not provide the maximum return per unit of risk."

Smart Beta strategies are not a new product of the financial industry, since researchers have identified the first factors risk premiums almost 50 years ago and they have been available for investors for decades. However, only active managers with very relaxed mandates, such as hedge funds, were able to exploit factor-based strategies, since the deviation from the benchmark and the connected active risk would have been too large for mutual funds. Alford (2016) explains that "what is new is the way that investors can access these common equity factors," without relying on the skills of active managers in identifying the best stocks but just "getting exposure to common equity factors using simple and transparent approaches." Furthermore, Smart Beta funds follow a low-cost strategy that make them very attractive to investors.

Consistent with these premises, Smart Beta funds and factor investing have increased their popularity in the last decade, with compounded growth rates above 20% per year during the period 2011-2016, when assets invested in Factor-Based Exchange Traded Funds went from $ 150 billion to over $ 450 billion (Morningstar). The growth pattern continued steadily until 2019 too, with a total amount of $ 880 billion

[23] Insider information, however, is still relevant and linked to arbitrage opportunities.

invested in Factor-Based ETFs. The amount does not include those mutual and hedge funds which are partly or fully implementing factor-like strategies in their management, because they normally change their approach too often and fall under the classification of "dynamic asset allocation" (Bloomberg). The amount invested is still small with respect to the total allocation to active equity funds ($ 4.2 trillion) and passive equity funds ($ 4.3 trillion), since investors, overall, prefer to stick to traditional rather than alternative investment like Factor-Based ETFs.[24]

The increase of the assets under management of Factor-Based funds and the popularity of Smart Beta strategies raise different concerns among investors. For example, many practitioners question the persistence of the risk premiums linked to the factors (Bender, 2013) and the risks connected to the implementation of a relatively new strategy in the traditional portfolio management practices. The main concerns are closely connected to the increasing size of the investments in funds with specific factor exposure, which can halt the risk premiums historically awarded to those factors.

We address this and other potential weaknesses of Smart Beta strategies in chapter 5, together with their likely evolution in the future as more Factor-Based funds are created and more sophisticated techniques are developed to identify and select the most exposed stocks.

In the next chapter we evaluate and explain the historical premiums awarded to the six most famous factors; Size, High Quality, Momentum, Value, Low Volatility and Dividend Yield. We discuss their consistency and persistence over the years, always in light of the researches made both by practitioners and academics.

[24] The total amount of asset under management of mutual funds totaled almost $ 50 trillion in 2019.

Chapter 2 - The Six Factors

2.1 Introduction

In the present chapter we review the literature on the six factors investigated in our paper: Size, Value, Momentum, High Quality, Low Volatility and Dividend Yield. They are the most common factors and the great majority of researchers agree that they are awarded with consistent and persistent risk premiums.

We explain the economic reasons that can justify these risk premiums, starting back from their discovery in the financial markets. Having a clear and deep understanding of the functioning of the factors is extremely important because they represent the basis to build our indexes.

In the last section we also discuss additional factors that have been identified by researchers but are not included in the regression, mostly because they would have been redundant or because their stability is still under debate among academics and practitioners.

2.2 Size Factor Premium: Small Vs Large

The Size factor expresses the risk premium awarded to small cap stocks with respect to large caps. It is the simplest factor among all and is identified by the market capitalization of the companies under examination. The factor is described for the first time in 1981 by R. Banz, who finds that "smaller firms have had higher risk adjusted returns, on average, than larger firms." The effect identified by Banz was present for at least forty years and was more relevant for very small firms in NYSE. The author also states that "it is not known whether size per se is responsible for the effect of is just a proxy for one or more true unknown factors correlated with size." (Banz, 1981)

More than 10 years later, Fama and French (1992) published their famous Three Factor Model, in which they add the Size and Value factors to the Market factor[25]. They suggest that the risk premium is based on many reasons, such as the limited investability in small firms for many funds, which leads to less usage of public information and leaves mispricing opportunities open for other investors able to capitalize on them. Small companies are also riskier, overall, than large corporations, so a great number of investors prefer to stay away from them, even if the historical returns, adjusted for their volatility, are higher.

[25] The Market factor is the traditional Beta introduced in the CAPM.

The debate over the persistence of this factor has increased across the years, with some researchers stating that the Size factor is not recording anymore a substantial premium over the benchmark index. In particular, Beck (2016), highlights that in most researches the size factor has delivered an extraordinary risk premium simply due to the selection process of "small cap stocks, which are subject to the delisting return bias." This bias brings the attention to one of the common problems with the exploration of past performances given a specific factor: if a company is delisted, the return is usually not accounted in the calculations. In Beck's opinion, this procedure generally leads to recording higher premiums than what they really are.

The growing implementation of the Size factor among practitioners has probably shrunk the associated extra return, due to the phenomenon called "crowding" (Alford, 2016), which explains the progressive decline of premiums depending on the number of investors following that particular strategy. On the other hand, MSCI (2016) shows that the Size factor has achieved significant returns both in the United States and in the rest of the world, continuing to outperform the market especially in periods of sharp rise[26].

Overall, the size effect exacerbates the magnitude of the swings of the market and generates large returns with its upward potential, following the main cycles of the market.

2.3 Momentum Factor Premium: Winners Vs Losers

The Momentum factor captures the premium awarded to strategies that rely on buying past winners and selling past losers. A stock is defined as "winner" when its previous 6 or 12-month return is above the average of the market, while a "loser" is a past underperformer. The Momentum factor is based on a strong persistence of the price pattern of stocks, fully relying on past performance as the unique tool to define the stocks to buy and to sell.

The first researchers identified this relationship in 1993 and, trying to find the determinants of the risk premium, they found that the profitability of Momentum-based strategies is not directly linked to the exposure to systematic risks or to slow stock price response to common factors (Jegadeesh and Titman, 1993). They conclude that the above-the-average return seem to be only linked to the previous performance which, however, partially disappears in the next two years. The time span considered to select Momentum stocks ranges from 3 months to 1 year.

[26] As with every factor, there is an abundance of papers supporting both its existence and the contrary. In every case, the predominant view is that all the six factors are present in the market.

Since its discovery, the Momentum factor has been incorporated in Carhart's extension of the Three Factor Model in 1997, named Four Factor Model. In his paper the author removes the survivor bias from his sample and demonstrates that the persistence of equity mutual funds' risk-adjusted returns can be almost entirely explained by the presence of common elements in investment expenses and stock returns. He refines Jegadeesh's results by showing that "funds that earn higher one-year returns do so not because fund managers successfully follow momentum strategies, but because some mutual funds just happen by chance to hold relatively larger positions in last year's winning stocks." (Carhart, 1997)[27] He concludes that managers do not have substantial skills and the overperformance must be awarded to the Momentum and the other style factors. He also adds that the high transaction expenses of most active mutual funds reduces momentum-related returns by a relevant amount.

Other researchers confirm the persistence of the Momentum factor, highlighting that it has been one of the factors with the most consistent excess returns over the years (MSCI, 2016), as long as the indexes are built as self-financing portfolios. We define a self-financing portfolio as a portfolio that doesn't need capital from the investors[28], since the amount of stocks bought are financed by the value of stocks sold. Nevertheless, this kind of strategy is not viable for mutual fund managers, given their strict leverage constraints. On the other hand, some hedge funds can follow this zero-weight strategy and reap returns both on the long and short side of the market, gaining full exposure to the momentum factor.

MSCI (2016) shows that the Momentum factor has generally reported a better performance when the "macroeconomic environment is characterized by a long cycle in underlying market trends," while instead it suffers from sudden reversal in market trends and during recessions. The major risk for investors is to buy a stock around its peak, just before a mean reversion trend begins, erasing most of gains from the previous period.

2.4 Value Factor Premium: Value Vs Growth

The Value factor captures the risk premium awarded to cheap stocks with respect to more pricey stocks. The definition of "cheap" and "pricey" stocks relates to the most famous multiples in the analysis of common stocks, Price/Earnings (P/E) and Price/Book (P/B). When the multiples are low, the stocks are defined as "Value stocks," otherwise they are classified as "Growth stocks." The former are expected to

[27] Carhart's main point is that the Momentum factor exists but managers don't add value to the security selection.
[28] It can only require margins for the short positions.

outperform the market since they are relatively underpriced and investors expect them to converge to their estimated value, while the latter trade at high multiples for their future potential.

The Value effect has been documented by Basu (1982), who examines stocks belonging to the NYSE and determines that "the Value effect is clearly significant even if experimental control is exercised over differences in firm size." His analysis only relies on the empirical relationship between returns and earnings yield, measured by the ratio of earnings over price (E/P)[29]. However, he states that the effects of Size and Value factors are much more complicated and interconnected that what former studies indicated[30].

The Value factor has been extensively documented since Basu's paper. Furthermore, it is also included in Fama and French's Three Factor Model (1992). However, its persistence is a matter of debate among academics, since during certain periods Growth stocks performed much better than Value stocks. In particular during the 90's, while the Internet bubble was growing the Value effect was not in place anymore, returning after the bursting of the bubble in 2000's (Al Root, 2020).

Further MSCI research (2016) address the main weaknesses in the proper identification of the factor, for example excluding temporary increases or drops in earnings by taking into consideration Forward Adjusted Earnings instead of Current Earnings.

An additional improvement included by MSCI in its Value Index is the substitution of the traditional market capitalization as price indicator with the enterprise value, which calculates also the debt held by a company. Doing so, highly leveraged firms are ruled out of the selection and the estimates are less biased. These are the so called "value traps," which are "stocks that appear cheap but in fact do not appreciate." (MSCI, 2016)

The factor is extremely cyclical and performs well in periods of economic expansion, while generally has a poor performance during bad times.

2.5 High Quality Factor Premium: Good Vs Bad Fundamentals

The High Quality Factor identifies stocks characterized by above-the-average standards in terms of fundamental variables. The most common indicators are Return on Equity (ROE), earnings stability over

[29] The reciprocal of the most common P/E. It leads to inverse ranking.
[30] The factors have interactions and traits in common when they are implemented, complicating the work of researchers who try to isolate them.

the years and low financial leverage. A stock is assigned the title of “High Quality stock” if the score calculated on the selected indicators is in a predetermined quantile of the distribution[31].

R. Sloan (1996) was the first to investigate the relationship between future stock prices and current earnings, identifying that “stock prices fail to reflect fully information contained in the accrual and cash flow components of current earnings until that information impacts future earnings.” He also identifies key components in the communication of current earnings to detect the potential for a future price increase. Additionally, there are also other pieces of information that are relevant for the investors, since they must have clean, reliable and verifiable data from the financial statements of the companies.

For these reasons, MSCI (2016) in the construction of the Quality Index takes into consideration financial leverage, discarding firms with high level of indebtedness, and stability of the earnings across time, excluding firms with inconstant results. The Index achieves diversification by imposing restrictions on the weight allocation and is rebalanced twice a year.

This factor has performed slightly better than its benchmark, without being more cyclical than the average stock in the market. Many researchers confirm the aforementioned result (MSCI, 2016). In particular, R. Novy-Marx (2012) illustrates that an investor can obtain the same exposure by adding high quality assets to her portfolio without overpaying them or following a value strategy in which she buys average quality assets at cheap prices. In his analysis he finds that, with the proper regression controls in place, “gross profitability has the same power as value strategies.” Gross profitability is another variable used by researchers to address the same quality characteristic that current earnings identify, showing an overlap between the two factors.

Novy Marx (2012) states that following a quality strategy based on gross profitability or a value strategy tailored on book-to-market ratios has a comparable accuracy in the forecast of the cross-section of average returns, which means that, in the end, they identify similar stocks. Moreover, he states that “Quality investing exploits another dimension of Value,” with the difference that “Value strategies buy assets at bargain prices; quality strategies do this by buying uncommonly productive assets.” Mixing the two dimensions fruitfully can help investors to discern between bargain stocks and value traps. In conclusion, he highlights that adding the Quality factor to the portfolio substantially increases the performance of Momentum-based strategy too. His research suggests that a balanced mix of factors, tailored on each market phase, can enhance the performance of investors who rely on factor investing.

[31] Some indexes use 10% of the investable stocks, others are capped in the total number of securities.

Summing up, the High Quality factor is highly interconnected with factors traditionally linked to companies whose profitability has been stable and significant over time (Alford, 2016).

2.6 Low Volatility Factor Premium: Low Vs High Volatility

The Low Volatility factor identifies stocks whose prices are more stable than average and less subject to extreme swings. The premium awarded to these stocks has been documented for the first time in 1972, when Haugen and Heins (1972) documented a surprisingly negative relation between return and volatility, both among stocks and bonds in the respective U.S. markets. Similar results have been found also by other researchers, such as Jagannathan and Ma (2003) who show how the minimum variance portfolio has both higher returns and lower risk than a cap-weighted benchmark in the U.S. Stock Market.

The impact of this research has been huge, with investors transferring assets from inefficient capitalization-weighted portfolios, overloaded with expensive growth stocks, into more efficient investments (Baker and Haugen, 2012). The last two researchers mention in their paper that "the fact that low risk stocks have higher expected returns is a remarkable anomaly in the field of finance," since it is persistent and comprehensive, being common to all equity markets in the world (Baker and Haugen, 2012). Furthermore, it also "contradicts the very core of finance: that risk bearing can be expected to produce a reward" (Baker and Haugen, 2012), as instead stated in the introduction to the Capital Asset Pricing Model (Sharpe, 1964) and commonly recognized in academia. In their study, the two authors select a large sample of stocks from developed and non-developed countries across the world, reaching similar results in each one of them. They conclude that "the basic pillar of finance, that greater risk can be expected to produce a greater reward, has fallen" and that "the reward for bearing risk can be negative." (Baker and Haugen, 2012) As this dramatic result contradicts the principles of theory of finance at their basis, some critics predicted that the low-volatility anomaly would be arbitraged away (Arnott, 2016). However, both MSCI and S&P have now published indexes based on the concept of Low Volatility to capture this risk premium.

