Mutual Funds:

Do active mutual fund characteristics influence performance during recession periods?

Author: Luis San Sebastian Gallejones / Student No. 516324

15th of August 2019

Master Thesis

MSc in Finance & Investments

Rotterdam School of Management, Erasmus University

Thesis supervisor: Mathijs Cosemans

Co-Reader: Xander Hut

Acknowledgements

I would like to express my sincere thankfulness to my supervisor Assoc. Prof. Dr. Mathijs Cosemans and co-reader PhD Candidate Xander Hut for their valuable guidance regarding the implementation of my research idea throughout the master thesis. Their constructive suggestions, specially at the initial stage of this document, greatly contributed to the focus of my research question and hypothesis.

I would also like to extend my gratitude to NN Investment Partners for partially funding my studies in Rotterdam and make this venture financially sustainable.

On a personal note, I feel I must acknowledge several people who contributed in one way or another to the consecution of this project. First, Maria Cora Quintana Portilla, whose patience and unconditional support have been a constant during the writing process of this thesis. Eternally grateful. Second, my fellow colleagues Simge, Bernardo, Dimitris, Lingling and Ezel, who provided academic and emotional support on top of great distraction which has been key to succeed and have a more enjoyable year. Last but not least, I would like to thank my parents for their wise advice and total trust in me. This would not have been possible without your help.

Luis San Sebastian Gallejones

Rotterdam, August 15th, 2019

Abstract

Using a sample of U.S. actively managed equity mutual funds between January 1988 and December 2015, this empirical study provides a comprehensive analysis of unconditional and conditional mutual fund performance during recession periods in an attempt to contribute to the resolution Gruber's puzzle (1996) and test whether certain fund characteristics play a key role in the hypothetical outperformance of actively managed mutual funds during bear markets. The results fail to demonstrate superior conditional performance and reveal no exploitable relationship between the level of active management, the fund size and net fund flows.

Key words: Mutual Funds, Conditional Performance, Recession, Fund Characteristics, Active Management, Active Share, Selectivity, Fund Flows

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Chapter 1: Introduction

Mutual funds have become one of the most popular investment vehicles for both institutional and retail investors, accounting for more than 90% of the investment management firms and managing more than 49 trillion dollars of assets worldwide (Investment Company Institute, 2018). According to a recent report by PwC (2017), the mutual fund industry is set for a rapid growth and expected to almost double its assets under management by 2025.

Actively managed mutual funds, seeking to beat the market through some combination of fundamental and technical analysis based on stock-picking and timing ability, have been historically proven to underperform their risk-adjusted benchmarks after expenses and management fees and its persistence in the performance is generally short-lived as discussed by Jensen (1968), Malkiel (1995), Carhart (1997), Wermers (2000) and Fama-French (2008, 2010) among others. However, reality exposes an uncomfortable truth: most investors keep trusting the skills of professional management to generate positive alpha and optimise their wealth. This paradox has been labelled the Gruber's puzzle (1996) and it is one of the greatest anomalies in finance. Even though passive investing has gained considerable ground in the last decade, the Gruber's puzzle is still relevant as the majority of investors may earn higher returns by means of passive index funds or ETFs, signalling that either investors do not act rationally or they are able to predict which funds will outperform in future or they find other reasons to compensate their losses in profitability.

If some investors can forecast future performance of mutual funds based on past results, they will generate outflows from the poor performers and inflows to the expected future winners, being the past performance the main driver of fund flows (Gruber, 1996; Sirri and Tufano, 1998). Funds with higher net inflows tend to perform better than those that have net outflows so these new cash flows, known as "Smart Money", will earn higher returns than the average money invested in mutual funds. This effect is more visible in small funds than in large funds as documented by Zheng (1999). Nevertheless, Frazzini and Lamont (2008) defend that flows are indeed "Dumb Money" as "Smart Money" effects are confined to shorter horizons that initially believed and net inflows towards previous top performers undermine future fund performance. This fact implies that investors harm the profitability of their investments as a consequence of their own fund reallocation decisions, resulting in a self-inflicted value destroying habit. A more elaborated explanation of this phenomenon had been previously discussed in a theoretical equilibrium model by Berk and Green (2004) who sustain that inflows provoke decreasing returns to scale due to liquidity and organisational issues that affect overall performance received by investors, making big funds uncapable to reflect the skill of their managers. Therefore, fund flows and size seem to play a key role in mutual fund performance.

On the other hand, if investors find other reasons to compensate their losses in profitability, what are these reasons? Behavioural finance theory indicates that most investors are naturally risk-averse and try to protect their wealth at all cost. Traditionally, most literature uses unconditional approaches to measure mutual fund performance which assume a constant level of risk. These approaches have a number of biases and are likely to be unreliable as they do not take into account time-varying performance due to changes in risk (beta) over the different stages of the economic cycle (Ferson and Schadt, 1996; Kosowski, 2001). As a result, value added by active managers is understated during recession periods. Moreover, time-varying performance asymmetries are found to be highly dependent on fund characteristics (Kosowski, 2001). For instance, small funds have a lower price impact that facilitates portfolio rebalancing and a more pronounced time-variation than larger funds (Bogle, 1999).

Applying conditional methods to measure mutual fund performance, some researchers have discovered that average mutual funds do outperform their passive benchmark in bear markets when it matters the most to investors because the marginal utility of wealth is higher during low consumption periods (Kosowski, 2001, 2011; Glode, 2011). If there is a consistent counter-cyclical performance effect — a feature just previously attributed to hedge funds which, unlike most U.S. equity funds, have low correlation with the market —, investors would be willing to pay a risk premium (or sacrifice overall performance) in exchange for protection of their capital during recession periods (Fung and Hsieh, 1997; Cochrane, 2011). These findings constitute a plausible explanation to solve the Gruber's puzzle.

This outperformance of the average mutual funds during down markets has been disputed by Sun, Wang and Zheng (2009) who point out that the aggregate sample of U.S. mutual funds conditionally underperform their benchmark net of fees and that only the most active funds are actually able to beat the market in down periods. They divide portfolios by activeness in order to evaluate the skill of the managers using the Active Share measure introduced by Cremers and Petajisto (2009), reaching the conclusion that active funds where managers showcase their ability and distant their portfolio from the market benchmark obtain higher performance. If managers do not follow the benchmark and obtain abnormal returns by doing so, it means that they engage in stock-picking or market-timing practices which add value to investors. Hence, level of active management as a measure of manager's skill appears to be a relevant feature on mutual fund performance evaluation.

The aim of this paper is to shed light on a literature contradiction testing whether mutual funds on aggregate actually outperform the market during downturn periods or only the most active funds manage to do so. In contrast to other studies that treat mutual funds as a whole sample of passive and active funds under unconditional methods (distorting reality in a way that may mislead investors), I add a cross-sectional dimension by sorting portfolios by its level of active management to analyse whether portfolio managers are able to add significant value during recessions. Specifically, I will focus on the conditional relationship between mutual fund performance and fund characteristics such as size and flows under distressed economic and market conditions. Consequently, my research question is:

Do active mutual fund characteristics influence performance during recession periods?

Intuitive finance theory indicates that marginal utility of wealth is higher during low consumption periods such as financial crises or contractions of the economy. Therefore, reaching an answer to my research question is highly relevant for both academic and practical purposes. First, it will help to clarify and expand the literature on different perspectives in terms of feasible explanations to solve the Gruber's puzzle. Next, if outperformance is detected, it will confirm and reinforce the currently controversial framework supporting the idea of counter-cyclical performance as the main reason for investors to engage in actively managed investing while sacrificing alpha. Lastly, analysing the interactions between fund characteristics and exposing its results may equip investors with better tools and understanding for investment decision-making in regards to how to manage their portfolio. For instance, if a combination of fund characteristics is discovered to be positively or negatively related to future outperformance under bear markets, investors may integrate this knowledge into their individual trading or investing strategies and use that information to their advantage.

Chapter 2: Literature Review

This chapter aims to provide a broad overview to the most relevant literature concerning mutual fund performance and the background that substantially influenced and inspired my research question. Specifically, I begin by describing the role and usefulness of mutual funds in our modern society and briefly reviewing its overall trend over the past decades. Then, I discuss and contrast the strength and weaknesses of active and passive management approaches and their implications within the wealth management industry. Afterwards, the conditional performance evaluation methods and its importance under time-varying risk conditions such as expansions and recession is explained. Finally, I illustrate some of the main theories regarding other potential fund characteristics such as size or net flows which may interact with the degree of active management and its relationship with performance.

2.1 Mutual Funds

According to the definition of the U.S. Securities Exchange Commission (2005), a mutual fund is defined as a company that brings together money from many people and invests in stocks, bonds or other assets. The combined holdings of stocks, bonds or other assets the fund owns are known as its portfolio. These portfolios are aligned with investor's preferences and risk profiles in order to meet specific objectives and investment policies that are publicly available.

The main attraction of mutual funds for the small investor is the diversification opportunities they offer at an affordable price. Diversification improves the investor's risk-return trade-off but transaction costs to build a well-diversified portfolio may be excessively high for individuals with limited wealth. Mutual funds provide a way in which the resources of many small investors are pooled so that the benefits of diversification are realised at a relatively low cost.

Open-end equity funds, the most common type of mutual funds (alone making up 55 percent of US mutual fund total assets under management) and the focus of this paper, are characterised by the lack of restrictions to the number of shares they can issue. Each participant owns shares which represent a part of the fund holdings. The number of shares go up or down as shares are bought or sold. These funds have been attracting capital from investors since the end of the Second World War and became popular in the United States of America in the 1950s but it has been in the last decades when their growth evolved exponentially.

TABLE 1

Growth of Assets of Open-End Mutual Funds in the United States of America

This table illustrates the evolution of the assets under management in the United States' open-end mutual fund industry. The sample is cronologically sorted in intervals of 20 years starting from 1940 up to the last observation in 2017, where assets under management are expressed in USD billion. Data extracted from the Investment Company Institute (2018).

Year	Assets under management (USD billion)
1940	0.5
1960	17.0
1980	134.8
2000	6964.6
2017	18746.0

2.2 Active vs. Passive Management: Value Added by Active Management

There are two opposite styles of management in terms of mutual funds and investing philosophies: active management and passive management.

Passively managed funds are designed to track an index benchmark and replicate its performance as accurately as possible by investing in and holding the index portfolio. Generally, their expense ratios and fees tend to be low due to infrequent trading.

Actively managed funds rely on the stock-picking and market-timing skills of the portfolio managers to presumably add significant value while attempting to beat their market benchmark. These funds tend to have much higher expense ratios and management fees as a result of their activity but that has not harmed their popularity among investors, who still mainly choose active mutual funds as their preferred option to manage their wealth.

The discussion about whether active portfolio managers have skills and are capable of adding value and generate abnormal returns has been largely discussed by both corporate and academic world, traditionally finding contradictory or unclear theoretical results and generally disappointing empirical results. One of the first and most influencing works in the field was developed by Jensen (1968) who performed tests to measure mutual fund performance using the Capital Asset Pricing Model over a 10-year sample on 115 funds. He found that the average alpha generated by actively management mutual funds was close to zero before expenses and fees and alpha turned negative when management fees were considered. Additionally, he tested persistence on performance discovering that the chances that a fund with positive risk-adjusted alpha continues to deliver positive alpha on the subsequent year is just slightly higher than 50%. The result suggests that managers achieving abnormal returns do so due to luck rather than skill.

Further studies such as Malkiel (1995), Carhart (1997), Wermers (2000), Fama-French (2008, 2010) and Busse, Goyal and Wahal (2010) have deepened the knowledge and supported similar results that seem to evidence that, on average, active management is not capable to generate any additional value to investors. Indeed, as alpha is negative after discounting expenses and fees. Therefore, actively managed mutual funds, on aggregate, seem to destroy value implying that investors would be better off trusting their wealth to passive funds or ETFs to replicate the market or index portfolio.

These findings are totally in line with one of the most famous and controversial theories in finance: the efficient markets hypothesis presented by Fama (1970). According to this hypothesis, financial markets reflect all public and private information affecting securities and almost instantly incorporate this available information in the price. If this theory is applied in its strong form and financial assets always trade at their fair value, it would be impossible for active asset managers to reach a consistent superior performance than the market through stock-picking or market-timing techniques. The only way to obtain abnormal returns would be to assume a higher level of risk. However, this hypothesis has been broadly challenged by numerous academics such as Grinblatt and Titman (1994) who found that turnover of active funds is significantly positively related with the ability of managers to earn abnormal returns over their benchmark, pointing to a relationship between the activity of the managers and their gross performance. In his acclaimed paper, Carhart (1997) expands the work of Fama-French (1992) and formulates a 4-factor model by adding a momentum factor to the equation in order to explain the equity mutual fund's returns on the cross-sectional variation on average returns. This study unveils interesting findings that directly undermine the efficient market hypothesis by using a sample free of survivor bias: first, persistence in the average mutual fund performance is short but existing and it is mainly driven by the one-year momentum effect of Jegadeesh and Titman (1993). Therefore, it is possible to implement a strategy based on buying past-winners and selling past-losers with the objective to earn higher than average excess returns. Second, the top-decile portfolio sorted by overall performance exhibit an unexplained longer-lasting persistence than its peers, potentially suggesting the presence of skill in a small number of active funds.