Several academics and practitioners have tried to find an explanation for the Low Volatility anomaly, showing how stocks characterized by this factor have a smaller demand that High Volatility stocks. The theories range from behavioral finance, with overconfident investors who overpay for famous and overhyped stocks (Blitz, 2019), to agency issues that create diverging interest between investors and their clients (Karcescki, 2002) and constraints on leverage and shorting (Frazzini, 2014). Another explanation lies in the typical fund manager's mandate to beat the benchmark which disincentivizes arbitrage operations (Baker, 2011). However, the most common justification is the "lottery effect," which indicates how investors prefer stocks with large potential upside even if the chances of winning are small, with respect to more stable stocks[32]. Vogel (2016) finds that, after controlling for the lottery effect, the Beta anomaly is not observed anymore and the results indicate the traditional, positive relationship between beta coefficients and expected returns, in accordance with the traditional Capital Asset Pricing Model.

An additional remark on the calculation of volatility across the different studies is that, even if the metrics used change[33], the results are consistent. In conclusion, the empirical evidence of this anomaly "is still a puzzle, since is it clearly at odds with one of the most basic principles of finance, that higher volatility is associated with higher returns." (Blitz, 2007)

Coming to the practitioners' world, the Index created by MSCI aims at capturing the Low Volatility premium by weighting stocks already included in a parent Index (MSCI World) and optimizing the mix based on a set of constraints to make the Index investable and replicable to investors. The weighting criteria is the inverse of historical variance, so that Low Volatility stocks have more importance than the others in the portfolio. Another methodology always brought to market by MSCI is the minimum variance optimization based on the calculation of the lowest forecast volatility.

In terms of performance and cyclicality, the Low Volatility factor has proved to be a great hedge during periods of economic downturn, especially because of the stability of the price of the selected stocks, which are less hit than others by market crashes. In particular, Low Volatility stocks outperformed the market after the crash of the Dot Com bubble in the early 2000's and in 2008, when the financial crisis unfolded, which is also why Low Volatility strategies are defined as "Conservative" and "Defensive" strategies.

2.7 Dividend Yield Factor Premium: High Vs Low Dividends

The Dividend Yield factor selects stocks with larger than average dividends. The discovery of a positive relationship between the expected Dividend Yield and the relative risk-adjusted return originally dates back to research conducted by Blume (1980). Fama and French (1988) reached the same results, especially considering a longer time span in the calculation of the performance, in the 2-4 year range.

A relevant consideration in the Dividend Yield analysis is related to the influence of taxation of dividends: in order to properly account for the differences among countries in capital gain and dividends taxation, it is necessary to compute pre-tax dividends and make comparisons only within the same

[32] Stable stocks have more wins but with smaller swings.
[33] For example historical and implied volatility, beta and/or idiosyncratic risk.

country. Furthermore, the Dividend Yield is "an unreliable indicator since it is smoothed and manipulated by the company," (Ang and Bekaert, 2007) which can slash or increase it depending on many internal company considerations. The authors state that this variable is inconsistent because it is not objective and its use in statistical regression produces inferences that are not significant or robust, contrary to what other researchers, such as Fama and French (1988) have found.

The same result, even if in a different context and before the Dividend Yield was considered a potential factor, was achieved by Black and Scholes (1974). After adjusting stock returns for volatility, the authors didn't find any statistically significant relationship between dividend yields and stock returns.

In terms of cyclicality, the Dividend Yield factor basically follows the trend of the market, since the amount of dividends that a company is expected to distribute to the shareholders is closely related to the expected future performance of the firm in the economy[34].

Some improvements in capturing the risk premium of this factor have been made by MSCI (2016), which includes different metrics in the construction of its High Yield Index, starting with a "screening process of securities with a track record of consistent dividend payments and with the capacity to sustain dividend payouts into the future." Moreover, MSCI blends this factor with characteristics that fall under the High Quality factor, such as ROE and leverage, and under the Momentum factor (12-month price performance), to ensure that the selected companies will not experience deterioration in their fundamentals, leading to cuts or reductions in the dividends.

2.8 Other Factor Theories

Since the inception of factor investing, the amount of theories and factors that have been investigated has been very large. The increase in computational power and the ability to run back testing, cross analysis and time series regression in a large scale has also helped the development of new strategies based on the concept that "assets are bundles of risk factors" and the relative premiums are the compensation for bearing those risks (Ang, 2014). Researchers have isolated 59 new factors just during 2010-2012 and the total amount has even crossed 300 (Harvey, 2015). Some authors raise the critique that not all these factors are relevant and most of them target the same characteristics (Berkin, 2016). Examples of newly discovered factors are the following: leverage, asset growth, R&D costs and liquidity.

[34] There are many reasons that can lead a company to increase or decrease its dividends, sometimes also partly unrelated to its performance.

Another approach, called "Fundamental Indexation" and described by Arnott (2005) applies concepts from fundamental analysis to determine ranking among securities, which are then weighted in the constructed portfolio depending on their fundamental factors. The results outperform the traditional cap-weighted portfolios, which are dominated by a small number of large stocks and can't capture other risk premiums (Invesco Research, 2017).

Other studies apply factor investing principles to other investable assets such as corporate and government bonds: Fama and French (1992) start from the idea of integration among different financial markets to explain how common factors between stocks and bonds can explain their returns. They identify Maturity and Default Risk as the two key determinants for the fixed income market, showing that bearing these risks generate superior returns for the investors. In the following years other bond factors have been isolated, such as Liquidity and the Steepness of the Yield Curve.

More recently, a new investment approach, called "Alternative Risk Premia," identifies and includes in the active portfolio stocks that have significant exposure to specific factors, accessing "uncorrelated, complimentary sources of return." (Reid, 2019) The novelty of this approach is that the focus is not only on common stocks, but across the entire spectrum of investable assets, including bonds, other funds, commodities, currencies and derivatives on interest rates[35]. To generate the appropriate exposure, this strategy needs to implement a long/short portfolio, which makes it available almost only to hedge funds, not subject to the traditional constraints of mutual funds.

2.9 Conclusions

The rise of factors and factor investing has led researchers to investigate and determine what the sources of risk premiums are and if they are persistent over time and consistent with the economic and financial theories. We have shown how the debate is still open for most of the factors, with academics split between different views on the importance and effectiveness in the explanation of the stock returns.

In the next chapter we turn to the implementation of the six factors in our analysis, describing the identification process and comparing the performance of our indexes among themselves and with respect to the common benchmark of S&P 500.

[35] This approach covers the entire portfolio construction and management process for active managers.

Chapter 3 - Factor Indexes and Relative Performance

3.1 Introduction to Chapter 3

In this chapter we analyze and discuss the main setting and structure of our analysis of mutual funds managers performance. In our analysis we take into consideration six different factors and build six indexes based on each of them, to capture the expected premium connected with these factors with respect to the return of the stocks of S&P 500 Index. After selecting the stocks and constructing the indexes with the proper weighting criteria, we employ the constructed indexes as the six variables to perform a multiple linear regression on the performance of the mutual funds selected for our study.

The mutual funds that we analyze are chosen based on specific criteria that are developed in chapter 4. Our analysis is commonly referred to as "Style Analysis" and allows us to determine which are the factors that can best explain the excess returns of the selected mutual funds. Starting from the results of our multiple regression, we will then assess whether or not the mutual funds managers really deserve their annual fees.

The chapter describes the construction of the six indexes and compares the returns among them and with respect to the reference index, the S&P 500.

3.2 The Six Factors Indexes and the Selection Criteria

As previously mentioned in chapter 2, over 300 relevant factors have been identified by the researchers. However, we are going to perform our analysis just by selecting the six factors that have been considered most relevant in the majority of papers on factor investing and whose historical premium have strong foundations. The aforementioned factors are the following: size, value, momentum, high quality, low volatility and dividend yield.

In our analysis, we obtained and gathered data from Bloomberg, ranking S&P 500 stocks depending on their specific characteristics and then built the relative indexes, which will then represent the variables of our constrained multiple regression over the excess return achieved by the mutual funds under examination. The stocks taken under consideration were only the stocks included in the S&P 500 Index in the period between March 31st 1999 and December 31st 2019. All values are adjusted for dividends and stock splits, so that the adjusted close price at the end of the day represent the actual price of the stock without being influenced by any of these operations.

We perform a full revaluation of our indexes every three months[36], in order to have a rebalancing frequency that can approximate that of mutual funds. Rebalancing the portfolio leads to some costs, such as transaction and computational costs. Every time the portfolio is rebalanced, the data is gathered for all securities available on the revaluation date and an updated ranking is produced. Based on that, the indexes are reweighted and an ideal portfolio manager mirroring the index would have to perform the necessary transactions in the market, adding new stocks, unwinding positions or changing her exposure. This is not computationally cumbersome or particularly time-consuming, since all the calculations are pretty simple, but the managers incur in transaction costs that can't be ignored.

The reasons to choose only S&P 500 stocks are manifold: the abundance of immediately accessible data via Bloomberg, the dimensions of the firms[37], the accuracy of their reports, the large number of funds whose strategy is exclusively based on S&P 500 and the very high liquidity in the market. Furthermore, many researchers have already applied factor investing theory to this market, finding the interesting results discussed in chapter 2.

We now turn to the introduction of the factor indexes and the relative criteria implemented to rank the stocks.

3.2.1 Size Index

The size factor is the most common factor, brought to the attention of investors since the early stages of factor investing in 1992 by Eugene Fama and Kenneth French in their Three Factor Model. The factor captures the premium linked to smaller firms, by market capitalization, with respect to the other companies included in the reference set. Market capitalization can be defined both as full or as free float; the latter is the one we have selected from Bloomberg to rank our firms.

An important drawback of this way of constructing indexes is the number of firms that are excluded from S&P 500 Index during each 3 months period and, subsequently, fall out of our universe portfolio too. If they are not included in our indexes, no problem arises, otherwise we face the risk of survivor bias. This bias, particularly exacerbated among the smallest firms of S&P 500, is fully addressed in section 5.5.

In line with the findings of the researchers E. Fama and K. French, who highlighted this factor as one the most relevant in determining the premium gained by stock market investors, the 20-year historical

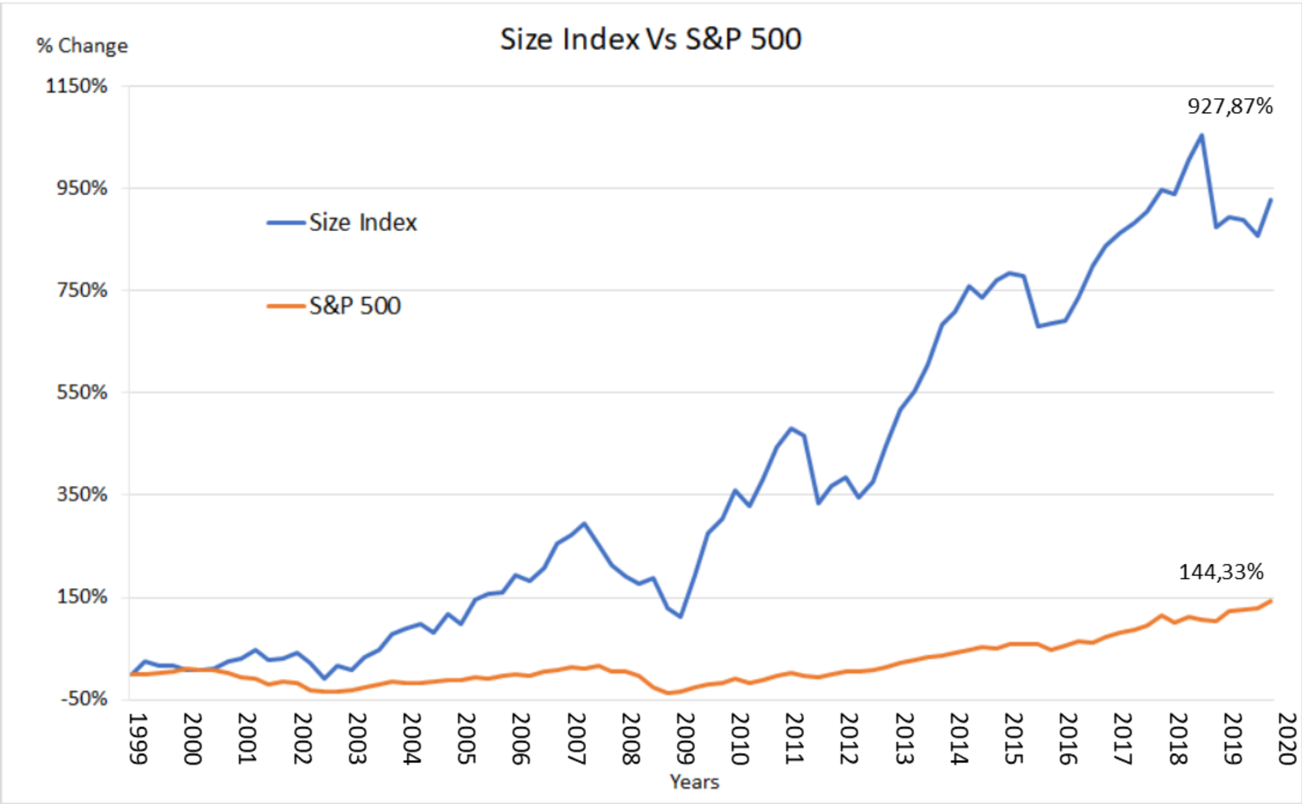
[36] We rebalance the indexes on the last available trading day of March, June, September and December.

[37] If firms have a too small market capitalization, the price can be altered by mutual funds increasing or decreasing their positions. S&P 500 stocks do not present this issue.

performance of the Size Index resulted in a very large 927.87%, more than six fold the return of the S&P 500 Index in the same period. In the following graph we confront the returns of the two indexes over time, where the difference in the cumulative performance is extremely clear.