Among different schools of thought, Cremers and Petajisto (2009) developed a revolutionary measure named "Active Share" to detect how active a portfolio manager really is or, strictly speaking, how much his fund holdings differ from the index benchmark. Many mutual funds define themselves as active but barely deviate from their reference index to prevent further losses when the market turns against them. By using this measure, those funds are easily identified and separated from other active funds where managers showcase their abilities in stock-picking and market-timing. Furthermore, previous methodologies used to measure activity such as "tracking error volatility" were constrained to quantify the volatility difference between a portfolio return and its reference index, not being able to differentiate between stock-selection and market-timing approaches across funds which follow different strategies. Active Share resolves this issue by providing a clear picture on the level of activity of a certain fund relatively to its peers. Similarly, Amihud and Goyenko (2013) introduced an alternative, simpler and more intuitive approach to evaluate the level of active management in a mutual fund called "Selectivity". This measure, based on the R^2 estimated from the regression of the fund returns on a multifactor benchmark model, does not require mutual fund holdings information and aims to identify the deviation from a theoretical benchmark in a different manner than Active Share, that measures deviation over the reported benchmark, making both approaches complementary.

However, the unexpected finding that greatly influenced my research question was that, taking a large sample of funds from the CRSP database between 1980 and 2003, Cremers and Petajisto (2009) found that a group of mutual funds with high Active Share score are able to outperform their benchmarks after expenses and exhibit stronger persistence that can be used to predict future positive alpha, signalling talent of certain managers. Most active funds with lower Active Share evidenced underperformance as expected. Later on, Amihud and Goyenko (2013) reach similar results with their Selectivity measure, showcasing that funds with high past alpha and high level of activeness (low R^2) significantly outperform their model benchmark producing an annual alpha of 3.8%. Hence, Selectivity can be used as a good predictor of future abnormal returns. This discovery may be connected with the unexplained long-term persistence of some mutual fund in the Carhart (1997) paper.

In an attempt to reconcile both visions regarding the presence or lack of manager's skill and their ability to transform that skill in valuable outcomes for investors, Berk and Green (2004) wonders around why portfolio managers are so highly rewarded and respected for their profession if the efficient market theory and most empirical studies signal that outperforming funds do so due to simple good luck. He pointed that the presence of heterogeneous levels of skill across asset managers and the well-documented average underperformance and lack of long-term persistence of active mutual funds are widely explained as a consequence of decreasing returns to scale related to fund characteristics (inflows and size), as it will be further explained in a following section. The outcome so far is that both universes can cohabit in harmony.

At this point, the Gruber's puzzle (1996) becomes a central topic in finance literature and in my research paper. How to reconcile the exponential growth of actively managed mutual funds while these funds on average have proven themselves consistently unable to outperform their passive counterparts after management fees and expenses?

The first logical attempt to make sense of this puzzle is to assume that investors do not act rationally and their financial decisions are justified by emotions rather than rational decision-making processes as exposed by Elton, Gruber and Busse (2004). Nevertheless, other threads of thinking exhibit a higher number of followers and call attention on two other possible solutions: one of them is related to overlooked benefits enjoyed by investors as a consequence of time-varying performance and its implications on previous mutual fund performance evaluation measure. The other explanation is closely connected to the effects of fund characteristics such as level of active management, fund flows and size on cross-sectional varying performance.

In the following sections of this literature review, the most relevant literature concerning both interpretations and their significance to the purpose of this research paper will be discussed.

2.3 Time-Varying (Conditional) Performance in Recessions and Expansions

The first potential solution to the Gruber's puzzle has its origin in the research carried out by Ferson and Schadt (1996) who analyse mutual fund performance in changing economic conditions and challenge the methods and results of previous literature covering mutual fund performance evaluation on aggregate. By using traditional methods, preceding literature found that the average actively managed mutual fund underperforms their benchmark after fees. Nevertheless, in order to measure performance in search of stock-picking or market-timing ability, these papers use unconditional expected returns, known to drag a number of biases. One of these biases directly affects the results of alpha as a measure of skill, leading to deceptive conclusions because unconditional measures rely heavily on the assumption that beta (as proxy of risk) is constant over time. This is a weak and unsupported claim in modern literature as time-varying risk and expected returns have been reported and evidenced by multiple authors that will be discussed in the following paragraphs.

As a continuation of the previous work, Kosowski (2001) applies conditional performance evaluation methods to a sample of 1,734 U.S. equity funds existing between 1962 to 1994 and tests the asymmetries in time performance during different stages of the economic cycle. Specifically, he uses conditional versions of CAPM, Fama-French 3-factor model and Carhart 4-factor model to assess the average mutual fund performance during recession and expansion periods using a Markov-Switching latent state mixture model to account for expansions and recessions. He finds robust evidence of correlation in the time-varying performance among funds that greatly depend on fund characteristics (Bogle, 1999), challenging the efficiency of the long-established factor models to describe the cross-sectional fund returns. However, his results shed light on a fact that had been previously overlooked by extensive literature: average U.S. mutual funds do outperform the market and generate positive alpha during recession periods. Finally, he concludes that unconditional methodologies that assume constant risk understate the value added by active management during time-varying conditions such as bear markets and financial crisis, periods of low consumption when the marginal utility of wealth is higher for investors.

In a more recent paper inspired by Kosowski's findings, Sun, Wang and Zheng (2009) keep investigating a potential explanation to the Gruber's puzzle by testing whether active funds deliver counter-cyclical performance that would allow investors to hedge against down markets. In order to do so, they greatly extend the data sample to 1,700 active mutual funds from 1980 until 2008, revealing contradictory results and finding that the average active funds (as a group) do not outperform passive index funds during bear markets as previous described. This unpredicted finding was initially attributed to the larger and more recent sample of data used in this paper in comparison to Kosowski (2001). Other authors such as Lynch, Wachter and Boudry (2008) had previously documented the aggregated time-series variation in mutual funds and existing literature had described a large cross-sectional variation in fund activity. For instance, Wermers (2000) evidenced that funds with higher turnover tend to outperform their benchmark, Vanguard Index 500, after deducting expenses and fees. Hence, focusing on most active funds is likely to signal higher levels of performance during the down markets. Applying Cremers and Petajisto (2009) Active Share to sort mutual funds by its level of active management as a measure of manager's skill, the authors discovered that, in contrast to their previous general conclusion, there is a group of highly active mutual funds that are successful to earn significantly higher returns and outperform the market.

In a review of his earlier work, Kosowski (2011) expands the data sample of U.S. equity funds to cover the period between 1962 and 2005, demonstrating that the average annual alpha from the conditional 4-factor Carhart model for equity mutual funds was 4.08% in recessions and -1.33% in expansion periods. These results are consistent with Glode (2011) research who extends Kosowski legacy adopting macroeconomic variables based on real consumption growth such as Industrial Production as a proxy to measure time-varying performance. The outcome of this empirical study is a similar conclusion supporting the systematic outperformance of average actively managed mutual funds during periods of economic downturn through the economic cycle and casting doubt on Sun, Wang and Zheng (2009) aggregate results on mutual fund conditional performance. These new empirical evidence on extensive samples contradicts each other creating a gap in the literature that my research question aims to resolve. Anyhow, all abovementioned researchers agree that the average outperformance (if present) is totally washed out during expansion stages of the economy.

Many authors have speculated about the reasons behind the outperformance of active mutual funds during recession periods. Odean (1998), Barber and Odean (1999), Hou, Xiong and Peng (2009) find that retail investors are more vigilant during bullish markets than in the down market as they are better informed and are more successful to control their emotional reactions against investing. Moreover, speculative traders tend to withdraw in down markets. An alternative explanation is provided by Shin (2003) and Kothari, Shu and Wysocki (2009) who manifest that information asymmetries in the securities market increase over downturn periods as company managers are reluctant to disclose bad news in comparison to good news that are quickly made publicly available. In this environment, portfolio managers have a privileged access to firm's financial forecasts and can benefit from insider information to make more informed trading decisions.

In any case, these discoveries exposed a counter-cyclical performance effect, an attribute that have traditionally only been associated with hedge funds, which frequently show little correlation with the market portfolio as explained by Fung and Hsieh (1997). According to Cochrane (2001) and basic financial theory, most investors are willing to pay a premium for assets whose payoffs are negatively correlated with consumption; this situation tends to occur during contractions of the economy when marginal utility of wealth is higher. If investors are happy to sacrifice overall performance in exchange of this recession insurance, this would partially explain the Gruber's puzzle.

2.4 Fund characteristics: Fund flows and size

The other thread of thinking addressing the resolution of the Gruber's puzzle is based on fund characteristics and comes from the work of Gruber (1996) himself. In this research, he tests whether investors are capable to detect the skill of mutual fund managers and pursue outperforming funds by means of past performance. If some "sophisticated" financiers can do so, net outflows should be present on the poorest performers and net inflows should flow towards the past winners. These new inflows which come from the most informed investors should earn higher returns than the average active mutual funds, compensating the general underperformance and providing a feasible explanation for the puzzle. Gruber evidences that past performance is the main driver to predict cash flows because investors chase past performance, fact that is subsequently supported by Sirri and Tufano (1998). However, larger funds always tend to have larger absolute cash flows, so Gruber suggests to quantify "normalised fund flows" in order to make fair comparisons among fund net flows. These normalised fund flows are calculated dividing the absolute cash flow between the Net Asset Value of the fund at the beginning of the period, giving us an easily comparable growth rate. On the other hand, "not sophisticated" investors will still leave their money in funds that perform poorly due to external influences such as institutional advice or simply lack of knowledge. Empirical evidence from Gruber's study reflects that the inflows into the best past performers is much larger than the outflow in the past worst performers, bringing to light the fact that most investors do not benefit from this strategy and, therefore, do not earn abnormal returns. This circumstance can be attributed to tax effects or just behavioural finance as investors expect to recover loses.

Zheng (1999) research expands Gruber's studies using a large sample of actively managed equity funds and introduces the nowadays well-known concept of "Smart Money" to refer to the wealth flowing among funds in a successful attempt to chase short-term persistence that had been previously documented and explained by abovementioned authors such as Jegadeesh and Titman (1993) or Carhart (1997). This study aims to determine whether investors can forecast future performance and make intelligent decisions and its results show that, even though some astute investors may earn abnormal returns by following a momentum strategy, there is no compelling indication that, on the aggregate, funds that receive higher amounts of money consequently beat their passive counterparts. Nevertheless, funds which receive net inflows are likely to perform better than those which have net outflows.

Another interesting finding from the Zheng (1999) paper is the appearance of a size-effect where investors can obtain approximately 2.2% abnormal yearly returns by chasing the "Smart Money" inflows to small funds rather than larger ones. Exploiting a performance measure presented by Grinblatt and Titman (1993), the study finds that average investors who decide to move their wealth are able to take advantage of persistence and are more rational than initially thought as they direct their capital towards funds with superior performance to average funds. This effect comes to highlight a connection with the time-varying school of thinking and the results of Bogle (1999) who signals that small funds are considerably more time-varying that large funds because they have a lower price-impact on their trades and possess an easier portfolio rebalancing that comes especially handy during periods of liquidity shortage such as sharp bearish markets where liquidity black holes can occasionally appear.

In contrast with Gruber (1996) and Zheng (1999) "Smart Money" theories, Frazzini and Lamont (2008) analysed net fund flows and stock returns over the period between 1980 and 2003, finding that on average, retail investors are not skilful at detecting manager's skill through past performance and allocate their money to funds with holdings in securities that have low future returns indeed. This effect gives birth to the concept of "Dumb Money" as investors are "dumb" in the sense that their own reallocation decisions hurt the growth of their wealth. According to this study, the average mutual fund investor could increase their Sharpe

Ratio just by not participating in his value destroying behaviour. Nevertheless, the "Smart Money" effect is not denied by this paper but confined to short horizons of about one quarter. After this period, "Dumb Money" effect takes control of the flows.

Finally, I would like to highlight a relevant research paper that gives rise to the fund characteristic variables that will be tested to answer the research questions object of this master thesis. The paper was developed by Berk and Green (2004) who employ a rational equilibrium model that computes returns, fund flows and performance outcomes to expose a relationship between performance and fund characteristics. In this model, rational investors compete among them chasing past performance as a proxy to measure the skill of the managers, moving their money into the best performing funds. This pattern continues until the fund reaches a certain size in which the manager is not able to outperform and inflows cease. Equivalently, funds that perform poorly will present outflows that will continue until the fund reaches an optimal size where its alpha comes close to zero. As a result, all mutual funds in equilibrium will have a net alpha equal to zero. Their main finding is the existence of decreasing returns to scale in regards to fund inflows that prevent skilled managers from delivering superior performance. The more inflows, the higher transaction cost and the higher impact in price. As mutual funds increase their net asset price, they face the problem that prices of less liquid stocks are sensitive to the fund's large trades, considerably affecting their price movement. As a result, management fees are gradually increased, cancelling out the gross abnormal returns generated by manager's skill. Moreover, their investment universe is restricted to highly liquid assets, leaving small firm's securities only available to smaller mutual funds. The most important implications of those findings are that, in rational equilibrium, alpha is not a good measure of skill and that past performance will quickly erode expected future performance and, therefore, any predictability.

Elton, Gruber and Blake (2012) support the main finding of Berk and Green (2004) theory in regards to diseconomies of scale in mutual fund performance but they broad the time horizon at which the reallocation of funds occurs, pointing that investors are not completely rational and take a longer period to interpret data and make decisions. Therefore, the growth in size of mutual funds is a much slower process than the one implied by the rational equilibrium model and predictability will exist in the short-run (disappearing over longer horizons) and will be more present in small funds where decreasing returns to scale are less likely to affect their performance. Further corroboration of these phenomenon is studied by Chen et al. (2004) that confirms an empirical evidence of a negative relationship between lagged fund size and excess returns interaction due to liquidity and organizational diseconomies. In addition, Sawicki and Finn (2002) report that small funds have a higher potential to outperform than large funds as they are not constrained by the abovementioned issues and can invest all their assets in their best investment ideas and take optimal position sizes more easily. Moreover, they conclude that small funds appear more frequently among the top performers and less frequently among the bottom performers than their bigger peers.

Taking into account the discussed literature, there is still ambiguity about the reasons why investors engage in value-destroying investments trusting their wealth to actively managed funds instead of allocating it to more profitable passive alternatives. With the aim of shedding some light over this irrational behaviour, I will have a closer look at mutual fund performance controlling for different economic environments, paying special attention to variation in excess returns in risk-varying conditions and the role that fund characteristics play under these circumstances.