Graph 3. 1

Size Index Vs S&P 500 Returns



Comparison of the cumulative percentage returns of Size Index and S&P 500 from 03-31-1999 to 12-31-2019

3.2.2 Value Index

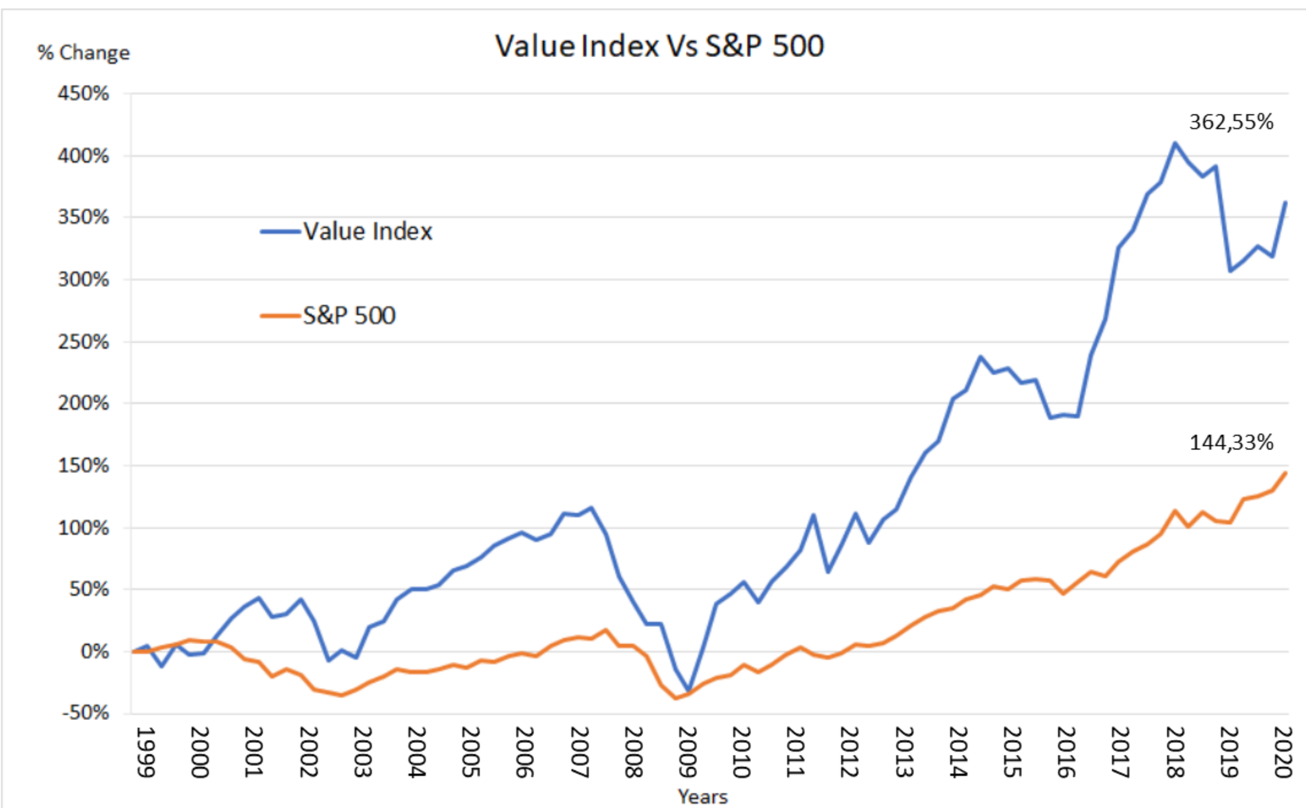
The value factor is commonly considered to be responsible for the premium that the so-called "value stocks" have typically returned over "growth stocks." This factor, however, has not been as constant over the years as the small-versus-large premium captured by the size factor. For example, growth stocks overperformed value stocks in the years of the Dot Com bubble before 2001, while afterwards the trend reversed in favor of value stocks. A stock is classified as "value" when its current price is lower with respect to its fundamentals, while if the stock is expected to return an above-the-average performance over time because of its future potential, it falls under the category of growth stocks.

There are several indicators traditionally used by investors to address this factor: among them, we select the price to book ratio (P/B ratio) and price over earnings (P/E ratio) to build our Index[38]. Both P/B and P/E are calculated over the previous 12 months at each rebalancing date. The stocks are then ranked twice, first based on their P/E, from lowest to highest, and then on their P/B, always from lowest to highest. The rationale behind this solution is strictly connected to the definition of "Value stocks," which are expected to be strongly undervalued. After that, we sum the two separated ranking to assess the final ranking among the stocks of S&P 500.

Also this Index has provided a consistent and absolutely relevant return in excess of S&P 500 in the 20 years of our analysis, in accordance with the prevailing literature that identifies in the contraposition of "Value versus Growth" another source of historical premiums in the stock market. The returns are compared in graph 3.2.

Graph 3. 2

Value Index Vs S&P 500 Returns



Comparison of the cumulative percentage returns of Value Index and S&P 500 from 03-31-1999 to 12-31-2019

[38] There are many other possible combinations of Value indicators, such as forward P/E and CAPE (Cyclically Adjusted P/E), which, however, are less common in the financial literature.

3.2.3 Momentum Index

The Momentum Index selects the stocks whose performances have been particularly strong during a specified period of time, relative to the other securities in our set. Given the outlook of the mutual fund managers we are analyzing[39] and the relative stability of their portfolio composition, with not too many adjustments per each period, we have decided to set our reference time for the Momentum Index to one year. Subsequently, at each rebalancing date we calculate the best performing stocks of the last 12 months and accordingly update the stocks listed in the Index.

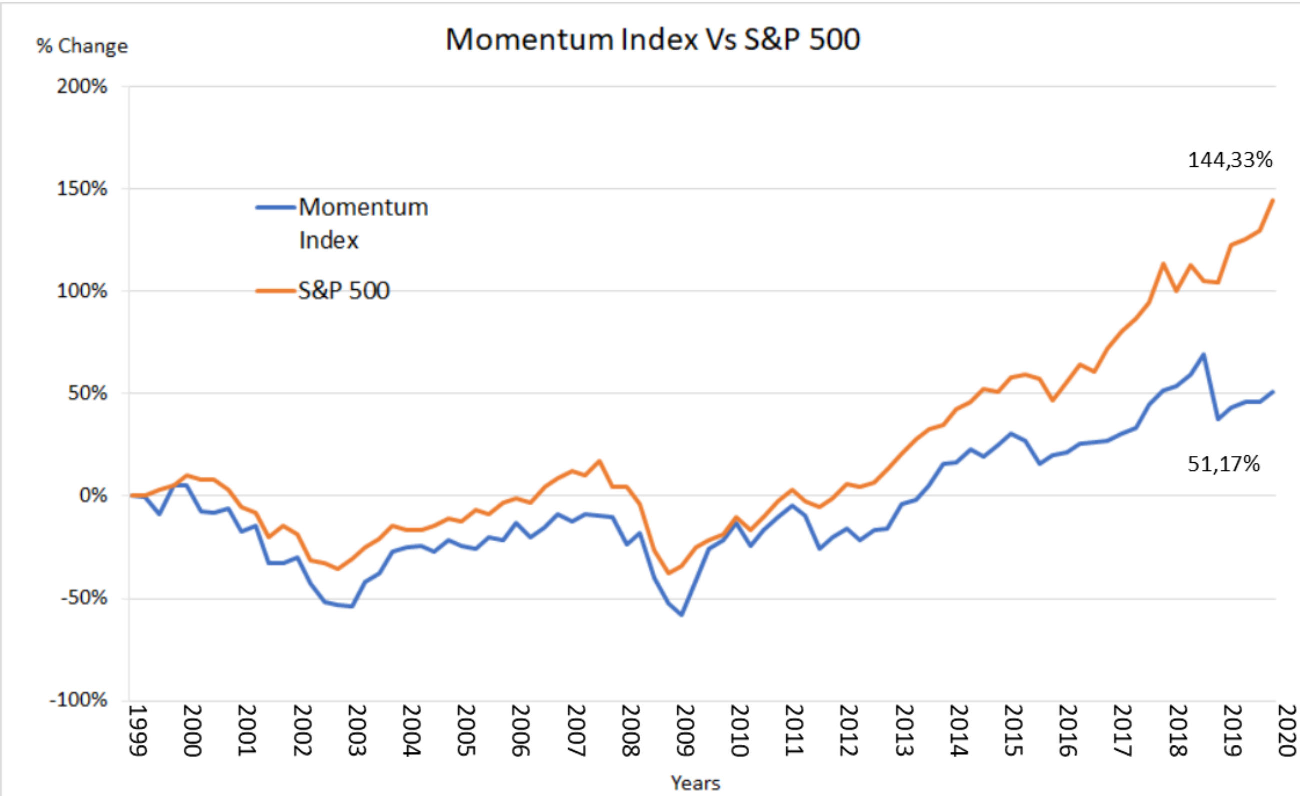
The expectation, as reported by Ang (2018), is that the Momentum Index would substantially outperform the main S&P 500 Index in periods of economic expansions and underperform in recessions, given its exposure to cyclicality. Nevertheless, our sample years didn't report the same strong positive performance, as can be easily spotted in graph 3.3. A possible explanation points to the selected time span, which particularly affects Momentum Indexes, as the main cause of the underperformance. As a matter of fact, our Index suffered especially during the financial crisis of 2007-2009, showing that this kind of selection strategy is not appropriate during periods of extraordinary financial turmoil. It is commonly recognized that the most defensive factor against periods of economic downturn is instead the Low Volatility factor.

An additional aspect that has to be taken into consideration is the length of the reference period implementing the Momentum Index, because one year might be too long and not sensitive enough to short-term runs in the market price. Furthermore, momentum strategies are usually constructed with a long-short portfolio, buying winners and selling losers. If, like in our Index, only long positions are allowed[40], the performance can be below expectations. Additionally, as reported by Harvey (2015), this factor is particularly exposed to entry point risk, which can determine a prolonged underperformance of the Index in the case its inception coincides with a sharp decline of the market.

[39] The managers under examination are long-term investors, focused on a buy-and-hold strategy and minimizing trades.
[40] The long-only constraint is consistent with the managers' mandate.

Graph 3. 3

Momentum Index Vs S&P 500 Returns



Comparison of the cumulative percentage returns of Momentum Index and S&P 500 from 03-31-1999 to 12-31-2019

3.2.4 High Quality Index

This factor is meant to capture the excess return on stocks characterized by specific quality metrics above the average of their peers. Most of the metrics are recollected from fundamental analysis, such as ROE, stability in earnings and growth, strength of the balance sheet[41] and low debt. Most investors focus on these indicators to select securities to add to their portfolio in a bottom-up approach, together with a more technical screening based on volatility, correlation and diversification among stocks.

We decided to focus on two of the most relevant and, at the same time, common key metrics: ROE, based on the last 12 months, and financial leverage ratio, calculated as total amount of debt outstanding over shareholders' equity. We then proceeded in ranking the stocks with the same mechanism in the construction of the Value Index. Other researchers have included different metrics in the calculation[42],

[41] Measured by positive cash flow, balanced capital structure and income generating assets.

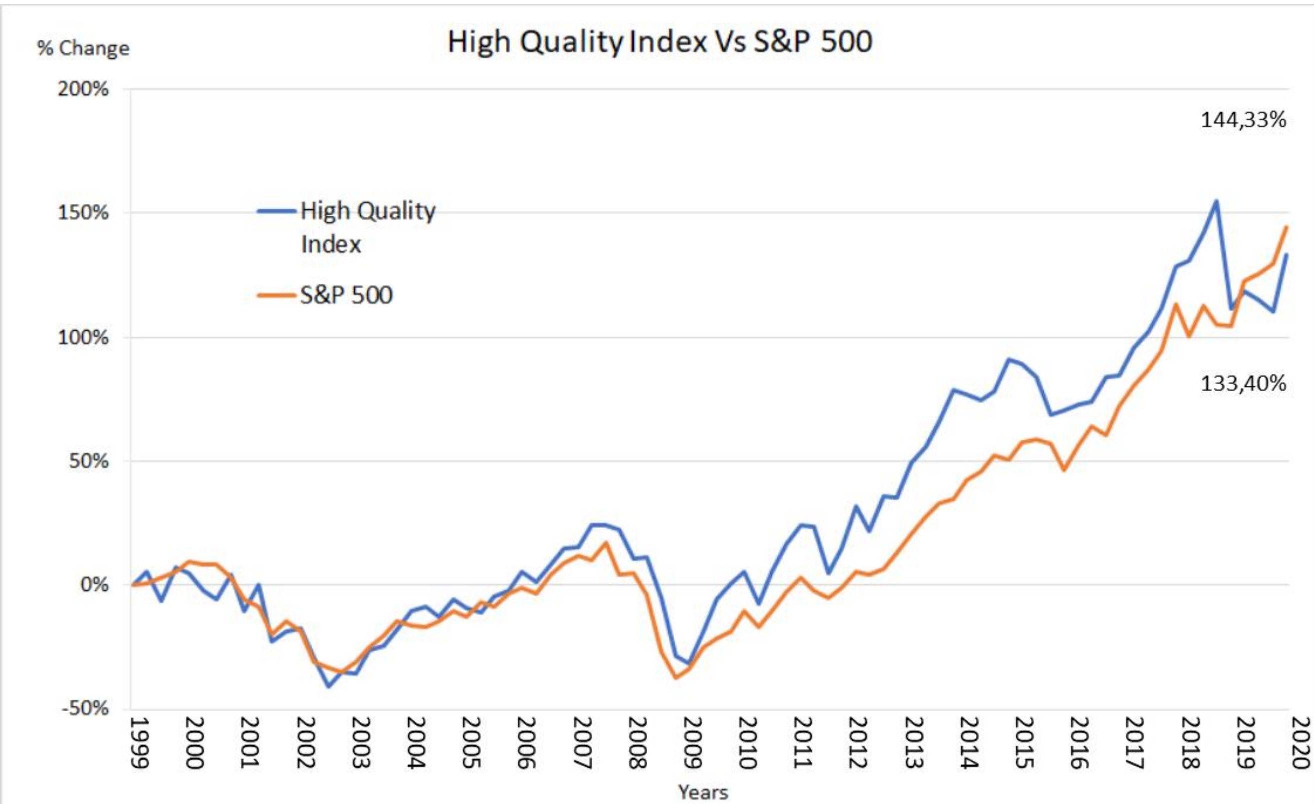
[42] Sloan (1996) used low accruals as proxy for earnings quality, Asness (2013) added profitability, growth and payout ratio.

always looking for an indicator reliable enough in the identification of stocks representing this systematic premium in the market.

The performance of this Index didn't exceed the return of the S&P 500, as it is shown in graph 3.4, proving not to be reliable enough in periods of crisis such as the 2001 Dot Com crisis or the 2008 Financial Crisis, where its value decreased by 38.39%. The final performance over the 20-year span is slightly below the S&P 500 (+133.40%).

Graph 3. 4

High Quality Index Vs S&P 500 Returns



Comparison of the cumulative percentage returns of High Quality Index and S&P 500 from 03-31-1999 to 12-31-2019

3.2.5 Low Volatility Index

Another well-known source of systematic excess return is the factor that identifies stocks with lower than average volatility, beta or idiosyncratic risk. We measure "Low Volatility" by the standard deviation of the returns throughout the last 12 months at each rebalancing date.

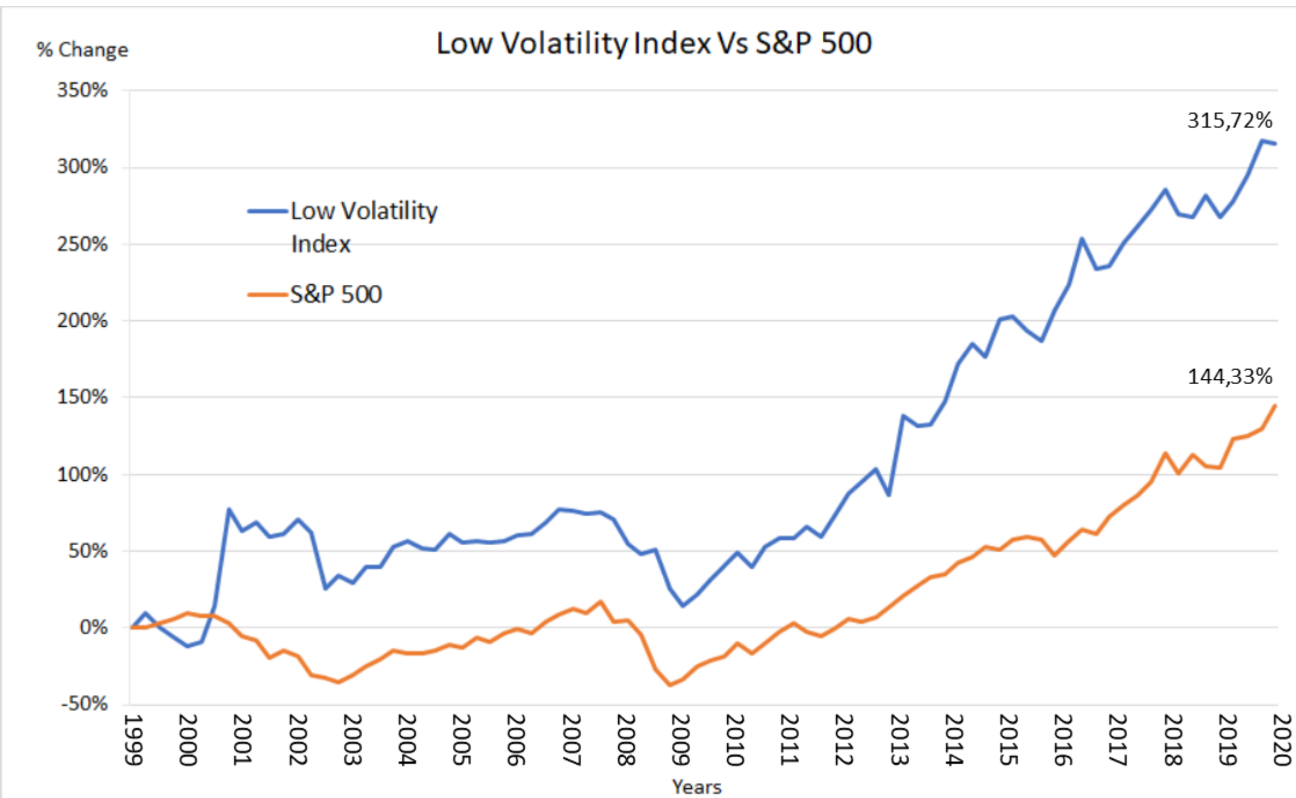
The Low Volatility Index is expected to perform well above the market during recessions and periods of uncertainty in the economy, where more volatile stocks underperform the market. It selects securities linked to non-cyclical, demand driven sectors such as Food, Beverage and other Consumer Staples.

Our Index responded well during the 2008 crisis too, recording a cumulative loss of -24.3% in the two worst quarters of 2008, when S&P 500 was hit by a total loss of -35.7%. On the other side, the Index is not expected to fully participate in the periods of recovery and market booms. Another drawback of the Index is that "low volatility can end abruptly and a volatility crash can ensue" (Williams, 2017), with the Index having sudden, unexpected jumps in its volatility.

The cumulative return over the 20 years span is substantial and well above the S&P 500 (graph 3.5).

Graph 3. 5

Low Volatility Index Vs S&P 500 Returns



Comparison of the cumulative percentage returns of Low Volatility Index and S&P 500 from 03-31-1999 to 12-31-2019

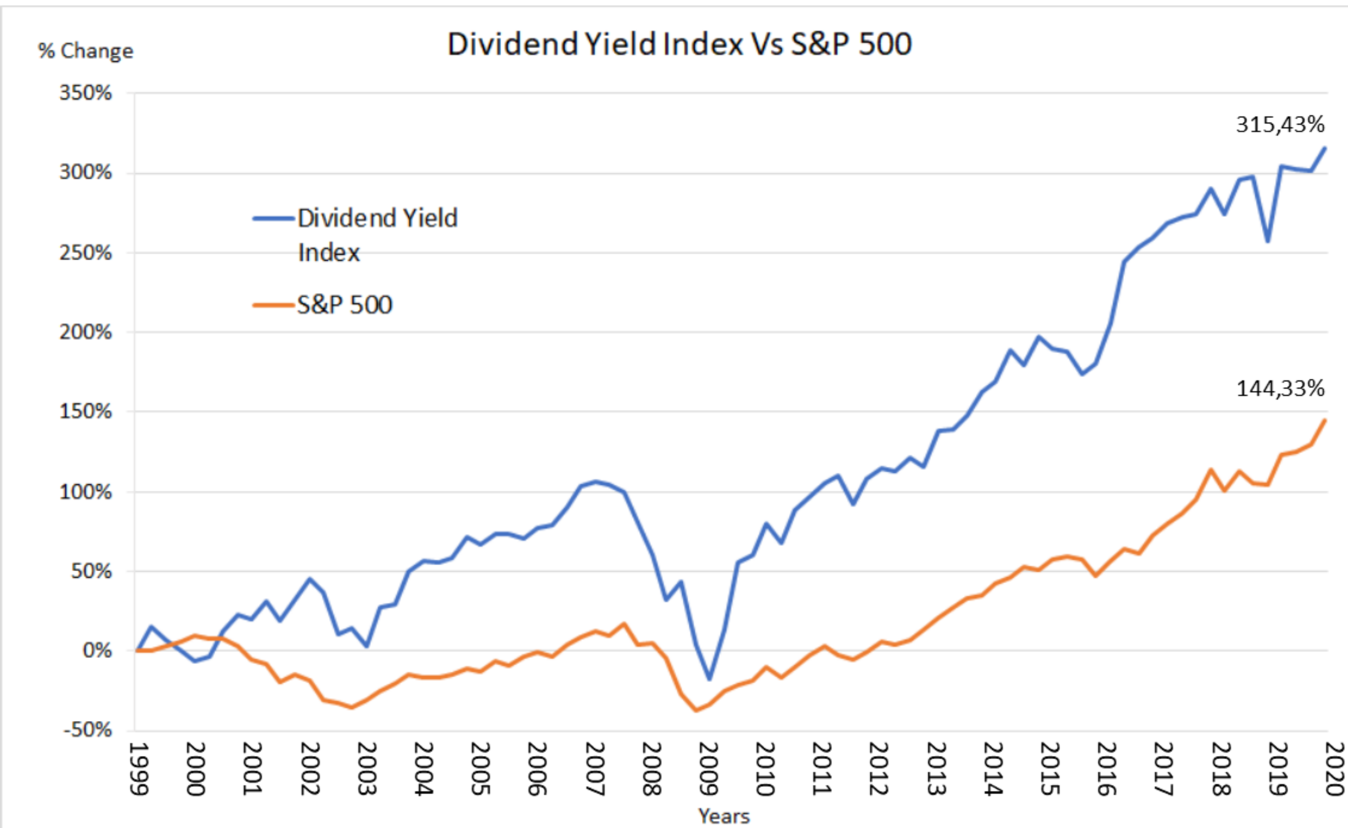
3.2.6 Dividend Yield Index

The last of our indexes is based on stocks whose dividend yield above the average should capture an excess return over the other securities. As a remark, all our calculations are based on the closing price of the stocks at each rebalancing date, adjusted for dividends and stock splits. By doing this, the results will not be affected by actions that do not impact the total value of the stocks but just their nominal price. The dividend yield is adjusted and calculated for the last 12 months before each rebalancing date.

The selected securities returned a performance well above the S&P 500, as depicted in graph 3.6.

Graph 3. 6

Dividend Yield Index Vs S&P 500 Returns



Comparison of the cumulative percentage returns of Dividend Yield Index and S&P 500 from 03-31-1999 to 12-31-2019

3.3 Weighting Criteria

There are multiple weighting criteria both in literature and in the factor indexes available to investors across the world. For example, Fama and French (1992) constructed both value-weighted and equally weighted portfolios. Other investors follow more complicated procedure, such as mean-variance optimization and risk models.

In our case, we decided to apply the following criteria to all indexes: the 25 stocks with the highest exposure to a specific factor are assigned a 2% weight for that specific index, the following 25 most exposed stocks have a 1% weight and the stocks ranked 51-100 are given a 0.5% weight. The remaining 400 stocks[43] are excluded from the index, since their exposure to the factor is not significative. The weights are revaluated again at every rebalancing date, which are March 31st, June 30th, September 30th and December 31st. When the market is closed on the selected rebalancing date, we select the last available trading day to perform the recalibration at the closing prices adjusted for dividends and stock splits. The rebalancing works in this way: we take the entire S&P 500 stocks and rank them again based on the exposure to one specific factor, performing the consequent adjustment to the index depending on the new ranking. The operation is repeated for each of the six indexes and the respective factors, each time classifying the stocks depending on their exposure.

The weighting criteria we choose fits our goal of constructing balanced indexes that are not influenced by the performance of a few overweighted stocks. Furthermore, given the objective of explaining the performance of mutual fund managers, our indexes not only need to capture the factors responsible for expected premiums, but they must also be broad enough to partly mirror the performance of S&P 500, the common benchmark among all the funds we analyze. In addition, we must not include too many stocks, in order to follow a strategy that maintains the rebalancing costs relatively low at every recalibration date, given the necessary adjustments and transactions. This weighting strategy is then a compromise between holding just a few very large investments or too many small positions.

Furthermore, since the stocks we are considering have a large market capitalization overall, there is no risk of directly influencing the share price by the managers buying or selling stakes worth of millions of dollars[44].

Another concern regarding the weighting criteria is linked to the survivor bias and the periodic recalibration of the indexes. Since our index is retroactively built, we excluded the stocks whose tickers disappeared from one rebalancing date to another, with no regards for the motivation (mergers, bankruptcy, cancellation from S&P 500 due to inadequate compliance to minimum requirements such as minimum capitalization or not enough floating shares available to investors). A more detailed digression

[43] The exact number ranges between 399 and 405, depending on how many stocks are included in S&P 500 in each period.
[44] On December 31st 2019, the average market capitalization was $ 53.85 billion, with the smallest firm (Nektar Therapeutics) having a free float of $ 3.19 billion.

on the effects of the survivor bias and its relationship with S&P 500 and mutual funds is addressed in section 5.5.

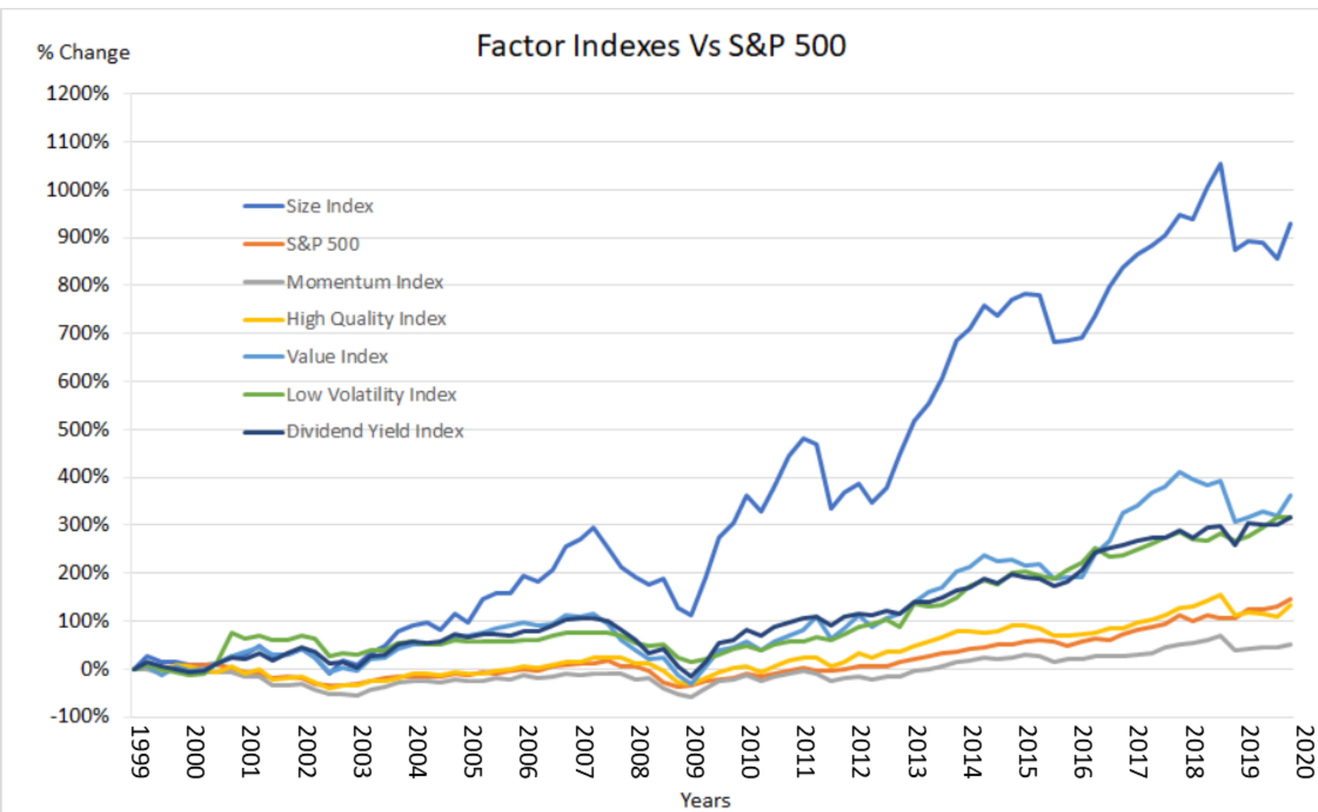
We avoided potential distortions of our indexes by assigning a zero weight to the securities involved in extraordinary operations or excluded from the indexes, so that the focus is only on capturing the six factors and their relative unbiased performance.