Chapter 3: Methodology and Data

In this chapter, the attention is focused on the approach to solve the research question and the presentation of the main variables, methodology, data and sample. First, the testable hypotheses along with some context from the literature review are clearly formulated. Then, I individually introduce each variable involved in this study and the chosen methodology and robustness checks to confront those hypotheses and evaluate mutual fund performance during recessions. Next, I present the data sources and sample of the studied period. Finally, descriptive statistics are reported and their most relevant aspects are assessed.

3.1 Research Hypotheses

There is a widely accepted consensus concerning the general underperformance of actively managed mutual funds in comparison with their passive counterparts under traditionally used unconditional methods. However, ambiguity among researchers dominates when the test is run using conditional methods and controlling for changing economic conditions such as recession and expansion periods within the business cycle.

In order to resolve a literature contradiction between Kosowski (2001, 2011) and Glode (2011) who sustain that the average active mutual fund outperforms its benchmark during bear markets and Sun, Wang and Zheng (2009) who found that only most active funds are able to outperform while the average active mutual fund still underperforms their benchmark, I propose the following hypothesis:

H01: The average actively managed mutual fund significantly outperforms its benchmark during recession periods.

As previously discussed in the literature review, Kosowski (2001) indicates that time-varying performance is highly dependent on fund characteristics but his tests are mainly focus on the aggregate sample of mutual funds as a whole and do not discriminate results by any fund characteristics and its consequence during different states of the economy. Similarly, Bogle (1999) suggests that small funds exhibit a more time varying performance than larger funds due to lower price impact that facilitate portfolio rebalancing among other advantages directly related with the fund size, which can be a differentiating factor during liquidity shortage periods in the stock market such as recessions.

According to Berk and Green (2004), small funds are associated with a lower level of skill among their portfolio managers as they are not able to generate abnormal returns in absence of fund size limitations. This vision collides with previous work from Sawicki and Finn (2002) who illustrate that small funds, benefiting from fewer constrains, are more often among the top performers and less frequently among the bottom performers than bigger mutual funds.

Reconciling both arguments, Elton, Gruber and Blake (2012) claim that the rational equilibrium model fails to accurately represent the human behaviour and conveys an unnecessarily strict interpretation of reality. Specifically, they state that the reallocation of wealth takes place in a much longer horizon and, as a consequence, the growth in size of outperforming mutual funds occurs at a slower pace. This fact signals a fair grade of performance predictability and the existence of skill managers among small funds that will subsequently become bigger over the years.

Possible outcomes of this hypothesis are uncertain due to the contradictory bibliography. Hence, I will try to test the presence of skill in small mutual funds throughout the level of activity and its interaction with the size of these funds. If manager's skill exists in small funds, the more active funds should reflect higher performance. Hence, in order to evaluate the interaction between level of activity and fund size, my second hypothesis is:

H02: Mutual funds with higher level of active management and smaller size show significantly higher abnormal returns during recession periods.

Another feasible explanation to the puzzle is pointed by Grubber (1996) who states that sophisticated investors can actually predict and chase manager's skill using past performance as a proxy to measure future outperformance, so new fund inflows should be able to earn abnormal returns. Zheng (1999) expands Gruber's research and indicates that the "Smart Money" effect last for a timeframe up to 30 months, long enough to take advantage of its benefits before they reverse towards its average. Nevertheless, the "Dumb Money" effect introduced by Frazzini and Lamont (2008) contradicts previous studies signalling that the "Smart Money" effect is much more short-lived and net inflows generate diseconomies of scale in relatively short periods of time. The "Dumb Money" effect is consistent with the fund size and net inflows issues and lack of predictability described by Berk and Green (2004) in their rational equilibrium model.

It is unclear what theory will weigh more in the regression results and whether more inflows will indicate better performance. In order to shed some light over this phenomenon and its relation with the level of activity while controlling for changing economic conditions, my third hypothesis is:

H03: Mutual funds with higher level of active management and positive net inflows show significantly higher abnormal returns during recession periods.

3.2 Methodology

In order to test the aforementioned hypotheses, it is imperative to select an appropriate multifactor benchmark which can be used to evaluate performance.

The globally acclaimed 4-factor model was introduced by Carhart (1997) as an expansion of the widely recognised 3-Factor model (Fama-French, 1992), introducing a momentum factor as a proxy to successfully capture stock market trends derived from behavioural finance inefficiencies. It quickly became an academic and industry standard risk-adjusted benchmark for active management and mutual fund performance evaluation, this being to main reason to include it in the research. The factors included in this benchmark model are $(R_{MKT,t} - R_{f,t})$ – market risk premium –, SMB – small firms minus big firms –, HML – high book-to-market ratio minus low book-to-market ratio – and PR1YR – prior winners minus prior losers – where α_i – performance measure – is the intercept of the regression of the excess returns on the abovementioned risk factors. The formulation of the model is represented as follows:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{1,i}(R_{MKT,t} - R_{f,t}) + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \beta_{4,i}PR1YR_t + \epsilon_{i,t}$$

Another model is used to ensure robustness in the results. In this case, I will also replicate the regressions under a 6-Factor benchmark model constructed and based on the recently presented 5-factor model (Fama-French, 2015) where the authors added two additional factors RMW – returns of high operating profitable firms minus returns of low operating profitability firms – and CMA – returns of firms with conservative investing style minus returns of firms with aggressive investing style – to improve the explanatory power of their previous and most influential model (Fama-French, 1992). However, this new model has been criticised by both academic and corporate users as it keeps ignoring the momentum premium which has been widely documented on the financial literature. Hence, I aggregate a momentum factor

(Carhart, 1997) to the model in order to capture this anomaly that plays a prominent role in active management strategies. The equation of the newly constructed 6-Factor model is represented as follows:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{1,i}(R_{MKT,t} - R_{f,t}) + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \beta_{4,i}RMW_t + \beta_{5,i}CMA_t + \beta_{6,i}PR1YR_t + \epsilon_{i,t}$$

The previous models are design to measure performance under classic unconditional methodology. Ferson and Schadt (1996) drew attention on the consequences of assuming constant risk conditions over time to calculate average alphas, signalling that doing so lead to unreliable results. Subsequently, Kosowski (2001) claimed that previous unconditional measures used in most mutual fund performance evaluation literature understate the value added by asset managers during recession periods due to expected returns and risks varying over time. Therefore, to prevent any misleading inferences in data alongside this study, I will conditionally adapt the benchmark models to account for changing economic conditions by using a binary vector (dummy variable) and interaction terms to control for expansions and recessions in expected returns and betas.

The adapted conditional 4-factor model (Carhart, 1997) is inspired by Christopherson, Ferson and Glassman (1998) and Glode (2011) work including time-varying alphas, obtaining the following regression model:

$$R_{i,t} - R_{f,t} = \alpha_i + \alpha'_i DUM_t + \beta_{1,i}(R_{MKT,t} - R_{f,t}) + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \beta_{4,i}PR1YR_t + \beta'_{1,i}DUM_t(R_{MKT,t} - R_{f,t}) + \beta'_{2,i}DUM_t SMB_t + \beta'_{3,i}DUM_t HML_t + \beta'_{4,i}DUM_t PR1YR_t + \epsilon_{i,t}$$

In this conditional model, the variable DUM is a binary dummy variable that will assume value of “0” during expansion periods of the economy and value “1” for recession periods. The economic environment data to feed the dummy variable will be extracted from two different sources to ensure robustness: a) the information on recessions and recoveries provided by the National Bureau of Economic Research (NBER) b) a manually created parameter using publicly available stock market historical returns from the S&P 500 index. The intercept α'_i and additional coefficients β' which interact with the dummy variable indicate the marginal contribution to excess returns during economic downturns. For instance, the term α_i represents manager’s skill during expansion periods whereas the terms $\alpha_i + \alpha'_i DUM_t$

showcase the conditional contribution of active management to the excess returns when the dummy variable takes the value of “1” during recessions or bear markets.

Equivalently, the adapted conditional 6-Factor model is estimated as follows:

$$\begin{aligned}R_{i,t} - R_{f,t} = \alpha_i + \alpha'_i DUM_t + \beta_{1,i}(R_{MKT,t} - R_{f,t}) + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \beta_{4,i} RMW_t \\ + \beta_{5,i} CMA_t + \beta_{6,i} PR1YR_t + \beta'_{1,i} DUM_t(R_{MKT,t} - R_{f,t}) + \beta'_{2,i} DUM_t SMB_t \\ + \beta'_{3,i} DUM_t HML_t + \beta'_{4,i} DUM_t RMW_t + \beta'_{5,i} DUM_t CMA_t \\ + \beta'_{6,i} DUM_t PR1YR_t + \epsilon_{i,t}\end{aligned}$$

All the abovementioned benchmark models will be used to test unconditional and conditional performance by running panel regressions sorted by monthly observations on an extensive number of actively managed mutual funds over the sample.

In order to test hypotheses H02 and H03, I choose a portfolio-building approach with variables controlling for fund characteristics such level of active management, fund size and net fund flows. To begin with, I organise excess returns, Minimum Active Share, Constant Selectivity, total net assets and normalised net fund flows in panel format. Next, I rank cross-sectional observations and assign them to a quintile portfolio at the beginning of each month based on the characteristics of the previous time period. Then, I compute the equally-weighted average excess returns for the 25 portfolios (5x5) resulted from the interaction between variables. For the second hypothesis, these interactions are the level of active management (reflected by Minimum Active Share and Constant Selectivity) and fund size sorted by total net assets (TNA). For the third hypothesis, the level of active management and normalised net fund flows are the variables intertwined. Both sets of portfolios will be rebalanced on a monthly basis to account for the changes in level of activeness, size and net fund flows. Later on, I regress the time-series average excess returns of each portfolio on the Fama-French factors and report their monthly alphas. This process will be performed for the recession periods detected by both NBER and market indicators to test robustness of the results.

The level of active management is one of the key variables in this study. Active management can be defined as a conscious attempt to maximise returns while minimising risk and beat the market making use of stock-picking ability, market timing ability or both. The incentive for active management firms is that the excess returns over the benchmark surpass the expenses incurred by transaction costs, equity research and analysts’ expenses and asset manager’s remuneration.

With the aim of ensuring robustness, I will use two different but complementary approaches to establish how active a mutual fund really is in regards to its trading operations. Both methods are relatively recent and have been included in this study due to its predictive power in mutual fund performance. Other traditional measures such as "Tracking Error" (Roll, 1992) focus exclusively on market timing which has not yet been proven to have any predictive power on future returns and are, therefore, excluded from this research.

The first and main tool used to measure the level of active management in this study is "Active Share", introduced by Cremers and Petajisto (2009), and represents the fraction of the mutual fund portfolio holdings which deviate from the reported benchmark holdings. Active Share is expressed as a percentage – always between 0% and 100% in the absence of leverage or net short positions – and can be interpreted as a proxy to measure stock picking ability where $w_{fund,i}$ and $w_{index,i}$ are the weights of a specific asset in the fund and in the benchmark index, respectively. Its major drawbacks are the lack of availability of public information in regards to fund holdings composition, which can be difficult to obtain for most investors, and the fact that index benchmarks may differ from the reported ones or simply vary over time. The latter can be solved by using the most similar benchmark as a reference instead of the reported one, known as "Minimum Active Share". On the other hand, it can be calculated at any point in time even for recently-established funds as it does not require historical data other than the current portfolio holdings. In any case, Active Share is a very powerful and indicative measure that has quickly gained popularity among academia, mutual fund industry and investors over the last years. Its formulation is presented as follows:

$$Active\ Share = \frac{1}{2}\sum_{i=1}^{N}|w_{fund,i} - w_{index,i}|$$

The second measure, used as a robustness check to detect the degree of active management, is called "Selectivity" and it is based on the work of Amihud and Goyenko (2013) who propose that R^2 – derived from the regression of excess returns on a multifactor benchmark model – can be interpreted not only as an activeness indicator but also as a good predictor of mutual fund alpha. One of the strongest points of the Selectivity measure is its simplicity and intuitive interpretation. Moreover, its calculation only requires information about historical returns that is publicly available for researchers and does not involve any input about portfolio holdings. R^2 is the proportion of the mutual fund return variance that is explained by the risk factors included in the benchmark model and, therefore, a low value in

R^2 – higher value in Selectivity – signals deviation from the passive benchmark and is positively related to higher expected returns. The creators of the measure used a prior 24-month calculation period to compute Selectivity. However, given the limited number of monthly observations for each fund in my data sample, I choose to implement a constant measure of selectivity regressed over the total time-series length of each fund, which is calculated in the following way:

$$Selectivity = 1 - R_i^2$$

The idea behind using both measures complementarily is to implement a safeguard against biases derived from self-reported benchmark indexes that do not correspond with the mutual fund actual strategies or holdings. Even though both Active Share and Selectivity aim to capture the level of active management in a mutual fund, their approach is different and, occasionally, so their results. Active Share reflects deviation from a pre-established benchmark when a manager allocates different weights of his portfolio in multiple passive investments, considering this activity as active management. Meanwhile, Selectivity classify this kind of strategy as passive investing due to its calculation from a theoretical index model.

To illustrate this concept, consider a mutual fund whose reported benchmark is the Dow Jones Index but invests most of its holdings passively in a high-yielding ETF than is expected to outperform the Dow Jones index systematically. In this case, Active Share will report a positive and high active management percentage for a mutual fund that is actually a passive index tracker. By contrast, Selectivity results will be close to zero as the fund will be detected as an index tracker by the selected multifactor model in use.