3.4 Indexes Comparison

Before turning to the multiple linear variable regression of the excess returns of mutual funds, we make a short digression comparing the returns of the six factor indexes and S&P 500 over the selected 20-year time span. Graph 3.7 provides a visual representation of their returns, while Table 3.1 reports the average return[45], volatility and Sharpe Ratio of each of them. The Sharpe Ratio is calculated using the risk-free rate, whose proxy is the 3-month average return on U.S. Treasury bills.

Graph 3. 7

Factor Indexes Vs S&P 500 Returns



Comparison of the cumulative percentage returns of factor indexes and S&P 500 from 03-31-1999 to 12-31-2019

[45] The average return is calculated with the arithmetic mean over 3 months, in accordance with the Sharpe Ratio.

Table 3. 1

Return, volatility and Sharpe Index of Factor Indexes and S&P 500 Index (Annualized)

	Dividend Yield	Low Volatility	Value	High Quality	Momentum	Size	S&P 500	Risk-free Rate
Arithmetic Return (R)	8.86%	8.42%	10.34%	5.73%	4.16%	13.90%	5.17%	1.70%
Volatility (St. Dev.)	19.96%	18.34%	24.32%	17.68%	20.83%	22.70%	12.71%	
Sharpe Ratio $(R\text{-}R_f)$/St. Dev	0.358	0.366	0.355	0.228	0.118	0.537	0.273	

The Sharpe Ratio measures the performance of the indexes with respect to the risk-free asset, after adjusting for their total risk. It can also be used as a ranking tool, providing insights on the best and worst performing indexes. In particular after adjusting for the risk, four factors out of six record a better Sharpe Ratio than the benchmark, with a substantial underperformance of Momentum and High Quality. Moreover, the Momentum factor has a lower average absolute return than the S&P 500, mainly due to the extremely negative performance during the Financial Crisis. The High Quality factor, instead, has a larger average return but at the same time is also more volatile and the Sharpe Ratio is reduced accordingly.

On the other hand, the Size factor provides a superior return with the highest Sharpe Ratio, in spite of being the second most volatile index. Given the larger diversification of the benchmark, it is not surprising that our indexes are overall more volatile, even the Low Volatility Index, which is supposed to select the less volatile stocks. However, as previously mentioned, this Index works very well during recessions but is also subject to sudden changes in its volatility.

After adjusting for the total risk, both the Value, Low Volatility and Dividend Yield Indexes report similar Sharpe Ratios, well above the reference index. This suggests that the historical premium is actually captured by our selection, as it is also done by the Size Index. Coming to the remaining two indexes with a performance in line or below with S&P 500, different indicators might have worked better. However, the debate for the persistence of historical premiums over time, independently from the time period under examination, is still open.

After these remarks on the performance of our indexes, we proceed with the introduction of the selected mutual funds and the relative multiple variable regression to determine the component of skill of the mutual fund managers and if the fees they charge are appropriate or not.

Chapter 4 - RBSA and Interpretation of the Results

4.1 Introduction

In this chapter we develop the analysis of mutual funds performances with respect to the six passive indexes by applying a multiple linear variable regression on their excess returns. The regression is also called Returns-Based Style Regression (RBSA) since it aims at determining the best composition of the portfolio made of the passive indexes that can best explain the performance of the mutual funds. Our main goal is to measure the statistical significance and the average value of the excess returns net of fees achieved by the managers, called Alpha. If this value is different from zero, the managers have skills, otherwise they do not add measurable value to the performance.

We only select top mutual funds meeting specific requirements and whose cumulative performance has been consistently above the S&P 500 Index. All these funds belong to the high tail of the distribution of mutual funds returns, indicating that they are all run by the most successful managers. We also add some constraints to fully isolate and identify the drivers of the excess returns measured across the years, without being influenced by leveraging, derivatives, or by other financial instruments different from stocks and cash. The first goal of the Style Analysis regression is to determine which factors are the most relevant to explain the performance of the selected managers.

The regression uses our six indexes to capture the effect of factor exposure on the returns achieved by the managers. The results determine that, overall, the performance of the selected mutual funds is best described by the following factors, in order of importance: High Quality, Dividend Yield and Low Volatility. The remaining Momentum, Size, and Value factors are not included in the results as they do not explain the mutual funds returns as well as the other passive indexes. The average explained variance of the regressions performed, also known as R^2, is 34.96%, showing that our indexes can only explain part of the excess returns achieved by the managers. This is consistent with the prevailing literature which affirms that if the analyzed managers are top performers, the analysis identifies some relevant component of skills in the explanation of their returns. (Fama and French, 2010)

We further investigate and exclude the potential explanations of the moderate R^2 of the regressions, such as luck and bad choices in the variables, concluding that at least most of the returns can’t be explained without assuming a certain degree of skills. Furthermore, we run a simple analysis to determine the Total Alpha Return of each fund: the relative T-statistics identifies 18 significant Alphas out of the 30 returns. Market timing and security selection are the two variables that explain the superior performance of these

18 managers. The analysis is concluded with the recognition of the management fees in the annualized Alphas, determining that these 18 managers granted a large adjusted Alpha of 3.98% to their investors and indeed deserved their fees. On the other hand, the average Alpha for the entire group of 30 managers is 3.25% but, given the lower significance of the returns of the remaining 12 managers, only the previously mentioned 18 managers deserve to be compensated for their skills.

The chapter makes also some final remarks on the analysis of the managers' performance, showing that the excess returns are not attributable to luck in the stock selection, but to managers' skills. Eventually, we relax the initial constraints and compare our results with some of the most important research on this topic.

4.2 Constraints in the Selection of Funds

In order to focus exclusively on the factors determining the performance of fund managers, we need to impose some restrictions on the selection of the funds that we add to our pool of analysis. First of all, we choose only mutual funds, not hedge funds. The main reason is the lack of available information regarding hedge funds, whose performances are very often disclosed only to the investors and, most importantly, are not as transparent as mutual funds in reporting their holdings, strategies and activities. Furthermore, their Net Asset Value (NAV) is not publicly reported and their valuation can be extremely difficult to assess, as some well-known failures demonstrate[46]. On the other hand, open-ended mutual funds are subject to the Investment Company Act of 1940, they are available to all investors and their holdings are disclosed to the public on a periodic basis. Subsequently, information regarding mutual funds is reliable and we gather the necessary information at each rebalancing date from Bloomberg database.

Nowadays managers have plenty of financial instruments to choose to add to their holdings, given the expansion of the financial markets, the constant innovation and introduction of new investable instruments. However, since our focus is on equity performance only, we do not analyze funds that can invest in other instruments rather than stocks and cash. Thereafter, no position in corporate bonds or government bonds is allowed and the selected mutual funds are bounded to invest only in the equity market or to hold liquidity. Derivatives are not allowed either, since they can substantially alter the managers' performance, for example by hedging or leveraging the positions, and are almost impossible to track with passive indexes.

[46] Just to name a few: Madoff Investment Securities LLC (2009), Amaranth Advisors LLC (2007) and LTCM (1998).

Furthermore, short positions are not allowed and the capital of the funds must be fully invested in the stock market or kept as cash. These constraints are reported in the multiple variable linear regression by imposing a non-strict inequality on the coefficients[47], which can only assume values larger or equal to zero. The inequality prevents short positions, since it bounds the net exposure to a specific factor to positive or null values. Additionally, the funds are prohibited from borrowing money from other sources: they can hold and raise more cash but the possibility to leverage their positions is precluded.

Furthermore, full investment of the capital paid up by the investors is addressed by imposing the following constraint: the sum of the coefficients must be equal to one. This constraint imposes that 100% of the fund, no more and no less, must be invested or kept liquid. We assign a risk-free rate of return to cash hold as liquidity by the investors. The best proxy of the risk-free rate is the return on 3-months U.S. Treasury Bills.

Additional restrictions are applied in the selection of mutual funds:

- they must have been active throughout the entire 20 years considered;
- they must have always been available to the public (NAV available daily)
- their benchmark must be the S&P 500 Index
- they must not be tilted toward a specific sector, but be allowed to invest broadly across the market[48]
- they must be denominated in U.S. dollars
- they must not invest in foreign equities or currencies

These restrictions are necessary to avoid inaccuracies in the correct determination of the managers' style, which otherwise would be imprecise because of incorrect style portfolios with respect to the actual holdings. Finally, among all the funds meeting these requirements, we select the 30 most successful funds which belong to the high tail of the distribution of mutual funds returns on a risk-adjusted basis.

[47] The estimated coefficients represent the weight assigned to each factor in the style portfolio.
[48] For example, a fund specialized in the Technology sector would be excluded.

4.3 Returns-Based Style Analysis

Returns-based style analysis (RBSA) is "a statistical technique that identifies what combination of long positions in passive indexes would have most closely replicated the actual performance of a fund over a specified time period." (Lucas, 1996) The coefficients of the regression determine the portfolio's effective mix, describing the weights assigned to the variables in the regression to best replicate the performance of the mutual funds. The R^2 coefficient, measuring the explained variance of the regression, is representative of the percentage of the returns attributed to asset allocation. Instead the R^2 complement to one, $1-R^2$, explains the component of the returns attributed to security selection and market timing. The latter coefficient defines the manager's skills we are assessing in the analysis.

RBSA has been developed by William F. Sharpe (1988). The success of his paper led to the release of a commercial software to conduct a RBSA and has become a widespread analysis tool across the mutual fund industry. The model is useful to assess the effective asset allocation strategy of mutual funds, since it doesn't rely on the portfolio holdings declared by the managers, but it is based only on the portfolio returns. By this way, RBSA is distinguished from holdings-based style analysis, which counts on the holdings reported in the prospectuses released by mutual fund managers to the public.

RBSA, as every analytical tool attempting to describe fund performance, has advantages and drawbacks. Its main advantage is to be transparent in its mechanism, while other models, much more sophisticated, lack clarity and simplicity and can be redeemed as "black boxes." (Lucas, 1996) On the other hand, RBSA relies heavily on assumptions and choices made before and during the analysis, such as the selection criteria and the appropriateness of the passive indexes. In fact, the indexes must be suited for the funds examined in terms of financial instruments and factor exposure, otherwise the results will not be informative, reporting a very low R^2.

4.4 Description of the Model

Based on the non-negativity and no-leverage constraints explained in section 4.2, we build the following model to conduct a return-based style analysis on each of the 30 mutual funds. The target variable is the excess rate of return of the mutual funds, while the explanatory variables are the excess rates of return of the six factor indexes that we have previously created[49]

The model is described in Equation 1.1, subject to the constraints in Equations 1.2 and 1.3.

[49] The excess rates of return is calculated over the risk-free rate for the corresponding time period.

Equation 1.1

$$R_t^{m.fund} = \alpha + \beta_1 \cdot RMom_t + \beta_2 \cdot RVal_t + \beta_3 \cdot RSize_t + \beta_4 \cdot RHQ_t + \beta_5 \cdot RDiv_t + \beta_6 \cdot RLowV_t + \varepsilon_t^{m.fund}, \qquad t = 1, \ . \ . \ . \ , T \ ,$$

where $R_t^{m.fund}$ denotes the excess returns of each one of the 30 mutual funds, α is the intercept, the six β coefficients are the estimated coefficients (weights of the style analysis portfolio), $RMom_t$, $RVal_t$, $RSize_t$, RHQ_t, $RDiv_t$ and $RLowV_t$ are the excess return of the factors indexes, $\varepsilon_t^{m.fund}$ are the fund-specific error terms. The regression is repeated for each fund.

Equation 1.2

The non-negativity constraint is satisfied by:

$$\beta_i \geq 0, \qquad i = 1, \ . \ . \ . \ , 6$$

Equation 1.2

The no-leverage constraint is satisfied by:

$$\sum_{i=1}^{6} \beta_i = 1$$

The estimated coefficients of the models represent the allocation weights to create a portfolio composed of the six indexes which best describes the managers' style. The coefficients are recalibrated for each fund. The results are reported in Table 1.1 and we discuss them in the next section.

4.5 Interpretation of the Results of the RBSA

This section provides an interpretation of the results of the RBSA conducted over the 30 selected mutual funds. First of all, it is interesting to note that almost all funds follow similar styles: about 76% of the weight is allocated to the High Quality Index, while 13% goes to the Dividend Yield Index and almost 10% to the Low Volatility Index.

Given the constraints of the funds examined, it is consistent that the Size, Momentum and Value factors do not play a relevant role or, in this case, they are already partially included in the other three factors of the regression which performs better in the explanation of the returns. In particular, taking into consideration the dimension of the mutual funds, the Size factor is not easy to be easily accounted for, since the investment would be too small to be relevant with respect to the total capital of the fund. The

Momentum factor, even if firstly identified in 1997 by M. Carhart, has many investability constraints and the Value factor, where the stocks added to the portfolio are underpriced with respect to their fundamentals, has been much more difficult to target due to the rise of technology[50] and "very often overwhelmed by the aggregate risks in the macroeconomy." (Doskov, 2016)

The main drivers of the selected mutual funds show that the managers rely heavily on the fundamental tools of investing, such as a consistent ROE together without excessive indebtedness, measured in our High Quality Index by the leverage ratio. Additional assets allocation takes into account the Low Volatility factor and the Dividend Yield factor. The former is well-known for its role in performing above its peers during periods of recession, granting a safer and more stable investment to the managers during bad times. The latter awards a positive stream of cash to the mutual funds and selects firms that are generally performing above their competitors and can afford to pay large dividends to the shareholders. The mutual fund managers can then use the proceeds to pay out dividends to the investors, without the need to sell some of their positions, avoiding additional transaction costs.

In the interpretation of the factor allocation identified by the RBSA, we must also recall the importance of reporting to investors, which, in the case of mutual funds, have daily access to their quotas in the financial markets and prevent the managers from implementing more complex or extreme strategies, unlike what a hedge fund is entitled to do, for example. This can well explain why the style is pretty similar across the funds. Furthermore, these funds have very tight investment constraints described in their prospectuses, which make them avoid investment in more aggressive factors, such as the aforementioned Size Index.

Coming to the accuracy of the analysis, we see that the R^2 coefficient is moderate. Some of the reasons that can explain this moderate value are turnover rates different from those of the factor indexes, inconsistencies in the manager's style and in its exposure to factors, inappropriateness of the benchmarks and financial instruments not included in the analysis.

It is important to discuss, identify and eventually discount the performance for these factors, if they can't be ruled out in the determination of the manager's skills. First of all, we exclude that additional financial instruments and inappropriateness of the benchmark can decrease the accuracy of the regression, given the strict constraints we have preventively imposed. Coming to the turnover rates, they are specific for each mutual fund and can have a minor role, since no index can perfectly replicate the manager's

[50] The technological progress has decreased the appeal of the Value factor in the 2000's, given the larger number of investors able to target it.

decisions. However, the rebalancing dates we have chosen are selected to specifically address this point and to decrease the discrepancy between the turnover ratios of the managers and of our indexes. On the other hand, inconsistencies in the manager's style arise when a manager changes many times his exposure to the factors, which are not able to properly track the returns anymore. However, considering the clear and specific description of the investment opportunities and the investment rules that the managers have to follow as depicted in the funds' prospectuses, this explanation of the moderate R^2 of the regressions can also be safely excluded.

Finally, we can conclude that the coefficient $1-R^2$ is only marginally influenced by turnover rates and inconsistencies in the managers' style, highlighting that the greatest part of the performance of these mutual funds is contributed by the managers' skills in the security selection. As a confirmation of our results, we recall that the selected managers are all top performers, capable of achieving and maintaining large total returns over the years, well above the performance of their benchmark, the S&P 500. Subsequently, it is expected that a consistent component of skill should arise from the RBSA conducted.

4.6 Total Alpha Returns

After finding out that the factors exposure can only explain to a certain degree the mutual funds' excess returns, we further investigate the magnitude of the skills of the managers and if they are statistically significant, by calculating the Total Alpha Returns and the related T-statistics. The Total Alpha Return identifies the total portion of the fund's returns which is not explained by the style analysis portfolio created (Lucas, 1996). It is calculated as the arithmetic difference between the mutual fund's returns and the returns of the style analysis portfolio, both measured quarterly.

The Total Alpha Return can be divided into two components: market timing return and security selection return. These are both representative of the manager's skills and their sum matches the total value added by the managers.

Market timing is defined as the ability of the manager to carefully choose the rebalancing dates, modifying his exposure to the factors more efficiently than the relative benchmark, consequently achieving a superior return. Security selection is also known as stock picking, which is the ability of the manager to select additional stocks – or fewer stocks – than the indexes, based on the opportunity set available for his investments, to get a return above the benchmark.

Coming to the estimated average Alpha[51] over the analyzed period of 20 years, it ranges from 0.63% to 1.57%. The number itself, however, is meaningless without the T-statistics, which confronts the null hypothesis in which the manager does not add any value to the passive investment ($\mu = 0$) with the alternative hypothesis of a relevant component of the manager's skill in the portfolio return, given the number of observation and its volatility.

The results are mixed, highlighting that, at the 95% confidence level, 18 managers out of 30 show substantial skills that can not be reconducted to noise in the performance. The remaining 12 managers, even if they all achieved positive returns over the benchmark and the constructed style analysis portfolio, are not deemed to be responsible of the returns since the alphas are not statistically significant enough, given the volatility of their quarterly returns. If we lower our confidence interval to 90%, the number of managers achieving a significant performance, which can't be attributed only to the factor exposure, rises to 24.

The next step in the analysis is to determine if their fees are appropriate with respect to the extra return achieved because of their skills. As described in chapter 1, the managers shouldn't be compensated just on their total return but also volatility must be taken into account into the calculation of their performance. This is what is measured by the coefficient 1-R^2 and explained by the components of the Total Alpha Return (market timing and security selection), given the fact that all our assumptions hold and the results are statistically significant in determining the manager's pure contribution to the returns.

At the 95% confidence level, 18 out of the 30 pre-selected managers have statistically significant skills: in the next paragraph we discuss their average annual fees, checking if they are appropriate for the returns and if the managers really create additional value to the investors or if it ends up in paying for their service. If the managers do not add enough value with their skills with respect to the fees they collect, the investors would be better off investing their money in passive indexes with extremely low management fees.

4.7 Do Managers Deserve Their Fees?

The average annual fees or the 18 managers is 1.06%, slightly above the average for the category of mutual funds selected. We do not report the fees for the remaining 12 mutual funds whose managers do not add value with their activities, since the Alphas are not statistically significant. However, we highlight that there is also no evidence that the activities of these 12 managers are detrimental for the funds'

[51] Always on a quarterly basis.

performances. The T-statistics only state that the skills do not play a key role in leading to the total returns, but there is no evidence that the investors would be better off by investing in passive indexes or that, after adjusting for the fees, the net returns would be inferior than those of the style portfolios.

The 18 managers, instead, contribute on average to a Total Annual Alpha Return of 5.04% with their skills, leading to a net adjusted annual return after the fees of 3.98%, achieved because of the ability of the managers in selecting the best stocks and in timing the market.

Our conclusion is that, among this pool of funds, the managers whose skills are statistically significant bring on an average 3.98% to the annual performance of their funds with their abilities, creating additional wealth for their investors. These managers, 60% of our selection, deserve to be compensated for their skills by receiving the management fees reported in Table 1.2. A discussion on how to distinguish ex ante the skillful managers is reported in section 5.4.

4.8 Additional Remarks

We now add some further remarks and considerations on the performance of the mutual fund managers and we also discuss what can happen if we relax some of the constraints.

First of all, we mention how can we determine if the superior performance recorded by the 18 skillful managers has relevant components of luck or if it is only connected to the managers' ability. Fama and French (2010) cover this question in their paper by applying a bootstrapping technique and running 10000 simulations on the cross-section of mutual funds returns within their population. The inferences that Fama and French draw based on the cross-section analysis are that just a "few funds produce benchmark-adjusted expected returns sufficient to cover their costs" and that evidence of superior performance is found only "in the extreme tails of the cross-section of mutual fund α estimates."

Given the a-priori selection of mutual funds that we made, we have studied the style and performances of superior managers only. They all belong to the top performers of the respective mutual fund classifications.

Furthermore, the long time period, from the second quarter of 1999 to the last quarter of 2019, prevents temporary, short-run oscillations to distort the performance, which can be subsequently considered immune from these fluctuations to a large degree of confidence. Based on these points and on the results of the researchers Fama and French (2010), we can rightfully assume that, if a component of luck is included in the performance of the 18 most skillful managers, it is not the main source in the determination of the Total Alpha Returns.

Our conclusion is then confirmed: a small number of active managers are able to provide superior cost-adjusted returns to their investors, highlighting that these managers have skills that deserve to be compensated by the fees they collect from their investors on an annual basis. It must be noted, however, that our sample excludes funds which failed during the period under examination. The absence of these funds from the analysis and its impact is defined as "survivor bias."

Other remarks on the performances include the relaxation of some of the investment constraints that bind the investment opportunities of the mutual fund managers.

For example, if we relax the constraints in Equation 1.1 and Equation 1.2, we allow for leverage and short selling, which can totally modify the performances of mutual funds. In fact, the managers can increase their weighting exposure to some factors by borrowing money and can also take short positions on the market, when they expect an economic downturn. The consequences would be that the returns can become more volatile (Aharon, 2019) and our indexes would not be suited to analyze the mutual funds anymore, resulting in a lot of statistical noise.

Additionally, the opportunity set can be expanded by allowing international investments, bonds and derivatives. As before, the increase of the types of financial instruments that a manager can add to his holdings needs to be properly balanced with updated indexes and relaxed constraints on their construction. The main framework of the analysis is always the same, but the style portfolios need to be tailored depending on the investment opportunities. Otherwise, the regression would lead to a very low R^2 due to inappropriate benchmarks and the results would not be statistically significant in determining the actual skills of the managers.

A final remark in the construction of the indexes is that we purposely ignored transaction costs, management fees and expenses connected to the passive indexes. The only goal of the construction passive indexes was to create a good proxy of the style of mutual fund managers in the determination of the degree of skills in their performance. Moreover, indexes are not directly investable and, if an investor wants to replicate their holdings, she would face transaction costs and the connected expenses. However, for the scope of our analysis, the relevance of these costs would not be significant, since passive investments have very low expenses, usually below 0.2% annually[52]. The inclusion of the expenses in the indexes would result in a small reduction of their performances (up to a total of 4.23% in the 20-year

[52] Bloomberg, data retrieved on March 11th 2020.

time span), which is not relevant in magnitude compared to their performance and would only slightly tilt the results in favor of the active managers.

4.9 Comparison of the Results with Other Researchers

After describing the additional opportunities for the managers if we relax some constraints and the relative adjustments needed to properly account for their performance, we present some of the previous studies in RBSA and performance attribution.

As mentioned before, RSBA was introduced by Sharpe (1988). After his publication, many researchers employed this technique looking for the determinants of superior returns in the market and their explanation. Sharpe himself (1992) presented an analysis of Trustees' Commingled Fund from 1985 to 1989. Without imposing constraints, the R^2 coefficient of Sharpe's regression totaled an extremely high 95.20%, substantially excluding whatever implications for the skills of the managers in the determination of the performance of the fund. However, the estimated coefficients of the regression include some extreme positions, like a 110.35% position invested on Value Stocks and a short position of -43.62% in Medium Stocks. These weights do not represent realistic positions available to mutual funds and the results should not be taken under consideration. The constrained regression, instead, reports that Value Stocks (69.81%), Small Stocks (30.04%) and European Stocks (0.15%) explain 92.22% of the returns, again leaving very small room for the manager's skills.

Another relevant point of research by Eugene Fama and Kenneth French (2010) applies a cross-section analysis to mutual funds returns from 1984 to 2006, finding evidence that only few managers show a superior performance that, after adjusting for the expenses, grants a positive Total Alpha Return to the investors. The regression is based on the Three Factor Model presented by Fama and French (1993): market risk[53], size effect and value effect. An additional factor is added to a second analysis, the Momentum effect identified by M. Carhart (1997). Both regressions highlight that "mutual fund investors in aggregate realize net returns that underperform" the models "by about the costs in expense ratios." (Fama and French, 2010) The researchers also conclude that, "if there are fund managers with enough skill, their tracks are hidden in the aggregate results by the performance of managers with insufficient skill." In fact, positive and significant Alphas are estimated only in the high tail of the distribution of the mutual funds returns. The final results of the bootstrap simulations "suggest that some managers do have sufficient skill to cover costs."

[53] This is measured by the traditional β of the Capital Asset Pricing Model (Sharpe, 1964).

Coming back to our analysis, the high tail of the distribution is exactly where we have tried to select the managers from, discarding all funds that didn't meet our criteria or didn't achieve a superior performance with respect to the benchmark. The most relevant literature supports the main results of our analysis.

Additional studies implement other solutions to increase the precision of the regression, introducing the concept of Returns-Based Style Analysis with Time-Varying Exposure (Van der Sluis, 2006) with improved results in the determination of the style portfolios and on performance measurement. Also, Markov (2004) implements a new framework based on a closer approach to the managers' performance: he presents the new technique denominated Dynamic Style Analysis. The DSA specifically accounts for portfolio dynamics such as "gradual style drift or rapid changes in strategy" which would decrease the precision of the traditional static RBSA. Markov tests the new approach in the paper and finds that the accuracy of the model is increased with the only drawback being computational complexity with respect to previous approaches.

Other research, instead, addresses different statistical problems connected with RBSA: Buetow (2012) shows that "multicollinearity is a common issue that arise when commercially-available indexes are used," leading to "volatile results with little meaning." The researchers suggest avoiding commercially-available indexes, building instead "portfolio-specific benchmarks that properly capture the investment objectives of the portfolio." On the basis of Buetow's findings, we decided not to implement our analysis with MSCI Factor Tilt Indexes, but we created customized indexes based on the selected funds and their holdings.

Another relevant point, which we have chosen not to cover in our statistical analysis but that can give additionally insights on the regressions, is discussed by Otten (2000). He recalls that "traditionally only point estimates of the style exposures have been reported," because of the strict constraints that are required. The researcher introduces a new computational methodology based on the "asymptotic distribution of the style weights," which allows him to calculate confidence intervals on the parameters and to draw inferences based on the T-tests too.