For the estimation of the net fund flows variable, I employ the "Normalised Net Fund Flows" approach following the work by Gruber (1996) instead of absolute net flows in order to avoid a known bias due to the fact that larger funds tend to present higher absolute flows regardless past performance. The first step is to subtract $TNA_{i,t-1}(1 + RET_{i,t})$ – total net asset value of the fund at the beginning of the period times one plus the return of the fund throughout the calculation period – from $TNA_{i,t}$ – total net asset value of the fund at the present point in time – to obtain the absolute net fund flows of the period. Subsequently, the Normalised Net Fund Flows are calculated dividing the absolute net fund flow between the total net asset value of the fund at the beginning of the period ($TNA_{i,t-1}$), providing an easily comparable growth rate which is represented as follows:

$$Normalised\ Net\ Fund\ Flows = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + RET_{i,t})}{TNA_{i,t-1}}$$

The result will be positive for funds that receive more inflows than outflows and negative for funds that experience more outflows than inflows.

3.3 Data

This research collects information from multiple data sources that will be discussed in this section.

First and foremost, historical data between 1962 and 2018 on monthly returns (net after fees, expenses, and brokerage commissions) and fund characteristics for over 64,000 U.S. publicly traded open-end mutual funds is retrieved from the CRSP Survivor-Bias-Free U.S. Mutual Fund Database – Center for Research in Security Prices – which provides information about multiple attributes such as unique identification number, monthly returns, total net assets, net asset value or fund objectives, among others. The main reason for choosing this specific database is that it has no minimum survival requirements and is, therefore, free of survivorship bias. This tendency has become a relevant issue in performance evaluation in the last decade and CRSP includes all active, merged and inactive or ceased open-end equity mutual funds for the U.S. region, correcting for this kind of bias in the sample.

Second, a variable to measure the level of activity is downloaded from two different sources. As previously discussed, the calculation of Active Share requires not publicly available information about mutual fund holdings. This fact could have presented a limitation in this study but, fortunately, readily constructed Active Share data for U.S. mutual funds have been made available in both Petajisto's website and University of Notre-Dame's website, which Active Share database is maintained by Cremers, the other designer of the measure. Following Petajisto (2013) methodology, Petajisto's database covers the period between 1980 and 2009 while Cremers' data sample extends from 1990 to 2015. For the cases where the official reported benchmark is inaccurate or misleading, the authors provide an alternative suggested benchmark that results on the lowest Active Share percentage. This calculation is known as "Minimum Active Share" and will be used as standard Active Share measure in this study.

From the downloaded information, I initially merge Active Share databases from Petajisto and Cremers using the MFLINKS conversion table to assign Wharton Financial Institution Center Number (WFICN) as a unique and permanent fund identifier to each mutual fund. In this case, Cremers database is linked to Thomson Reuters mutual fund database instead of CRSP so the use of WFICN ensures accuracy of the merged dataset and facilitates subsequent merging with other sources such as the CRSP database. Unfortunately, MFLINKS does not provide conversion for all known funds in CRSP so I only keep Active Share observations which can be associated to either WFICN or CRSP fund number. Furthermore, both data sets share part of their time periods. When overlapping occurs, Petajisto dataset is kept due to its direct link with CRPS database, a higher consistency in data reporting and the inclusion of other identifiers such as ticker or fund name.

Subsequently, I merge the newly created Active Share data set with the CRSP returns and summary information in a unique database making use of the CRSP Fund Number, WFICN and, as a last resort, ticker and fund name. I construct the data set used in this study following various of the clearing, merging and organising steps described in Berk and Van Binsbergen (2011) by replacing "-99" and other missing values with blanks and excluding funds with no information about returns, total net assets or net asset value per share as they are essential for the calculation of the fund size and net fund flow variables. In this sense, quality and frequency of data is substantially more reliable after 1988 when monthly observations begin to be consistently reported for most of the funds. Hence, I eliminate all observations prior to this year and after 2015, when Active Share information is not publicly available anymore. Next, I rearrange asset classes under the same mutual fund (classified with different fund number in CRSP) by adding up its TNA and taking the weighted average of its net returns, that will slightly differ due to expenses. As the interest of this study is to analyse actively managed mutual funds only, I erase index funds by dropping funds with a Minimum Active Share less than 0.2 (20%) or including the terms "index" or "market fund" in its name. Then, I discard funds with TNA smaller than $15 million due to a known bias pointed by Elton, Gruber and Blake (1996) consisting in small funds showing a recurring upward bias in reported returns. From the remaining, I also erase funds with less than 10 monthly observations from the sample to ensure a sufficient number of periods when performing time-series and panel regressions. To correct for outliers, winsorization at 1% and 99% level is applied to the total net assets. Other variables such as Minimum Active Share and Constant Selectivty did not present relevant outliers while Normalised Net Fund Flows were constructed from the winsorised variables.

After following the aforementioned steps, I ended up with a total of 253,899 monthly observations and 2,078 actively managed mutual funds covering the 1988-2015 period.

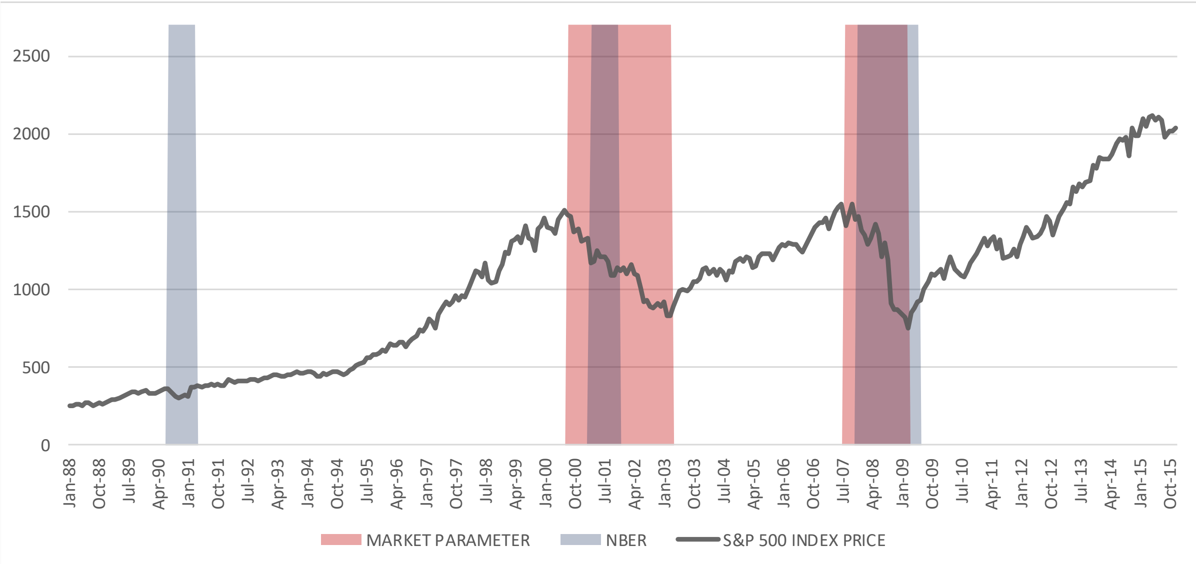
In order to control for the time-varying risk within the economic cycle, I use two different measures to establish the limits between expansion and recession periods. The first one is based on economic growth and it is directly retrieved from the NBER – National Bureau of Economic Research – which defines a recession as “a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales”. The second parameter is meant to capture anomalies in the stock market performance that do not necessarily translate into macroeconomic noticeable changes in the economic growth. This parameter is manually created using stock market historical absolute returns in the S&P500 index which is a fair reflection of the financial behaviour of the U.S. stock market as it captures approximately 80% of the total market capitalisation of the North American market. In this parameter, a drop of 19% or more from a previous peak in the price of an index is considered a bear market as it is considered by most technical analysts. The calculation is performed over the whole sample as it does not differ from establish a standard holding period of 60 months. Under these conditions, a bullish market is considered to start from the previous lowest point in price until the next bear market signal triggers. Given the large data set used in this research, both measures will lead to a sufficient number of upturns and downturns that will facilitate the analysis to answer the research question.

Figure 1 showcases the significant downturn periods detected by the two measures used in this study. Overall, there are three remarkable periods of economic decline in the sample period between January 1988 and December 2015: the early 1990s recession, the burst of the dotcom bubble and the “Great Recession”. As initially expected, both measures overlap during a considerable number of monthly observations but also present relevant differences derived from its calculation methods. Specifically, the NBER indicator presents 299 months in expansion against 37 months in economic recession while the market parameter exhibits 284 months in bull or lateral markets against 52 months in bear markets. It is noticeable that the NBER indicator reflects the three aforementioned crises while the market parameter does not decline enough to trigger the bear market signal during the early 1990s recession. Furthermore, the market parameter signals recession several months before the NBER indicator (delayed due its macroeconomic features) in both the dotcom bubble and 2008 financial crisis and, in the case of the dotcom bubble crisis, the NBER indicator comes back towards an expansion stage while the S&P 500 index is still dropping sharply. The most noteworthy overlapping between the indicators is exposed during the “Great Recession” when both NBER and market parameters reveal an equivalent length for the recession period, varying only in the chronology of the inception and closure of that period.

FIGURE 1

Recession Indicators Based on NBER and S&P 500 Index Performance

This figure represents the evolution of the S&P 500 index price for the sample period between January 1988 and December 2015 and the downturn stages of the economy during this timeframe. S&P 500 index prices, represented by the grey line, display closing prices at the end of every trading day and were extracted from the DataStream database. The shadowed areas, which ocassionally overlap, indicate recession periods measured by two financial cycle proxies: NBER and Market Parameter. The light blue shadowed areas correspond to the NBER indicator which highlights contractions of the real economy (declines in economic activity) calculated by the National Bureau of Economic Research based on macroeconomic parameters such as real GDP, real income, employment rates, industrial production, and wholesale-retail sales. The red shadowed areas correspond to the Market Parameter indicator which signals severe bear markets (≥19% decline from previous market peak over the whole sample) in the U.S. stock exchange.



Finally, historical information on the construction of the risk factors used in the unconditional and conditional benchmark models are directly downloaded from Kenneth R. French Data Library. Since this study focus on U.S. open-end equity mutual funds, data on the traditional Fama-French and momentum factors are extracted from the United States of America library.

3.4 Descriptive Statistics

Table 2 aims to provide a comprehensive summary of the descriptive statistics of the actively managed equity mutual fund characteristics and excess returns in the sample period between January 1988 and December 2015. First, Panel A reports mean, median, minimum, maximum and standard deviation values of the whole sample that will be used to test performance under unconditional methods. Then, Panel B exhibits the same statistics dividing the previous sample in expansion and recession periods according to both NBER indicator and S&P500 market parameter. This segregation illustrates the differences in fund characteristics and excess returns among subsamples when using conditional methods for the state of the economy.

Concerning the whole sample of 2,078 actively managed mutual funds, the average fund size was $479.34 million, ranging from the smallest $15 million funds (lower limit imposed in the data filtering) to $8219.6 million after winsorising the variable and exhibiting, therefore, a high standard deviation. The normalised net fund flows ratio is close to zero and just slightly positive, exposing the rapid growth of passive funds and ETFs in the last decade at the expense of their purely active counterparts which have lost a significant percentage of the market share that used to belong to them. While the extreme observations are distant from each other, most values in the sample of normalised net fund flows float around zero.

Minimum Active Share has an average ratio of 0.772 signalling than the 77.2% of the holdings of the average active mutual fund are different than its most similar index benchmark. Its minimum value is 0.2 because funds below that threshold were identified as index funds or funds claiming to be active but behaving like enhanced index trackers. In both cases, they were erased from the purely actively managed mutual fund sample of this study. On the other hand, Constant Selectivity has an average value is 0.163, indicating that R-Squared is “only” able to explain 83.7% of the excess returns of the average active mutual fund. Looking at the maximum and minimum values, it seems apparent that there is a high degree of variation in the cross-sectional dimension of this variable.

Lastly, the monthly excess returns over the risk-free rate has a positive net average of 0.468%, in other words, a yearly average of 5.62% after fees. The worst monthly return for a certain fund was -46.48% and the best result was 67.92% by contrast.

TABLE 2

Summary Statistics on Actively Managed Equity Mutual Funds

This table illustrates a summary of descriptive statistics of the main variables corresponding to the sample of actively managed equity mutual funds between January 1988 and December 2015. Panel A displays the group of fund characteristics and excess returns which are object of this study on an unconditional basis over the whole sample. Panel B represents the summary statistics divided into subsamples representing the expansion and recession periods of the economy according to the two proxies for the state of the economy: NBER and Market Parameter. *No. Funds* refers to the number of funds which are present in each sample for both unconditional and conditional observations. *TNA* is the total net assets under management expressed in USD millions for each sample period. *Normalised Net Fund Flows* is an easily comparable growth rate for the inflows and outflows which accounts for deposits and withdraws amongs funds. *Minimum Active Share* is a proxy for the level of active management implemented as per Cremers and Petajisto (2009) that can be interpreted as the fraction of a portfolio that is different from the closest possible index. *Constant Selectivity* refers to a steady measure of activeness introduced by Amihud and Goyenko (2013) based on the R-Squared of the fund over its time-series observations. *Excess Returns* is the dependent variable that refers to the absolute monthly return of a fund expressed as percentage once the risk-free rate has been substracted.

Panel A: Fund Characteristics (Unconditional)

Total No. Funds: 2,078	Mean	Median	Min	Max	Std. Dev.
TNA ($ millions)	479.34	111	15	8219.6	1155.35
Normalised Net Fund Flows (ratio)	0.007	-0.003	-0.966	46.26	0.187
Minimum Active Share (ratio)	0.772	0.799	0.20	1.00	0.154
Constant Selectivity (ratio)	0.163	0.118	0.011	0.983	0.151
Excess Returns (% per month)	0.468	0.766	-46.484	67.917	4.959

Panel B: Fund Characteristics (Conditional)

NBER	Expansion (NBER)					Recession (NBER)				
No. Funds Expansion: 2,078 *No. Funds Recession: 1,669*	Mean	Median	Min	Max	Std. Dev.	Mean	Median	Min	Max	Std. Dev.
TNA ($ millions)	484.56	112	15	8219.6	1161.1	441.32	103.8	15	8219.6	1111.9
Normalised Net Fund Flows (ratio)	0.007	-0.003	-0.966	32.994	0.168	0.008	-0.004	-0.903	46.26	0.291
Minimum Active Share (ratio)	0.773	0.801	0.20	1.00	0.153	0.762	0.792	0.234	1.00	0.159
Constant Selectivity (ratio)	0.164	0.118	0.011	0.983	0.151	0.159	0.114	0.011	0.983	0.15
Excess Returns (% per month)	0.737	0.908	-46.48	67.917	4.499	-1.492	-0.936	-37.84	51.886	7.204

Market Parameter	Expansion (Market Parameter)					Recession (Market Parameter)				
No. Funds Expansion: 2,069 *No. Funds Recession - 1,620*	Mean	Median	Min	Max	Std. Dev.	Mean	Median	Min	Max	Std. Dev.
TNA ($ millions)	484.43	112.7	15	8219.6	1156.9	459.51	104.9	15	8219.6	1148.8
Normalised Net Fund Flows (ratio)	0.006	-0.003	-0.966	24.03	0.146	0.01	-0.003	-0.903	46.26	0.297
Minimum Active Share (ratio)	0.775	0.802	0.201	1.00	0.152	0.759	0.788	0.20	1.00	0.159
Constant Selectivity (ratio)	0.164	0.118	0.011	0.983	0.152	0.159	0.116	0.011	0.983	0.146
Excess Returns (% per month)	1.055	1.091	-34.57	67.917	4.286	-1.821	-1.217	-46.48	40.046	6.501

Regarding the NBER and market parameter subsamples, their statistics seem robust. For the NBER subperiods, all funds are present during expansions while only 1,669 funds experienced recessionary periods. For the S&P500 market parameter, 2,069 funds come into view in expansion and 1,620 funds do the equivalent in bear markets. Even though the average total net assets under management declines between states of the economy as a result of negative returns in bear markets, it is remarkable that net inflows become larger during downturns for both state indicators. The reason behind this phenomenon may be attributed to investor’s fear of being dragged by the negative performance of index funds and would signal increasing trust in the ability of portfolio managers to generate abnormal returns during adverse times. Contrarily, average Minimum Active Share and Constant Selectivity tend to decrease during recessions, evidencing that active bets are reduced in number and minimising tracking error becomes increasingly important for fund managers.

In line with expectations, the monthly excess returns substantially are higher during expansions, being 0.74% for NBER and 1.05% for the market parameter, and decrease during contractions of the economy to -1.49% for NBER and -1.82%. On aggregate, these returns yield a yearly average of 10.72% during expansions and -19.86% during recessions. Curiously enough, it turns out that the most negative return of the unconditional sample is present on the expansion period of the NBER indicator and not on the recessionary as naturally one would expect. This occurs because NBER parameter is an ex post indicator which takes information from the delayed macroeconomic variables whereas the market parameter accounts for the contraction period since the start of the change of the downward trend.

Table 3 exhibits the pairwise correlation coefficients among the fund characteristics analysed in this research paper to account for fund size (TNA), fund flows (Normalised Net Fund Flows) and level of active management (Minimum Active Share and Constant Selectivity). The statistics reveal significant but very weak positive and negative correlations among most variables, which do not have any interdependent relationship. Furthermore, in line with previous expectations, the strongest correlation is detected between Minimum Active Share and Constant Selectivity, which are both used as proxies for active management. However, it is initially surprising to find that the correlation between these variables is indeed negative with a -0.401 value. This unforeseen contrarian relationship was nevertheless consistent with Amihud and Goyenko (2013) and recently revisited by Dos Santos Guzella and Campani (2017) who found a moderate negative correlation of -0.45 between Active Share and Selectivity in the Brazilian equity fund market. The inverse relationship is associated with the fact that each measure of activeness captures information about mutual funds that is not incorporated into the calculation of the other.

TABLE 3

Correlation Matrix

This table reports the pairwise correlation coefficients among the independent variables across the whole sample of actively managed mutual funds between January 1988 and December 2015. *TNA* is the total net assets under management expressed in USD millions for each sample period. *Normalised Net Fund Flows* is an easily comparable growth rate for the inflows and outflows which accounts for deposits and withdraws amongs funds. *Minimum Active Share* is a proxy for the level of active management implemented as per Cremers and Petajisto (2009) that can be interpreted as the fraction of a portfolio that is different from the closest possible index. *Constant Selectivity* refers to a steady measure of activeness introduced by Amihud and Goyenko (2013) based on the R-Squared of the fund over its time-series observations. The coefficients denoted with * are significant at 10% level, with ** are significant at 5% level and with *** are significant at 1% level.

	TNA	Normalised Net Fund Flows	Minimum Active Share	Constant Selectivity
TNA	1.00			
Normalised Net Fund Flows	0.003*	1.00		
Minimum Active Share	-0.117***	-0.005***	1.00	
Constant Selectivity	-0.009***	-0.011***	-0.401***	1.00

Correlations among factors of the benchmark models are not separately reported as they can be easily extracted from the Kenneth R. French Data Library for any specific time period. Nevertheless, all factors present weak correlation in the Carhart 4-factor model, evidencing the good fit of the model and the distinguishability of the independent variables. Concerning the Fama-French 5-factor model plus momentum, the RMW factor reveals moderate negative correlation of -0.417 and -0.4573 with the MKT-RF and SMB factor respectively. Moreover, a strong positive pairwise correlation of 0.662 is presented between the HML and CMA factors, which is still lower than the 0.70 reported by Fama-French (2015). In conclusion, correlation coefficients are in line with previous expectations and no multicollinearity is observed among factors.

Chapter 4: Empirical Results and Discussion

Following the previous steps discussed in the methodology section, this chapter discloses and comments on the results of the analysis of the data sample and aims to answer the three aforementioned hypotheses. First, I revisit and test the previous literature regarding unconditional performance of actively managed equity mutual funds. Then, I present the results of the conditional benchmarks over the whole sample controlling for the state of the economy. Later on, conditional performance on the NBER indicator and market parameter recession subsamples is analysed by means of portfolio approach implementation between level of activeness and fund size. Lastly, I repeat the previous approach to test the performance on recessions while controlling for level of active management and fund flows.

TABLE 4

Unconditional Performance of Actively Managed Equity Mutual Funds

This table reports the monthly coefficients of the panel regression of the time-series excess returns in the cross-section of actively managed mutual funds over two benchmark models: Carhart 4-Factor Model and the Fama-French 5-Factor Model + Momentum. The sample period extends from January 1988 until December 2015. *Alpha* is the constant term of the regression results which is not explained by the independent factors and signals relative performance against the benchmark. *MKT-RF* is the beta on the market risk premium. *SMB* is the beta on small minus big firm's return. *HML* refers to the beta on difference between high and low book-to-market ratio returns. *PR1YR* is the beta on 1-year prior winners minus losers (momentum). *RMW* refers to the beta on robust minus weak operating profitability firm's returns. *CMA* stands for the beta on conservative minus aggresive firm's returns. Numbers in parentheses represent the t-statistics of the coefficients. Those denoted with * are significant at 10% level, with ** are significant at 5% level and with *** are significant at 1% level.

	Carhart 4-Factor Model	Fama-French 5-Factor Model + Momentum
Alpha (α)	-0.088	-0.076
	(-15.31)***	(-12.77)***
MKT-RF (β)	0.906	0.899
	(647.08)***	(560.43)***
SMB (β)	0.163	0.164
	(89.13)***	(78.68)***
HML (β)	0.149	-0.001
	(7.59)***	(-0.08)
PR1YR (β)	0.172	0.020
	(14.64)***	(16.78)***
RMW (β)		-0.022
		(-7.74)***
CMA (β)		-0.018
		(-4.74)***

Table 4 shows the results of the panel regressions of excess returns under the Carhart 4-factor model and the Fama-French 5-factor model plus momentum. Constant terms and beta coefficients are reported along with their t-statistics and level of significance. This first test attempts to confirm the widely-accepted idea that, on average, active mutual funds are not able to obtain the same returns as their passive counterparts after fees and expenses.

The results expose a clear pattern in alpha, also known as the active return on an investment, that is robust and significant at 1% level for both benchmark model: there is a consistent monthly underperformance between -0.088% and -0.076% for the Carhart 4-factor model and the Fama-French 5-factor model plus momentum. This accounts for a notorious yearly gap against the index funds of -1.06% and -0.91% respectively. It is, therefore, confirmed that the average mutual fund consistently underperforms its benchmark.

Looking at the beta coefficients, it becomes apparent that most of the explanatory power over returns comes from the exposure the market premium risk factor which presents the highest coefficient with the highest level of significance regardless the model used. All other factor loadings are highly significant at 1% level for both benchmark models except the HML factor which appears to be insignificantly different from zero in the Fama-French 5-factor model plus momentum.

The next step to resolve H01 is to test whether the average actively managed mutual fund is able to deliver significant outperformance under distressed economic and market conditions as suggested by Kosowski (2001, 2011) and Glode (2011) or it is indeed underperforming their passive benchmark as sustained by Sun, Wang and Zheng (2009). In order to do so, the conditional models with a binary state-dependent variable and interaction terms presented in the methodology section will be used to test the full sample.

Table 5 exhibits the results of the panel regressions of the excess returns over the conditional Carhart 4-factor model and Fama-French 5-factor model plus momentum accounting for the state of the economy according to the dummies delivered by the NBER indicator and S&P500 market parameter.

Concerning the NBER indicator under the Carhart 4-factor conditional model, the constant term reports a highly significant negative monthly alpha of -0.084% during expansion periods whereas the dummy alpha term indicates that the marginal contribution of the managers is not different from zero, suggesting that the state of the economy does not have an effect in mutual fund performance. However, this result is not robust as it substantially differs from the outcome under the Fama-French 5-factor plus momentum conditional model. For the latter, the monthly alpha during expansionary times is -0.064% and significant at 1% level while the dummy alpha has a highly significant monthly negative contribution of -0.083% to the distressed alpha (sum of alpha and dummy alpha), adding up to a -0.147% underperformance during recessions. These findings are not consistent which each other and the result is dependent on the benchmark model applied.

TABLE 5

Conditional Performance of Actively Managed Equity Mutual Funds during Recessions and Expansions

This table reports the conditional monthly coefficients of the panel regression of the time-series excess returns in the cross-section of actively managed mutual funds over two benchmark models: Carhart 4-Factor Model and the Fama-French 5-Factor Model + Momentum. The sample period extends from January 1988 until December 2015 and it distinguishes between expansion and recession stages using a binary dummy variable and interaction terms across the factors of each model to account for time-varying exposure to those factors. The information about the state of the economy emanates from two independent sources: NBER indicator and S&P500 market parameter. *Alpha* is the constant term of the regression results which is not explained by the independent factors and signals relative performance against the benchmark. *MKT-RF* is the beta on the market risk premium. *SMB* is the beta on small minus big firm's return. *HML* refers to the beta on difference between high and low book-to-market ratio returns. *PR1YR* is the beta on 1-year prior winners minus losers (momentum). *RMW* refers to the beta on robust minus weak operating profitability firm's returns. *CMA* stands for the beta on conservative minus aggresive firm's returns. All coefficients with the suffix *DUM* refer to the the binary dummy variable and interaction terms which indicate the marginal contribution to the dependent variable (excess returns) during recession periods. Numbers in parentheses represent the t-statistics of the coefficients. Those denoted with * are significant at 10% level, with ** are significant at 5% level and with *** are significant at 1% level.

	Carhart 4-Factor Model		Fama-French 5-Factor Model + Momentum	
	NBER	S&P500	NBER	S&P500
Alpha (α)	-0.084	-0.045	-0.064	-0.032
	(-13.36)***	(-6.66)***	(-9.88)***	(-4.65)***
Alpha (α) DUM	0.000	-0.021	-0.083	-0.063
	0.01	-1.42	(-3.85)***	(-3.91)***
MKT-RF (β)	0.893	0.882	0.882	0.873
	(548.31)***	(490.06)***	(495.40)***	(455.81)***
MKT-RF (β) DUM	0.069	0.092	0.096	0.102
	(17.93)***	(28.96)***	(20.03)***	(26.93)***
SMB (β)	0.169	0.177	0.166	0.177
	(86.14)***	(85.04)***	(72.02)***	(68.11)***
SMB (β) DUM	-0.069	0.003	-0.057	0.013
	(-10.86)***	0.7	(-8.79)***	(2.48)**
HML (β)	0.050	0.017	0.052	0.022
	(21.61)***	(5.98)***	(15.54)***	(5.76)***
HML (β) DUM	-0.167	-0.030	-0.212	-0.089
	(-36.46)***	(-7.42)***	(-32.81)***	(-15.26)***
PR1YR (β)	0.034	-0.006	0.039	-0.001
	(23.35)***	(-3.92)***	(26.20)***	-0.40
PR1YR (β) DUM	-0.035	0.091	-0.044	0.082
	(-12.34)***	(33.91)***	(-15.11)***	(29.80)***
RMW (β)			-0.042	-0.031
			(-13.72)***	(-8.39)***
RMW (β) DUM			0.097	0.031
			(9.18)***	(4.41)***
CMA (β)			-0.033	-0.051
			(-8.01)***	(-9.85)***
CMA (β) DUM			0.067	0.082
			(5.41)***	(10.55)***

Regarding the S&P500 market parameter under the Carhart 4-factor conditional model, its expansionary monthly alpha is highly significant and negative (-0.045%) whereas the marginal contribution of the dummy alpha is -0.021% but not significant at the 10% level required. In this case, bear markets do not seem to play a significant role in active funds. Once again, the outcome is different under the Fama-French 5-factor plus momentum conditional model: monthly alpha during expansions is -0.032% and significant at 1% level while the marginal contribution of the dummy term is -0.063% and also highly significant, accounting for a monthly negative alpha of -0.095% during crashes in the stock markets.