4.10 Conclusions

The main result of our analysis is that 18 out of the 30 selected managers, at the 95% confidence level, show substantial and significant skills, deserving the fees that they collect. The annual Total Alpha Return, adjusted for the expenses, is on average 3.98% for these 18 skillful managers.

The RSBA analysis, instead, defined the style portfolio for each mutual fund, determining the relative benchmark to assess the performance that can be attributed to the manager's skills. The average fund allocation can be described by the following factors: 76% High Quality factor, 13% Dividend Yield factor and 10% Low Volatility factor.[54] The remaining factors - not included in the portfolio allocation by the multiple linear regression - are Momentum, Size and Value.

The moderate R^2 of the regressions have been analyzed and discounted for the possible explanation, in accordance with the traditional tools of performance attribution analysis. Security selection and market timing are the two key determinants that explain the superior performance of the 18 managers whose extra return over the assigned style portfolio has been considered significant by the T-tests.

The fundamental results of the analysis are in accordance with the conclusions of most researchers, who determined that "few funds produce benchmark-adjusted expected returns sufficient to cover their costs." (Fama and French, 2010) The mutual funds that we analyzed are a-priori selected to belong to that subgroup of successful funds from the high tail of the distribution.

In conclusion, 60% of the selected managers have substantial skills, provide extra total return to their investors and deserve their fees. The performance of the 18 active mutual funds run by skillful managers, adjusted for the management fees and expenses, is significantly higher than the correspondent passive indexes' returns built on their factor exposure.

In the next chapter we discuss the growing number of mutual funds and hedge funds that, during the last years, have started to implement strategies based on factor exposure, leading the rise of the so called "Smart Beta Funds" in the market. We also present the views of some researchers on the potential consequences for the traditional extra premiums historically awarded to the six factors of our analysis.

[54] Values are rounded.

Chapter 5 - Further Considerations

5.1 Introduction

The present chapter is divided into two main parts: in the former we discuss the main concerns connected to the rapid rise of Smart Beta funds, while in the latter we make additional remarks on the main question of the paper – if mutual fund managers deserve their fees.

First of all, we introduce implications for risk management practices on Smart Beta Funds, which have peculiar risks due to their characteristics which are shared at the same time with both passive and active funds and which classify them into a new category. Furthermore, we describe potential threats to the persistence of factor risk premiums, like crowding.

The remaining sections of the chapter are devoted to the exploration of alternative methods to select a priori the most skilled managers. If investors are not able to distinguish skilled managers, they would be better off investing in passive indexes and avoiding large fees. Furthermore, we describe two of the problems encountered in the calculation of mutual funds performances: selection bias and survivor bias. Both distortions are relevant to our results and, overall, to research conducted on this topic. In conclusion, we make some final remarks and observations on our analysis and we point out the implications of the results for the average investor.

5.2 Risks linked to Smart Beta Funds

Smart Beta funds present characteristics common to both passive funds, such as low fees and rules-based investments, and active funds, like the deviation from the reference benchmark. Their rise in the last two decades, which has brought up to almost $ 1 Trillion the total amount of assets under administration of Factor-based ETFs, has led many investors to raise concerns about the most appropriate risk management practices. Smart Beta funds are, in fact, a new category of funds due to their specific characteristics, which needs tailored risk measurement and management tools.

Most risk managers agree (Williams, 2017) that factor investing shares risks both with passive and active investment styles, with exposures varying more towards one or the other depending on the aggressiveness of Smart Beta strategies and other portfolio metrics. The common denominator, however, is that investors face a new mix of risks when they decide to allocate their money to these types of funds.

The first type of risk, shared by all investors, is the Entry Risk, remarking that the moment in which the investment is made can produce a very different performance. Properly selecting the entry point is complicated and can't be determined by the average investor, who may face substantial drawdowns if she enters a fund just before a market crash. Among factor investing, the factor which is most exposed to the entry risk is the Momentum factor, especially if, like in our analysis, investors can only add long positions. When Momentum stocks go out of favor, as during the Dot Com and Financial Crisis, the underperformance can be very severe.

Another type of risk, mostly linked to the High Quality, Value and Momentum factors, is the Valuation Risk. This is the typical overvaluation risk of those firms able to increase their earnings even in the current low-growth market environment and whose multiples have increased well above the historical average. It is almost impossible to discern whether the overvaluation will be justified by the future performance of these companies or if they will go back to a price more in line with the rest of the market. Investors can protect themselves from this risk by diversifying their holdings into funds exposed to different factors, instead of focusing just on one of them. Nevertheless, diversification may come at the expense of the total performance of the portfolio but, if the economy experiences a market shock, a diversified portfolio reduces the negative consequences of overvaluation risk. However, investors must also take into consideration the correlation risk when they build a diversified portfolio: during market crashes the traditional correlation among different stocks or even across asset classes can be completely altered in the so-called "correlation breakdown." During periods of extreme volatility in the market, correlations can temporarily change and what was considered a good protection or hedging tool may not behave as expected.

Another relevant risk, connected to the previous one too, is the horizon risk: investors must consider that drawdowns can be prolonged in time, especially when following factor investing strategies[55]. Investors can navigate through the horizon and overvaluation risk only if their investment outlook is very long, otherwise they will be exposed to these risks. As before, diversification is a great tool in managing and containing the risks, especially if investors are not able to protect themselves by purchasing derivatives or other financial instruments that can provide a hedge towards market downturns.

Furthermore, even if an investor follows all the rules of diversification, she can still be exposed to other types of risk, usually hidden in the portfolio construction: model risk and specification risk. The first one captures the fact that all models are, in the end, simplified description of economic and financial processes and might not be suited for all market environments. Models can fail in the description of

[55] For example, Value stocks underperformed Growth stocks during the 90's; afterwards the trend reversed until the last couple of years.

market situations, especially if they are out of the ordinary. This risk potentially exposes all investors to inaccurate estimates and valuations, in particular during moments of crisis and when the so-called "Black Swans" happen. A Black Swan is defined by Taleb (2007) as a "rare and unpredictable outlier event" with extreme impact on the markets and which models totally fail to forecast.

Also, the specification risk is incorporated in the portfolio construction process and, more specifically, in the phase when stocks are ranked based on their exposure to factors. A very important step is the definition of the key variables in the identification of factors: if a variable is not appropriate, the selection might be biased and generate undesired exposures to other market risks and factors. For example, an inconsistent factor identification can lead to increased exposure to macroeconomic risks and potential unexpected downsides.

Summing up, factor investing poses a new challenge to investors: properly measuring and managing the risks associated with the new strategies. They must identify these risks and protect their portfolios with adequate diversification practices and, if they are available, other risk management tools.

In the next section we highlight additional concerns that investors have to consider when they decide to invest in Smart Beta funds.

5.3 Will the Risk Premiums Persist?

Factors earn higher-than-average returns because they are exposed to specific risks. However, a recurring question among investors is how likely and how long these risk premiums will persist. The debate is still open, involving both academics and practitioners: overall, most of them agree upon a future decrease of the magnitude of the risk premiums, mainly due to the increased number of investors following factor strategies. The terminology that identifies the progressive disappearance of a profitable opportunity in the market due to increased participation of investors is "crowding." As long as a way to achieve Alpha works, it will be exploited by a growing number of investors until it disappears. If the Alpha-generating strategy is known to the public and is reproducible at a low cost, more and more investors will allocate their funds until the opportunity disappears.

Bender (2013) suggests that, however, not all the risk premiums will eventually be eroded by crowding. The researcher distinguishes between "systematic risks" and "systematic errors": the former are connected to risk premiums that he doesn't expect to vanish, while systematic errors are just temporary and, even if they can produce very large returns, they won't last for a long time. For example, systematic risks are connected to major economic factors and shocks which can't be diversified away. Investors bearing these type or risks, which can sometimes hit even the whole economy, are compensated with excess returns.

On the other hand, systematic errors are mostly linked to human irrational behavior in the stock market, as defined in behavioral finance. Some examples of irrational behavior are overconfidence, over-reacting and herding. They are all related to investors' biases that can determine a deviation of prices and can contribute to the factor anomalies that we observe in the markets. Overconfidence describes the tendency of investors to rely on their judgement ability much more than they should, given the accuracy of their evaluations. Over-reaction is the behavior that is connected to extreme swings in the market, leading to temporary under or overvaluation of stocks on the base of miscalibrated and often emotional judgements. Herding, instead, refers to "an obvious intent by investors to copy the behavior of other investors," (Bikhchandani and Sharma, 2000) a behavioral bias that can lead prices to rise due to the concentration of the investors in the same investable stocks. This tendency can be explained by the investors' objective of not underperforming their peers, which drives most of them to make similar investing choices instead of fully expressing their personal views.

For an investor, it is important to discern what is the actual source of a price arbitrage identified in the market, to understand if it will persist in the future (systematic risk) or if it will only be temporary (systematic errors or behavioral biases). Most researchers agree that both strands of thought are accurate and partially describe the risk premiums accorded to factors.

Lastly, another relevant point for investors regards the new evaluation framework of fund managers: their performance should be evaluated accordingly to the fact that Smart Beta funds share characteristics both with passive and active funds, as described in the next section. Furthermore, we describe additional manager selection strategies besides the analysis of their past performance.

5.4 Managers' Evaluation and Selection

One of the most critical points in factor investing is how to assess and evaluate the performance of fund managers. The need for an appropriate evaluation framework is discussed by Alford (2016), who suggests that each fund's performance must be accounted depending on how much of the strategy is based on a proprietary strategy offering a superior performance or whether it simply replicates a passive index tilted towards certain factors. Clearly, the more a strategy is left to the managers' discretion, the more they should be considered responsible for the final results.

Besides the evaluation problem, another extremely relevant aspect is connected to the a priori selection of talented managers: how can investors identify skillful managers before destinating their money to their funds and without relying exclusively on past performance?

As commonly reported, past performance is not indicative of future performance (SEC Rule 156, 2013) and shouldn't be used to estimate it. Even though, when it comes to managers evaluation, past performance plays a central role but is not sufficient since the returns and their allocation strategy must also be stable over the years.

Moreover, Ang (2014) affirms that it is very difficult to identify outperforming mutual funds on a consistent basis, concluding that the necessary statistical research is too complicated for the average investor. On the other hand, he suggests that the selection can be beneficial to institutional investors with the necessary human and computational resources available. Starting from these premises, we report some studies that show how, besides considering past returns and mutual funds holdings, the best indicators in the selection process are strictly connected to the managers themselves.

First of all, higher education plays a key role and is a common trait among the most successful managers: those who went to the best colleges usually achieve the largest risk-adjusted returns. Furthermore, standardized tests taken by a large majority of individuals represent another reliable indicator, like the SAT exam for the admission to undergraduate programs of universities or colleges. Analyzing the personal background of managers substantially improves the selection process and the related portfolio performance (Chevalier, 1998).

Frazzini (2008) introduces an additional relevant variable, showing the close relationship between the personal connections of mutual funds managers and their performance in the financial markets. Personal connections can influence the managers' results if they know people working in boards of companies they are investing in. The main result of this paper is that connections matter and selecting a manager with many significant relations can increase the chances of achieving higher returns. The author measures managers' personal connection by checking if they went to the same college of board members. The conclusion of the author highlights again the importance of conducting in-depth research on the managers and not just on their performance.

Notwithstanding, Ang (2014) summarizes these findings by indicating that, even accounting for all these measures, selecting outperforming managers remains a challenging task. Furthermore, he states that "the managers themselves benefit from their skill," attracting additional funds and earning more fees instead of transferring the gains to their investors. The 40-Act provision of symmetrical performance fees[56] is considered inefficient by Ang (2014) in reducing this distortion, since the great majority of mutual funds have adapted their fee structure linking most of the revenue to the asset under management and not to the performance. This complication has more consequences on the most talented managers and makes the identification and selection process even more difficult. Investors face the risk that, even if they manage to carefully choose high-performing funds, their asset under management might grow in dimension over the course of the years and gradually lower the returns. The mutual funds industry is in fact characterized by decreasing returns to scale (Berk, 2004).

In the next section we describe two biases that must be taken into consideration during the statistical analysis of mutual funds returns.

5.5 Selection Bias and Survivor Bias

Most of the studies on mutual funds returns are exposed to the following two biases: selection and survivor bias. Our analysis is not an exception, however the effects of both biases on our sample can be disregarded as not particularly significant due to the strict constraints that we have imposed on the fund selection process. In particular, no relevant differences would have been produced including corrections for the biases since our sample is already a subgroup of the entire universe of managers. Moreover, we are drawing conclusions only within the range of the high tail of the distribution of mutual funds returns and not to the entire group[57].

The selection bias arises when a proper randomization of input data is not realized, leading to incorrect inferences because the sample is not representative of the population. In the case of mutual funds the effect can be particularly relevant and impossible to avoid, since the common strategy for some families of mutual funds is to bring them to market after an evaluation period in which the funds are private and not available to the public. If the funds turn out to be successful and capable of attracting enough interest on the investors' side, the private incubation period ends and the funds are marketed. The bias arises from the fact that the trial process is only adopted by a share of mutual funds families, estimated by Evans (2009) at 23% of the market: the distortion would not happen if all or none of the funds were subjects to the evaluation period, creating a homogeneous population. The remaining three quarters of the funds are instead immediately available to public subscription. As Ang (2014) underlines, the

[56] With symmetrical performance fees the managers earn or lose a certain percentage depending on their results relative to the benchmark.

[57] Our sample, in fact, would have not been random due to the constraints imposed.

consequence of these different initiation processes is that opened funds are subject to selection bias. The effect of this distortion on the returns is to enhance the performance of the funds examined in research, because low-performing funds are terminated before being brought to the market. Evans (2009) shows that the consequences of the selection can be mitigated by filtering funds for longevity and ticker date creation.