With respect to the factor loadings, some trends appear to be robust to both models and state indicators. For instance, the cross-sectional exposure to the market risk premium significantly increases during recessions on an average value of 0.089 while there is a highly significant average marginal decay of 0.124 in the HML loading throughout the same period.

Ultimately, these results reveal that the annualised alpha during recession varies between -1% and -1.76% for the NBER indicator and between -0.54% and -1.14% according to the market parameter. As abovementioned, the outcome changes substantially depending on the chosen benchmark model: the Carhart 4-factor conditional model signals insignificant zero or negative alphas while the Fama-French 5-factor plus momentum conditional model points at negative and highly significant alphas. Therefore, in spite of not obtaining robust results for both models and state variables, everything seems to point towards an equal or deeper underperformance of the active funds during distressing states of the economic cycle. As a consequence, the null hypothesis H01 which states that the average actively managed mutual fund significantly outperforms its benchmark during recessions can be rejected.

Once demonstrated that the average mutual fund fails to beat its passive counterparts during recessions, the following step is evaluating whether fund characteristics such as the level of active management, the fund size or the fund flows affect performance during declining economic periods and how they interact among them. Furthermore, I will try to detect recurring characteristics among funds that intimately relate to outperformance and which investors may take advantage of.

Table 6 exhibits the alphas and t-statistics of the 25 portfolios (5x5) sorted by Minimum Active Share and total net assets (TNA) as proxies for the level of activity and fund size and the differences between extreme portfolios over both dimensions combined and individually. The subsample includes all recession periods identified by the NBER indicator between

January 1988 and December 2015. Panel A and B illustrate the relative performance of the 1-month lagged time-series regressions of excess returns of each portfolio under the Carhart 4-factor model and the Fama-French 5-factor model plus momentum respectively.

The results indicate that, for the smallest size quintile, portfolios with higher Minimum Active Share perform better by 0.127% Carhart 4-factor model and by 0.045% in the Fama-French 5-factor model plus momentum, even though this is only statistically significant at 10% level for the latter. No more significant differences are found but it is noteworthy that the only two portfolios outperforming the Carhart 4-factor model are small-medium funds among the highest Active Share quintile whereas the worst performers are big funds which are very active, being robust for both models. Moreover, controlling for activeness, small funds systematically outperform big funds for each quintile in the Carhart 4-factor model even though this pattern is not significant.

Table 7 replicates the same approach and sample followed in table 6 but introduces an additional robustness check by replacing Minimum Active Share with Constant Selectivity as a measure of active management.

The alphas under the Carhart 4-factor model reveal that, controlling for size on the smallest quintile, lower Selectivity significantly improves performance by 0.346%. The positive reinforcement in performance stands for all size quintiles except number 4 but the pattern is not significant. Controlling for Selectivity, small funds outperform big funds for all quintiles except number 3 but this is once again not statistically significant.

The results under the Fama-French 5-factor model plus momentum show that, consistent with the previous model, lower Selectivity in the smallest size quintile significantly improves performance by 0.347% at 10% level. In fact, controlling for size, all quintiles but number 4 hold this pattern even though this is still not significant. Controlling for Selectivity, small funds in the lowest Selectivity quintile significantly enhance performance by 0.245% at 5% level.

TABLE 6

Portfolio Approach: Minimum Active Share and Fund Size according to NBER Recession Subsample

This table displays the *alphas (α)* obtained from the time-series regression of the average excess returns of 25 portfolios derived from funds sorted into quintiles based on their 1-month lagged level of active management (Minimum Active Share) and fund size (Total Net Assets). The sample period corresponds to a subsample of all monthly observations classified as recession by the NBER indicator between January 1988 and December 2015. Panel A illustrates the results of the regressions under the Carhart 4-factor model. Panel B presents the results of the portfolio implementation under the Fama-French 5-factor model plus momentum. *All* category represents each independent quintile over one dimension only. *Difference 1-5* exhibits the alpha range between the extreme portfolios on a certain level of active management or fund size. Numbers in parentheses represent the t-statistics of the coefficients. Those denoted with * are significant at 10% level, with ** are significant at 5% level and with *** are significant at 1% level.

Alpha (α)	Fund Size Quintiles (TNA)													
	Panel A: Carhart 4-Factor Model							Panel B: Fama-French 5-Factor Model + Momentum						
Minimum Active Share Quintiles	(Small) 1	2	3	4	(Big) 5	All	Difference 1-5	(Small) 1	2	3	4	(Big) 5	All	Difference 1-5
(Low) 1	-0.115	-0.088	-0.091	-0.157	-0.119	-0.117	0.005	-0.106	-0.033	-0.135	-0.267	-0.078	-0.118	-0.028
	(-0.28)	(-0.83)	(-0.80)	(-1.17)	(-1.03)	(-0.97)	(0.70)	(-0.59)	(-0.27)	(-1.01)	(-1.72)*	(-0.58)	(-0.95)	(-0.06)
2	-0.095	-0.205	-0.217	-0.310	-0.147	-0.203	0.052	-0.090	-0.012	-0.216	-0.305	-0.100	-0.118	0.010
	(-0.41)	(-1.37)	(-1.71)*	(-2.80)***	(-1.07)	(-1.65)*	(0.92)	(-0.53)	(-0.07)	(-1.42)	(-2.31)**	(-0.62)	(-0.86)	(1.58)
3	-0.102	-0.319	-0.313	-0.101	-0.325	-0.231	0.223	-0.101	-0.036	-0.266	0.073	0.057	-0.037	-0.158
	(-0.59)	(-1.42)	(-1.39)	(-0.48)	(-1.22)	(-1.18)	(1.37)	(-0.27)	(-0.15)	(-0.99)	(0.31)	(0.20)	(-0.16)	(0.09)
4	-0.116	-0.412	-0.274	-0.115	-0.156	-0.210	0.040	-0.153	-0.251	-0.286	-0.309	-0.282	-0.258	0.130
	(-0.62)	(-1.80)*	(-1.36)	(-0.52)	(-0.64)	(-1.18)	(0.22)	(-0.70)	(-0.94)	(-1.20)	(-1.22)	(-0.99)	(-1.22)	(0.60)
5 (High)	0.013	-0.298	0.048	-0.309	-0.580	-0.159	0.593	-0.061	-0.097	-0.155	-0.556	-0.481	-0.318	0.420
	(0.37)	(-0.82)	(0.27)	(-0.96)	(-1.18)	(-0.57)	(1.06)	(-1.80)*	(-0.14)	(-0.41)	(-1.53)	(-0.88)	(-1.04)	(0.04)
All	-0.088	-0.249	-0.173	-0.191	-0.194	-0.119	0.106	-0.152	-0.073	-0.211	-0.279	-0.123	-0.199	-0.028
	(-0.65)	(-1.37)	(-1.13)	(-1.36)	(-1.21)	(-5.13)***	(1.06)	(-0.96)	(-0.36)	(-1.17)	(-1.69)*	(-0.65)	(-7.31)***	(-0.27)
Difference 1-5	-0.127	0.210	-0.139	0.151	0.461	0.042		-0.045	0.064	0.020	0.289	0.402	0.204	
	(-0.29)	(0.65)	(-0.76)	(0.49)	(0.98)	(0.26)		(-1.82)*	(0.07)	(0.09)	(0.82)	(0.81)	(0.80)	

TABLE 7

Portfolio Approach: Constant Selectivity and Fund Size according to NBER Recession Subsample

This table displays the *alphas (α)* obtained from the time-series regression of the average excess returns of 25 portfolios derived from funds sorted into quintiles based on their 1-month lagged level of active management (Constant Selectivity) and fund size (Total Net Assets). The sample period corresponds to a subsample of all monthly observations classified as recession by the NBER indicator between January 1988 and December 2015. Panel A illustrates the results of the regressions under the Carhart 4-factor model. Panel B presents the results of the portfolio implementation under the Fama-French 5-factor model plus momentum. *All* category represents each independent quintile over one dimension only. *Difference 1-5* exhibits the alpha range between the extreme portfolios on a certain level of active management or fund size. Numbers in parentheses represent the t-statistics of the coefficients. Those denoted with * are significant at 10% level, with ** are significant at 5% level and with *** are significant at 1% level.

		Fund Size Quintiles (TNA)													
	Alpha (α)	Panel A: Carhart 4-Factor Model							Panel B: Fama-French 5-Factor Model + Momentum						
		(Small) 1	2	3	4	(Big) 5	All	Difference 1-5	(Small) 1	2	3	4	(Big) 5	All	Difference 1-5
Constant Selectivity Quintiles	(Low) 1	0.043	-0.145	-0.152	-0.245	-0.135	-0.126	0.178	0.051	-0.038	-0.113	-0.404	-0.194	-0.135	0.245
		(0.36)	(-1.13)	(-1.23)	(-2.47)**	(-1.81)*	(-1.48)	(1.43)	(0.65)	(-0.39)	(-0.98)	(-3.92)***	(-2.22)**	(-1.32)	(2.07)**
	2	-0.042	-0.146	-0.211	-0.125	-0.214	-0.147	0.172	0.019	-0.054	-0.259	-0.228	-0.165	-0.123	0.183
		(-0.27)	(-1.01)	(-1.78)*	(-1.05)	(-1.93)*	(-1.29)	(1.45)	(0.10)	(-0.31)	(-1.86)*	(-1.65)*	(-1.25)	(-0.90)	(1.30)
	3	-0.037	-0.155	-0.204	-0.229	-0.030	-0.157	-0.006	0.033	-0.104	-0.175	-0.005	0.209	-0.060	-0.176
		(-0.20)	(-0.78)	(-1.32)	(-1.26)	(-0.15)	(-1.07)	(-0.04)	(0.15)	(-0.44)	(-0.94)	(-0.02)	(0.97)	(-0.35)	(-1.00)
	4	-0.066	-0.329	-0.176	-0.225	-0.219	-0.195	0.153	-0.567	-0.219	-0.199	-0.281	-0.133	-0.271	-0.434
		(-0.19)	(-1.62)	(-0.84)	(-1.23)	(-0.99)	(-1.16)	(0.49)	(-1.97)**	(-0.92)	(-0.80)	(-1.28)	(-0.52)	(-1.36)	(-1.30)
	5 (High)	-0.303	-0.503	-0.237	-0.186	-0.313	-0.282	0.009	-0.296	-0.087	-0.295	-0.398	-0.304	-0.261	0.008
		(-1.54)	(-1.19)	(-0.73)	(-0.34)	(-0.81)	(-0.97)	(-0.33)	(-1.32)	(-0.04)	(-0.85)	(-1.02)	(-0.69)	(-0.79)	(-0.19)
	All	-0.088	-0.249	-0.173	-0.191	-0.194	-0.119	0.106	-0.152	-0.073	-0.211	-0.279	-0.123	-0.199	-0.028
		(-0.65)	(-1.37)	(-1.13)	(-1.36)	(-1.21)	(-5.13)***	(1.06)	(-0.96)	(-0.36)	(-1.17)	(-1.69)*	(-0.65)	(-7.31)***	(-0.27)
	Difference 1-5	0.346	0.358	0.085	-0.059	0.178	0.156		0.347	0.049	0.183	-0.006	0.110	0.126	
		(1.68)*	(1.05)	(0.25)	(-0.41)	(0.48)	(0.63)		(1.70)*	(-0.12)	(0.50)	(-0.02)	(0.26)	(0.46)	

Similarly, table 8 interacts 25 portfolios (5x5) sorted by Minimum Active Share and total net assets (TNA) adding a new layer of robustness. On this occasion, a new subsample based on the S&P500 index including all bear markets between January 1988 and December 2015 is chosen to run the time-series regressions over each portfolio excess returns.

The outcome exhibits several common patterns among models. Under the Carhart 4-factor model, controlling for size among the 1 and 2 smallest quintiles, funds in the highest quintile of Active Share performs significantly better by 0.284% and 0.262% per month respectively. This pattern is also visible on the remaining size quintiles, but it is not statistically significant at the level required. However, only the funds in the smallest size quintile are able to significantly outperform their benchmark. Indeed, the best performing portfolio is the smallest size and highest Active Share quintile, followed by the second highest Active Share quintile. It seems clear that the level of active management matters in this sample. In addition, controlling for Active Share, small funds perform better than bigger funds, being this relationship significant in all quintiles but the smallest Active Share. Moreover, small funds obtain higher differential benefits on the highest Active Share quintiles. Leaving activeness aside, it is also statistically significant at 5% than small fund outperforms big ones by 0.237% over the sample.

The Fama-French 5-factor model plus momentum confirms that, controlling for size among the smallest quintile, higher Active Share relates to higher performance and that only the most active and small-medium size funds are able to outperform the benchmark, being the smallest size and highest Active Share quintile the best performer. Despite not being significant, the worst performing portfolio is again within the biggest and most active funds. When controlling for the highest Active Share quintile, there is significant evidence that funds perform 0.395% better when they are among the smallest quintile rather than the biggest. This also occurs for all remaining quintiles and enhancement is more noticeable when the Active Share is also higher but it is not statistically significant.

Table 9 continues to report the alphas obtained by each of the 25 portfolios (5x5) sorted by Constant Selectivity and total net assets (TNA) over the subsample based on recessions signalled by the S&P500 market parameter.

TABLE 8

Portfolio Approach: Minimum Active Share and Fund Size according to S&P500 Recession Subsample

This table displays the *alphas (α)* obtained from the time-series regression of the average excess returns of 25 portfolios derived from funds sorted into quintiles based on their 1-month lagged level of active management (Minimum Active Share) and fund size (Total Net Assets). The sample period corresponds to a subsample of all monthly observations classified as recession by the S&P500 market parameter between January 1988 and December 2015. Panel A illustrates the results of the regressions under the Carhart 4-factor model. Panel B presents the results of the portfolio implementation under the Fama-French 5-factor model plus momentum. *All* category represents each independent quintile over one dimension only. *Difference 1-5* exhibits the alpha range between the extreme portfolios on a certain level of active management or fund size. Numbers in parentheses represent the t-statistics of the coefficients. Those denoted with * are significant at 10% level, with ** are significant at 5% level and with *** are significant at 1% level.

Minimum Active Share Quintiles	Alpha (α)	Fund Size Quintiles (TNA)													
		Panel A: Carhart 4-Factor Model							Panel B: Fama-French 5-Factor Model + Momentum						
		(Small) 1	2	3	4	(Big) 5	All	Difference 1-5	(Small) 1	2	3	4	(Big) 5	All	Difference 1-5
	(Low) 1	-0.149 (-1.42)	-0.183 (-2.45)**	-0.229 (-1.56)	-0.240 (-2.59)***	-0.204 (-2.13)**	-0.189 (-2.23)**	0.056 (0.58)	-0.185 (-1.61)	-0.244 (-2.67)***	-0.222 (-1.97)**	-0.260 (-2.58)***	-0.202 (-1.81)*	-0.217 (-2.35)**	0.017 (0.07)
	2	0.025 (0.20)	-0.121 (-1.10)	-0.284 (-2.71)***	-0.191 (-1.44)	-0.139 (-1.36)	-0.151 (-1.45)	0.164 (1.75)*	-0.076 (-0.11)	-0.169 (-0.97)	-0.271 (-2.27)**	-0.175 (-1.17)	-0.102 (-0.65)	-0.133 (-1.14)	0.027 (0.58)
	3	0.109 (1.67)*	-0.098 (-0.50)	-0.070 (-0.31)	-0.261 (-1.39)	-0.149 (-1.05)	-0.108 (-0.89)	0.258 (1.92)*	-0.038 (-0.99)	-0.137 (-0.71)	-0.152 (-0.65)	-0.155 (-0.74)	-0.067 (-0.18)	-0.096 (-0.49)	0.028 (0.68)
	4	0.120 (1.99)**	0.027 (0.23)	0.001 (0.01)	-0.179 (-0.80)	-0.137 (-0.61)	-0.026 (-0.52)	0.258 (1.79)*	0.068 (1.27)	0.001 (0.21)	0.071 (0.30)	-0.224 (-0.91)	-0.040 (-0.16)	-0.025 (-0.31)	0.108 (0.77)
	5 (High)	0.136 (2.64)***	0.079 (0.93)	0.079 (0.32)	-0.047 (-0.16)	-0.102 (-0.17)	0.030 (0.43)	0.237 (1.98)**	0.076 (2.03)**	0.026 (0.44)	0.009 (0.06)	-0.261 (-0.85)	-0.319 (-0.99)	-0.128 (-0.69)	0.395 (1.68)*
	All	0.062 (1.62)	-0.043 (-0.52)	-0.084 (-0.53)	-0.190 (-1.26)	-0.175 (-1.32)	-0.075 (-4.14)***	0.237 (2.25)**	0.023 (0.63)	-0.087 (-0.64)	-0.125 (-0.72)	-0.220 (-1.30)	-0.133 (-0.90)	-0.105 (-5.30)**	0.156 (1.05)
	Difference 1-5	-0.284 (-2.74)***	-0.262 (-1.71)*	-0.307 (-1.11)	-0.193 (-0.70)	-0.102 (-0.52)	-0.219 (-1.31)		-0.261 (-2.31)**	-0.270 (-1.25)	-0.231 (-1.01)	0.001 (0.03)	0.117 (0.41)	-0.088 (-0.81)	

TABLE 9

Portfolio Approach: Constant Selectivity and Fund Size according to S&P500 Recession Subsample

This table displays the *alphas (α)* obtained from the time-series regression of the average excess returns of 25 portfolios derived from funds sorted into quintiles based on their 1-month lagged level of active management (Constant Selectivity) and fund size (Total Net Assets). The sample period corresponds to a subsample of all monthly observations classified as recession by the S&P500 market parameter between January 1988 and December 2015. Panel A illustrates the results of the regressions under the Carhart 4-factor model. Panel B presents the results of the portfolio implementation under the Fama-French 5-factor model plus momentum. *All* category represents each independent quintile over one dimension only. *Difference 1-5* exhibits the alpha range between the extreme portfolios on a certain level of active management or fund size. Numbers in parentheses represent the t-statistics of the coefficients. Those denoted with * are significant at 10% level, with ** are significant at 5% level and with *** are significant at 1% level.

		Fund Size Quintiles (TNA)													
	Alpha (α)	Panel A: Carhart 4-Factor Model							Panel B: Fama-French 5-Factor Model + Momentum						
		(Small) 1	2	3	4	(Big) 5	All	Difference 1-5	(Small) 1	2	3	4	(Big) 5	All	Difference 1-5
Constant Selectivity Quintiles	(Low) 1	-0.092	-0.180	-0.201	-0.311	-0.236	-0.192	0.144	-0.064	-0.172	-0.316	-0.320	-0.267	-0.214	0.203
		(-1.06)	(-2.72)***	(-2.27)**	(-3.72)***	(-3.60)***	(-3.06)***	(1.75)*	(-0.65)	(-2.29)**	(-3.53)***	(-3.51)***	(-3.79)***	(-3.08)***	(2.37)**
	2	0.140	-0.089	-0.185	-0.226	-0.223	-0.106	0.366	0.125	-0.071	-0.159	-0.191	-0.214	-0.095	0.339
		(0.84)	(-0.58)	(-1.30)	(-2.19)**	(-2.27)**	(-0.86)	(3.54)***	(0.69)	(-0.41)	(-1.00)	(-1.73)*	(-1.96)**	(-0.69)	(3.02)***
	3	0.046	-0.086	-0.149	-0.294	-0.241	-0.148	0.287	-0.048	-0.131	-0.214	-0.233	-0.112	-0.142	0.063
		(0.18)	(-0.49)	(-0.94)	(-1.65)*	(-1.72)*	(-0.96)	(1.16)	(-0.17)	(-0.69)	(-1.21)	(-1.19)	(-0.75)	(-0.83)	(0.24)
	4	0.030	0.029	0.030	-0.063	-0.197	-0.017	0.227	-0.172	-0.110	0.045	-0.036	-0.009	-0.039	-0.163
		(0.13)	(0.12)	(0.14)	(-0.27)	(-0.95)	(-0.09)	(0.91)	(-0.69)	(-0.43)	(0.20)	(-0.15)	(-0.04)	(-0.18)	(-0.69)
	5 (High)	0.171	0.062	0.026	-0.093	-0.030	0.021	0.201	0.012	-0.017	-0.084	-0.271	-0.103	-0.106	0.115
		(0.62)	(0.24)	(0.09)	(-0.33)	(-0.11)	(0.08)	(0.95)	(0.04)	(-0.06)	(-0.28)	(-0.88)	(-0.35)	(-0.39)	(0.49)
	All	0.062	-0.043	-0.084	-0.190	-0.175	-0.075	0.237	0.023	-0.087	-0.125	-0.220	-0.133	-0.105	0.156
		(1.62)	(-0.52)	(-0.53)	(-1.26)	(-1.32)	(-4.14)***	(2.25)**	(0.63)	(-0.64)	(-0.72)	(-1.30)	(-0.90)	(-5.30)***	(1.05)
	Difference 1-5	-0.263	-0.242	-0.227	-0.218	-0.207	-0.212		-0.076	-0.155	-0.232	-0.049	-0.165	-0.108	
		(-1.00)	(-1.01)	(-0.99)	(-0.85)	(-0.81)	(-0.98)		(-0.28)	(-0.58)	(-0.92)	(-0.17)	(-0.59)	(-0.46)	

The results under both models point that, controlling for Selectivity in the two lowest quintiles, small funds perform better than big funds in a range from 0.144% to 0.366% and that this pattern holds for all other quintiles but not at the significance level required. Even not controlling for activeness, small funds also perform significantly better under the Carhart 4-factor model. When controlling for size, a higher degree of Selectivity enhances performance for all quintiles under both models but this relationship is not statistically significant. Pointing in the same direction, the portfolios outperforming their benchmark tend to be small-medium funds with medium or high Selectivity, but they are once again not significant. However, there is another significant and recurring pattern: the worst performers are among the biggest funds, despite they are not among the most active as measured by Constant Selectivity.

Recapitulating, conditional and relative mutual fund performance has been tested trying to find evidence of skill in small funds throughout the level of active management and its interaction with the size of these funds over different models and recessionary subsamples.

From the aforementioned results, the underperformance of the average actively managed mutual funds is significant and robust across recessionary subsamples and benchmark models and its range between -0.9% and 2.39% is consistent with the previously rejected H01.

Regardless the subsample used in the analysis, controlling for size within the smallest quintile of funds, a higher degree of Minimum Active Share seems to be significantly associated with higher performance in line with H02 expectations, ranging this enhancement from 0.54% to 3.40% annually. However, Constant Selectivity is not robust to these results and, occasionally, even signals a contrarian trend such as in the NBER subsample.

Controlling for the level of active management, funds among the smaller quintiles significantly outperform their bigger peers by a range from 1.73% to 4.74% yearly, increasing proportionally to the Active Share value. Nevertheless, when the control variable is Constant Selectivity, no clear pattern is discovered as it varies considerably across NBER and market recessionary subsamples. Moreover, considering the bear markets subsample based on the S&P500 and not controlling for activeness, smaller funds also perform significantly better than bigger ones by up to 284 basis points annually. Indeed, the best performers in this samples are the funds with higher Minimum Active Share and smallest size whereas the worst performers are among the biggest funds. This is consistent with the effects of diseconomies to scale and liquidity constraints for big funds which were discussed in the literature review.

In spite of finding evidence supporting higher performance among the smallest and more active funds measured by Minimum Active Share, the finding does not hold when activeness is measured by Constant Selectivity. Furthermore, the results are not robust across all samples and benchmark models. Overall, no evidence was found to support the hypothesis that mutual funds with higher level of active management and smaller size show significantly higher abnormal returns during recession periods as most of those funds keep underperforming their passive benchmark. Hence, H02 must be rejected.

The last analysis attempts to discover whether net fund flows play a role in the performance of equity mutual funds during recession periods, confirming that investors can actually predict and chase manager's skill to protect their wealth during downturns. In order to do so, a bidimensional portfolio approach is applied by interacting the level of active management (Minimum Active Share and Constant Selectivity) and the normalised net fund flows.

Table 10 exhibits the alphas and t-statistics of the 25 portfolios (5x5) sorted by Minimum Active Share and normalised net fund flows and the differences between extreme portfolios over the two dimensions, combined and individually. The subsample includes all recession periods identified by the NBER indicator between January 1988 and December 2015. Panel A and B illustrate the relative performance of the 1-month lagged time-series regressions of excess returns of each portfolio under the Carhart 4-factor model and the Fama-French 5-factor model plus momentum respectively.

The results indicate that, controlling for Active Share in the Carhart 4-factor model, quintiles with more positive normalised net fund flows perform significantly better than the ones with more negative net flows for all quintiles but Active Share number 2. Moreover, in absence of controlling groups, funds with higher positive inflows significantly outperform fund with outflows by 0.58% on a monthly basis. In fact, funds in the lowest and second lower quintile by net flows significantly underperform the passive benchmark by -0.44% and 0.33% respectively every month. It is remarkable that the worst performing funds are concentrated among the quintiles with more negative net flows and medium level of activeness. Furthermore, the only funds which manage to outperform their benchmarks are among the most positive quintiles regarding flows, even though none of them is statistically significant.

TABLE 10

Portfolio Approach: Minimum Active Share and Normalised Net Fund Flows according to NBER Recession Subsample

This table displays the *alphas (α)* obtained from the time-series regression of the average excess returns of 25 portfolios derived from funds sorted into quintiles based on their 1-month lagged level of active management (Minimum Active Share) and fund flows (Normalised Net Fund Flows). The sample period corresponds to a subsample of all monthly observations classified as recession by the NBER indicator between January 1988 and December 2015. Panel A illustrates the results of the regressions under the Carhart 4-factor model. Panel B presents the results of the portfolio implementation under the Fama-French 5-factor model plus momentum. *All* category represents each independent quintile over one dimension only. *Difference 1-5* exhibits the alpha range between the extreme portfolios on a certain level of active management or fund flows. Numbers in parentheses represent the t-statistics of the coefficients. Those denoted with * are significant at 10% level, with ** are significant at 5% level and with *** are significant at 1% level.