The survivor bias, instead, has a wider and potentially more severe impact on inferences drawn on funds population if proper statistical corrections are not included in the analysis. This distortion is due to the exclusion of funds that disappear during the period examined because of failure or, less often, because of merger with other funds. Ang (2014) reports the example of Janus Worldwide and Janus Global Research: the merger between the two funds was conducted to make the combined fund inheriting only the performance of the best fund, while the worst one simply vanished. This strategy of closing or merging bad performing funds is widely followed by funds management companies, in order to improve the overall results of their entire family of marketed funds. Low returns simply disappear because the worst funds are merged or liquidated and not reported anymore.

The effect of the survivor bias, as well as the selection bias, is to enhance funds return and lead to inaccurate inferences on the fund population. The upward bias on funds returns is consistent and Carhart (2002) estimates a 3.7% difference in the risk-adjusted performance of live and dissolved funds. The bias can be mitigated by including the dead funds into the original database. In our research, however, the focus was already restricted to top managers only and the inclusion of dead funds in the initial pool of funds would have not changed our selection, given the high-performance constraint imposed. Moreover, funds that failed were obviously not run by successful or skilled managers and are therefore excluded ex ante from our focus on top performers only.

Overall, the recognition of the selection bias and the survivor bias has a critical importance in the evaluation of the results of statistical analysis, since their effects can lead to flawed inferences and inaccurate conclusions.

In the next section we summarize, based on all the complications and concerns discussed in the chapter, what can be the most suitable solutions to the average investor in relation to her needs and goals.

5.6 Conclusions

The selection of skilled managers is, indeed, a complicated process that requires appropriate resources to be effective. Average investors typically don't have access to these extensive resources and, even if it was the case, they would still be left with some degree of uncertainty.

A further consideration regards the fee structure of funds which traditionally includes an entry fee, operating annual expenses,[58] and an exit fee[59]. The presence of entry and exit fees introduces another element in the investing process: the amount of fixed costs that investors sustain as soon as they destinate their money to mutual funds. To attract more money, some funds have started waiving their one-time entry and exit fees and are known as "no-load funds." However, for investors these fixed costs represent an additional constraint on the possibility of switching to another fund if the former performance is not satisfactory enough.

Institutional investors, on the other hand, are usually entitled with special agreement and lower fees due to the large amount of assets that they administrate. The different expertise and resources make the selection of skilled managers less complicated for institutional investors who, however, are still subject to all the risks and concerns analyzed before and must take adequate countermeasures. Actively managed funds seem to be more suitable for institutional investors than retail investors, who can be better off destinating their money to passive funds. This conclusion is reinforced by the problems highlighted in the present chapter and is reached also by Ang (2014). In support to this point, the author reports that, even if fees have been following a downward trend starting from the 90's, their amount is still relevant and most benefits of mutual funds are captured by the managers themselves with their large compensation. Furthermore, other hidden costs such as trading costs[60] further shrink the returns achieved by mutual fund managers. Their impact increases with turnover ratios, so active funds are particularly subject to hidden costs and higher fees, further reducing their attractiveness for individual investors.

Ang (2014) remarks that for most retail investors the results achieved by destinating their savings to mutual funds is to tie or, more often, underperform the market benchmark. Skillful active managers are the final beneficiaries of their abilities, through the collection of fees and high operating expenses.

[58] The typical operating expenses cover management fees, performance fees, and other expenses like legal, administrative, marketing and advertising costs.
[59] Entry and exit fees are also referred to as front-load and back-load charges.
[60] Especially commissions and bid-ask spreads.

Disregarding the chances of achieving returns above the market, passive funds represent a good alternative to retail investors pursuing a fee-reducing strategy.

In this context, the introduction and progressive expansion of Smart Beta funds can, however, have a positive role in the diversification of the portfolio for retail investors. The characteristics shared among passive and active funds make them good candidates for the allocation of a small percentage of investors' savings, in spite of the aforementioned risks connected to crowding and the possible future reduction of risk premiums. Alford (2016) shows that the interest raised by Smart Beta funds is not backed yet by an equivalent share of funds allocated to these strategies. He suggests that the modest allocation is mainly due to the fact that, even if their discovery dates back to many decades ago, Smart Beta funds are still relatively new in the mutual fund industry. The author concludes by highlighting that the overall trend of factor investing seems to be stable and he expects the increase in popularity to continue, even with shrinking returns.

Concluding, if average investors don't have the ability and knowledge to conduct appropriate and accurate research into the managers' performance and personal background, they can have better results, on average, by allocating their money to passive funds and adding a small portion of Smart Beta strategies to their holdings. On the other hand, institutional investors competent in selecting skillful active managers can take advantage of their resources and add all the different types of funds (active, passive and Smart Beta strategies) to their portfolio, depending on their risk aversion and investment targets.

In the next and last part we summarize the results and review the findings of our paper, making also some suggestions for further research.

Conclusions

The main result of the thesis is that only 60% of the top 1% of the fund managers in our sample, which is 0.60% of the universe of managers, are able to reach a performance that can only be explained by attributing it to their skills. Hence, only these talented mutual fund managers deserve their fees. They generate Alpha returns significantly different from zero and are able to transfer an average annual net Alpha return of 3.98% to their investors.

Our findings are in line with Fama and French's (2010) conclusion on the skills of the managers that achieved top returns and that belong to the high tail of the distribution of mutual funds returns. More specifically, in our analysis the managers are selected from the top 1% of the distribution of 5001 funds. However, our research also shows that the remaining 40% of the managers from the first percentile of the distribution achieve positive Alphas, but they are not significant enough to be considered different from zero in the respective T-tests. Furthermore, it must be remember than the large majority of managers, estimated between 60% and 80% depending on the time period, couldn't even beat the S&P 500 benchmark. This observation raises a further question: how is it possible to determine a-priori if a manager is skilled, without fully relying on the measurement of past performance? The majority of the studies on this topic head toward an in-depth analysis of the manager's personal background, education and connections as the best alternative solution to select skillful managers.

Furthermore, we point out that the evaluation and selection process is too complicated for the average investor, who doesn't have the necessary resources and knowledge to handle the complexity of the statistical analysis. Our conclusion is that the average investor would be better off avoiding active funds and investing instead her holdings in passive funds. We also consider that the new Smart Beta funds can provide an excellent alternative to passive holdings for a small portion of the wealth of retail investors, with the percentage devoted to Smart Beta strategies depending on the personal targets and risk aversion of each individual. On the other hand, institutional investors with all the resources available to successfully identify skilled managers should take advantage of this ability by investing also in active funds.

Another relevant aspect discussed in the thesis is the determination of the investment style of the selected mutual fund managers. We have used six factor indexes to understand whether the manager's performance was simply based on the exposure to the factors or whether a substantial skill component was present. The average portfolio style reported a similar exposure to factors across the funds, with about 76% of the weight allocated to the High Quality Index, 13% to the Dividend Yield Index and almost 10% to the Low Volatility Index. The remaining factors (Size, Value and Momentum) didn't have a relevant role in the identification of most style portfolios.

Additionally, we investigated if the risk premiums connected to the six factors are likely to persist in the future as a compensation to the investors for bearing the related risks or not, especially in light of the recent rise of Smart Beta funds. Our conclusion is that crowding will play a relevant role in the future, shrinking the returns but not up to the point of their disappearance because factor investing entails the exposure to peculiar risks that not all investors are willing to bear.

Coming back to our main analysis, some adjustments and improvements can be made to further investigate the critical aspects highlighted in the research. For example, some of the constraints can be relaxed, allowing managers to allocate their funds to a wider range of financial instruments outside of S&P 500 stocks, like corporate and government bonds, derivatives, and other currencies. Furthermore, factor indexes can be constructed with alternative criteria, choosing different variables and indicators with respect to ours and those reported in previous studies. Advanced statistical tools can also be used to assess the impact of statistical biases and to investigate the precise influence of luck on the 40% of successful managers who are not deemed to be skillful even if they have achieved positive Alphas. For example, adapting the RBSA to a dynamic process able to adjust the style portfolio quickly and more effectively to changes in the fund's holdings and strategy could be a valuable improvement, especially if managers have a very dynamic factor exposure.

Furthermore, another possibility is to integrate and compare different performance measurement models, such as the Brinson-Fachler model which provides the setting to calculate the manager's contribution to the returns in three sections: allocation, selection and interaction (Brinson, 1986). More specifically, the Brinson-Fachler model assesses the impact on the active return of each manager's allocation choice (overweighting or underweighting a sector included in the benchmark), her stock picking ability in selecting securities outside the benchmark and the combined effect of these decisions. The integration of the results of this model with our Return-Based Style Analysis may lead to some improvements in the identification of skilled managers, together with the additional filter provided by the information on the manager's personal background and private connections.

In conclusion, our research has determined that among the most successful mutual fund managers only a portion of them, 60% of the 1% of the universe, deserves their fees and is capable of granting positive Alpha returns to the investors. On the other hand, our results have also highlighted that the selection process of skilled managers is complicated and exposes the average investor to the risk of allocating her money to active funds that require the payment of large fees and may not outperform the benchmark on a consistent basis. The inclusion of additional information and variables, together with the aforementioned improvements in the statistical model, could provide further insights in the identification of skillful active mutual fund managers and help in measuring whether they rightfully deserve their fees or not.

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Appendices

Table 1.1 – Coefficients of the Regression

	DTMGX	COPLX	CAMOX	DAVPX	DGAGX	DRIPX
Intercept	0.00215	0.00492	0.00593	0.0061	0.00322	0.00533
Dividend Yield	0.10322	0.05237	0.24353	0.09287	0.10184	0.13838
Volatility	0.15426	0.25962	0.04581	0.12128	0.14929	0.12108
Value	0	0	0	0	0	0
High Quality	0.74037	0.68039	0.70473	0.77975	0.74565	0.7352
Momentum	0	0	0	0	0	0
Size	0	0	0	0	0	0

	BHBFX	FRSGX	FRDPX	SRVEX	GVEQX	HAIAX
Intercept	0.00502	0.01282	0.00912	0.00663	0.00421	0.00566
Dividend Yield	0.17907	0.19238	0.15922	0.10951	0.08951	0.11397
Volatility	0.14103	0	0.20372	0.14439	0.10889	0.13779
Value	0	0	0	0	0	0
High Quality	0.67488	0.7948	0.62795	0.73946	0.79738	0.74258
Momentum	0	0	0	0	0	0
Size	0	0	0	0	0	0

	JENSX	LOMAX	MFOCX	MINVX	MONTX	PIODX
Intercept	0.00915	0.00283	0.00797	0.00636	0.01169	0.00495
Dividend Yield	0.19605	0.14744	0.14532	0.17709	0.14655	0.1039
Volatility	0.11614	0.17122	0.03486	0.10244	0	0.12603
Value	0	0	0	0	0	0
High Quality	0.67866	0.6785	0.81185	0.7141	0.84176	0.76511
Momentum	0	0	0	0	0	0
Size	0	0	0	0	0	0

Table 1.1 – Coefficients of the Regression (Continuation)

	PROVX	PTWAX	RYLIX	SENCX	SGFFX	STFGX
Intercept	0.00671	0.00974	0.00355	0.00718	0.00376	0.00449
Dividend Yield	0.04731	0.17502	0.27768	0.10944	0.08221	0.06317
Volatility	0.08511	0.14408	0.03108	0.16395	0.03705	0.13695
Value	0	0	0	0	0	0
High Quality	0.86087	0.67116	0.68769	0.71942	0.87699	0.79539
Momentum	0	0	0	0	0	0
Size	0	0	0	0	0	0
	TOCQX	**VALSX**	**VPMCX**	**USBOX**	**WMKGX**	**PDFDX**
Intercept	0.00876	0.01469	0.01528	0.00349	0.00721	0.01028
Dividend Yield	0.11778	0.19821	0.05878	0.14124	0.07523	0
Volatility	0.15894	0.01507	0.08206	0.05872	0.16428	0
Value	0	0	0	0	0	0
High Quality	0.71452	0.77203	0.84388	0.79656	0.75328	0.98972
Momentum	0	0	0	0	0	0
Size	0	0	0	0	0	0

Table 1.2 – Funds Performances and Fees

	DTMGX	COPLX	CAMOX	DAVPX	DGAGX	DRIPX
Alpha (Annualized)	2.53%	3.86%	3.78%	4.05%	2.99%	3.75%
Fees	1.20%	2.69%	0.75%	0.89%	0.90%	0.72%
Net Alpha to Investors	1.33%	1.17%	3.03%	3.16%	2.09%	3.03%
T-Test	1.368	1.715	1.900	2.231	1.607	2.020
	BHBFX	FRSGX	FRDPX	SRVEX	GVEQX	HAIAX
Alpha (Annualized)	3.53%	6.41%	5.33%	4.05%	3.25%	3.92%
Fees	0.95%	0.91%	0.87%	1.08%	0.89%	0.74%
Net Alpha to Investors	2.58%	5.50%	4.46%	2.97%	2.36%	3.18%
T-Test	1.848	2.567	2.846	2.160	1.793	2.102
	JENSX	LOMAX	MFOCX	MINVX	MONTX	PIODX
Alpha (Annualized)	5.24%	2.94%	4.63%	3.99%	5.82%	3.60%
Fees	0.87%	0.71%	1.04%	0.95%	1.39%	0.96%
Net Alpha to Investors	4.37%	2.23%	3.59%	3.04%	4.43%	2.64%
T-Test	2.657	1.624	2.265	2.119	2.340	2.001
	PROVX	PTWAX	RYLIX	SENCX	SGFFX	STFGX
Alpha (Annualized)	4.69%	5.36%	2.77%	4.56%	3.15%	3.38%
Fees	1.00%	1.22%	1.46%	1.02%	2.10%	0.12%
Net Alpha to Investors	3.69%	4.14%	1.31%	3.54%	1.05%	3.26%
T-Test	1.707	2.545	1.269	2.497	1.447	1.805
	TOCQX	VALSX	VPMCX	USBOX	WMKGX	PDFDX
Alpha (Annualized)	5.16%	7.31%	7.67%	2.96%	4.55%	5.41%
Fees	1.25%	1.20%	0.38%	1.25%	1.15%	2.50%
Net Alpha to Investors	3.91%	6.11%	7.29%	1.71%	3.40%	2.91%
T-Test	2.700	3.444	3.817	1.407	2.142	2.076