	Alpha (α)	Normalised Net Fund Flow Quintiles													
		Panel A: Carhart 4-Factor Model							Panel B: Fama-French 5-Factor Model + Momentum						
		(Negative) 1	2	3	4	(Positive) 5	All	Difference 1-5	(Negative) 1	2	3	4	(Positive) 5	All	Difference 1-5
Minimum Active Share Quintiles	(Low) 1	-0.238	-0.198	-0.016	-0.128	0.140	-0.097	-0.378	-0.210	-0.231	0.057	-0.118	-0.002	-0.114	-0.207
		(-1.95)*	(-1.59)	(-0.15)	(-1.15)	(0.88)	(-0.97)	(-2.24)**	(-1.48)	(-1.56)	(0.47)	(-0.89)	(-0.01)	(-0.95)	(-1.07)
	2	-0.249	-0.250	-0.170	-0.234	-0.120	-0.193	-0.129	-0.162	-0.067	-0.019	-0.338	-0.017	-0.118	-0.145
		(-1.83)*	(-1.48)	(-1.23)	(-1.69)*	(-0.66)	(-1.65)*	(-0.89)	(-1.02)	(-0.35)	(-0.12)	(-2.10)**	(-0.08)	(-0.86)	(-0.88)
	3	-0.633	-0.510	-0.121	-0.192	0.269	-0.241	-0.902	-0.378	-0.160	0.152	-0.014	0.166	-0.037	-0.543
		(-3.02)***	(-2.08)**	(-0.46)	(-0.80)	(1.06)	(-1.18)	(-3.39)***	(-1.65)*	(-0.66)	(0.50)	(-0.05)	(0.55)	(-0.16)	(-1.97)**
	4	-0.571	-0.534	-0.091	-0.215	0.223	-0.210	-0.794	-0.474	-0.658	-0.147	-0.136	-0.072	-0.258	-0.401
		(-2.63)***	(-2.73)***	(-0.36)	(-0.94)	(0.67)	(-1.18)	(-1.80)*	(-1.83)*	(-2.60)***	(-0.49)	(-0.51)	(-0.19)	(-1.22)	(-0.79)
	5 (High)	-0.502	-0.214	0.040	-0.346	0.084	-0.159	-0.586	-0.546	-0.182	-0.020	-0.629	-0.170	-0.318	-0.376
		(-1.64)	(-0.92)	(0.11)	(-0.88)	(0.22)	(-0.57)	(-1.92)*	(-1.65)*	(-0.66)	(-0.05)	(-1.44)	(-0.39)	(-1.04)	(-1.07)
	All	-0.436	-0.328	-0.063	-0.235	0.142	-0.119	-0.578	-0.377	-0.230	-0.003	-0.243	-0.007	-0.199	-0.370
		(-3.14)***	(-2.12)**	(-0.41)	(-1.51)	(0.66)	(-5.13)***	(-3.06)***	(-2.31)**	(-1.27)	(-0.01)	(-1.32)	(-0.03)	(-7.31)***	(-1.74)*
	Difference 1-5	0.263	0.016	-0.056	0.218	0.056	0.062		0.337	-0.049	0.077	0.512	0.168	0.204	
		(0.94)	(0.08)	(-0.16)	(0.61)	(0.17)	(0.26)		(1.12)	(-0.21)	(0.20)	(1.34)	(0.44)	(0.80)	

The Fama-French 5-factor model plus momentum is robust to the majority of the previous results and confirms that, controlling for Active Share, quintiles with more positive normalised net fund flows perform significantly better than the ones with more negative net flows despite only being significant at 5% level for the mid Active Share quintile. It also restates that, without controlling for activeness, funds with higher positive inflows significantly outperform fund with outflows, accounting for a 0.37% monthly difference on this occasion. Again, the worst performers are concentrated among the quintiles with more negative net flows and medium to high Active Share while the outperformers, located within the quintile with most positive net inflows, are not significant.

Table 11 replicates the same approach and sample as per table 10 but introduces an additional robustness check by replacing Minimum Active Share with Constant Selectivity as a measure of active management.

The alphas under the Carhart 4-factor model reveal that, controlling for Selectivity, higher normalised net fund flows significantly improve performance by a monthly average of 0.64% and that this positive reinforcement in performance stands for all size quintiles except the highest Selectivity quintile where the difference is not significant. Without controlling for activeness, the quintile with highest net inflows outperforms the quintile with highest net outflows by 0.58% on a monthly basis. Once again, the worst performers are concentrated on the cross section of the most negative net flow quintiles with intermediate Selectivity quintiles. The outperformers are again among the portfolios with highest net inflows but they are not statistically significant at the level required.

The results under the Fama-French 5-factor model plus momentum show that, consistent with previous observations, higher inflows are related with higher performance in all quintiles when controlling for Constant Selectivity but only significant in the 1, 2 and 4 quintiles. Freed from controlling variables, the quintile with more positive net flows outperforms the quintile with more negative net flows by 0.37% on a monthly basis, being this significant at 10% level. Moreover, the worst performing funds are present among the most negative and intermediate quintiles by net flows while the only outperformers are not statistically significant but are concentrated, once again, within the funds obtaining a higher increase in the normalised net fund flows and medium-high Selectivity values.

TABLE 11

Portfolio Approach: Constant Selectivity and Normalised Net Fund Flows according to NBER Recession Subsample

This table displays the *alphas (α)* obtained from the time-series regression of the average excess returns of 25 portfolios derived from funds sorted into quintiles based on their 1-month lagged level of active management (Constant Selectivity) and fund flows (Normalised Net Fund Flows). The sample period corresponds to a subsample of all monthly observations classified as recession by the NBER indicator between January 1988 and December 2015. Panel A illustrates the results of the regressions under the Carhart 4-factor model. Panel B presents the results of the portfolio implementation under the Fama-French 5-factor model plus momentum. *All* category represents each independent quintile over one dimension only. *Difference 1-5* exhibits the alpha range between the extreme portfolios on a certain level of active management or fund size. Numbers in parentheses represent the t-statistics of the coefficients. Those denoted with * are significant at 10% level, with ** are significant at 5% level and with *** are significant at 1% level.

Alpha (α)		Normalised Net Fund Flow Quintiles													
		Panel A: Carhart 4-Factor Model							Panel B: Fama-French 5-Factor Model + Momentum						
		(Negative) 1	2	3	4	(Positive) 5	All	Difference 1-5	(Negative) 1	2	3	4	(Positive) 5	All	Difference 1-5
Constant Selectivity	(Low) 1	-0.209	-0.254	-0.132	-0.112	0.093	-0.126	-0.302	-0.231	-0.207	-0.112	-0.195	0.111	-0.135	-0.342
		(-1.99)**	(-2.05)**	(-1.30)	(-1.37)	(0.59)	(-1.48)	(-2.04)**	(-1.83)*	(-1.43)	(-0.92)	(-2.12)**	(0.61)	(-1.32)	(-2.05)**
	2	-0.389	-0.186	-0.051	-0.186	0.175	-0.147	-0.564	-0.333	-0.150	0.007	-0.155	0.128	-0.123	-0.461
		(-2.51)**	(-1.29)	(-0.37)	(-1.41)	(0.95)	(-1.29)	(-2.53)**	(-1.78)*	(-0.87)	(0.05)	(-0.98)	(0.59)	(-0.90)	(-1.75)*
	3	-0.561	-0.312	-0.202	-0.034	0.284	-0.157	-0.845	-0.285	-0.266	-0.031	0.132	0.184	-0.060	-0.469
		(-2.70)***	(-1.81)*	(-1.10)	(-0.17)	(1.08)	(-1.07)	(-2.68)***	(-1.26)	(-1.32)	(-0.15)	(0.57)	(0.59)	(-0.35)	(-1.34)
	4	-0.432	-0.472	-0.237	-0.200	0.298	-0.195	-0.729	-0.528	-0.244	-0.431	-0.255	0.082	-0.271	-0.609
		(-2.70)***	(-2.00)**	(-1.09)	(-0.92)	(1.18)	(-1.16)	(-3.22)***	(-2.80)***	(-0.91)	(-1.73)*	(-1.00)	(0.28)	(-1.36)	(-2.31)**
	5 (High)	-0.444	-0.477	0.124	-0.622	0.141	-0.282	-0.585	-0.329	-0.316	0.399	-0.733	-0.253	-0.261	-0.076
		(-1.27)	(-2.01)**	(0.32)	(-1.37)	(0.30)	(-0.97)	(-1.08)	(-0.85)	(-1.14)	(0.91)	(-1.42)	(-0.48)	(-0.79)	(-0.12)
	All	-0.436	-0.328	-0.063	-0.235	0.142	-0.119	-0.578	-0.377	-0.230	-0.003	-0.243	-0.007	-0.199	-0.370
		(-3.14)***	(-2.12)**	(-0.41)	(-1.51)	(0.66)	(-5.13)***	(-3.06)***	(-2.31)**	(-1.27)	(-0.01)	(-1.32)	(-0.03)	(-7.31)***	(-1.74)*
	Difference 1-5	0.235	0.224	-0.256	0.510	-0.048	0.156		0.098	0.109	-0.511	0.538	0.364	0.126	
		(0.72)	(1.22)	(-0.69)	(1.14)	(-0.10)	(0.63)		(0.27)	(0.53)	(-1.23)	(1.05)	(0.68)	(0.46)	

Similarly, table 12 interacts 25 portfolios (5x5) sorted by Minimum Active Share and normalised net fund flows adding a new coating to test robustness. This time, a new subsample based on the S&P500 index including all bear markets between January 1988 and December 2015 is chosen to run the time-series regressions over each portfolio excess returns.

The outcome exhibits several common patterns with the NBER recessionary subsample. Controlling for the 3 and 4 Minimum Active Share quintiles under the Carhart 4-factor model, more positive normalised net flows are associated with higher performance than the most negative net flows quintile by 0.40% and 0.51% per month respectively. This pattern is also visible on the remaining quintiles, but it is not statistically significant at the level required. Furthermore, higher level of Active Share seems to provide higher returns when controlling for net flows but this pattern is not significant at the level required. In the absence of control for activeness, the quintile with highest net inflows outperforms the quintile with highest net outflows by 0.18% on a monthly basis. The worst significantly performing funds are present within the less active funds. On the other hand, the only portfolios that manage to outperform the passive benchmark are among the mid-flows and high Active Share quintiles but they are not statistically significant.

The Fama-French 5-factor model plus momentum confirms that, controlling for Active Share, the difference between extreme portfolios yields higher monthly returns averaging 0.27% for all quintiles, even though this difference only significant in the Active Share quintiles 1, 3 and 4. Without controlling for the level of active management, the most positive net flows quintile outperforms the most negative by 0.326% on a monthly basis. Despite not being significant, the outperformers are only present on the most positive ratios (quintiles 4 and 5) of normalised net fund flows and mid-high quintiles by Active Share. By contract, the worst performers concentrated among the interaction of the most negative quintiles in term of flows with the mid-low Active Share quintiles, being statistically significant at between 1% and 10% level.

TABLE 12

Portfolio Approach: Minimum Active Share and Normalised Net Fund Flows according to S&P500 Recession Subsample

This table displays the *alphas (α)* obtained from the time-series regression of the average excess returns of 25 portfolios derived from funds sorted into quintiles based on their 1-month lagged level of active management (Minimum Active Share) and fund flows (Normalised Net Fund Flows). The sample period corresponds to a subsample of all monthly observations classified as recession by the S&P500 market parameter between January 1988 and December 2015. Panel A illustrates the results of the regressions under the Carhart 4-factor model. Panel B presents the results of the portfolio implementation under the Fama-French 5-factor model plus momentum. *All* category represents each independent quintile over one dimension only. *Difference 1-5* exhibits the alpha range between the extreme portfolios on a certain level of active management or fund size. Numbers in parentheses represent the t-statistics of the coefficients. Those denoted with * are significant at 10% level, with ** are significant at 5% level and with *** are significant at 1% level.

	Alpha (α)	Normalised Net Fund Flow Quintiles													
		Panel A: Carhart 4-Factor Model							Panel B: Fama-French 5-Factor Model + Momentum						
		(Negative) 1	2	3	4	(Positive) 5	All	Difference 1-5	(Negative) 1	2	3	4	(Positive) 5	All	Difference 1-5
Minimum Active Share	(Low) 1	-0.197	-0.214	-0.133	-0.222	-0.155	-0.189	-0.042	-0.336	-0.343	-0.081	-0.182	-0.131	-0.217	-0.205
		(-1.85)*	(-1.77)*	(-1.43)	(-1.98)**	(-1.32)	(-2.23)**	(-0.30)	(-3.12)***	(-2.73)***	(-0.81)	(-1.52)	(-1.24)	(-2.35)**	(-1.72)*
	2	-0.109	-0.095	-0.202	-0.150	-0.100	-0.151	-0.009	-0.213	-0.101	-0.183	-0.149	-0.178	-0.133	-0.035
		(-0.24)	(-0.27)	(-1.87)*	(-2.06)**	(-1.84)*	(-1.45)	(1.11)	(-0.62)	(-0.56)	(-1.57)	(-1.22)	(-1.23)	(-1.14)	(0.33)
	3	-0.234	-0.159	-0.098	-0.084	0.045	-0.108	-0.279	-0.358	-0.176	-0.126	0.045	0.044	-0.096	-0.402
		(-1.06)	(-0.66)	(-0.52)	(-0.45)	(1.12)	(-0.69)	(-1.98)**	(-1.83)*	(-0.64)	(-0.58)	(0.22)	(0.20)	(-0.46)	(-1.67)*
	4	-0.178	-0.218	-0.139	0.092	0.113	-0.026	-0.291	-0.324	-0.211	-0.071	0.071	0.191	-0.025	-0.514
		(-1.24)	(-0.78)	(-0.61)	(0.43)	(0.66)	(-0.42)	(-1.71)*	(-1.64)	(-0.69)	(-0.28)	(0.31)	(0.99)	(-0.11)	(-2.03)**
	5 (High)	-0.138	-0.002	0.253	-0.135	0.097	0.030	-0.234	-0.241	-0.062	-0.021	-0.211	-0.059	-0.128	-0.182
		(-0.51)	(-0.01)	(0.93)	(-0.48)	(0.35)	(0.13)	(-1.16)	(-1.20)	(-0.05)	(0.10)	(-1.03)	(-0.20)	(-0.49)	(-1.25)
	All	-0.168	-0.121	-0.063	-0.114	0.012	-0.075	-0.180	-0.314	-0.168	-0.069	-0.091	0.012	-0.105	-0.326
		(-1.34)	(-0.71)	(-0.45)	(-0.86)	(0.60)	(-4.14)***	(-1.74)*	(-1.54)	(-0.88)	(-0.44)	(-0.62)	(0.07)	(-5.30)***	(-1.88)*
	Difference 1-5	-0.059	-0.211	-0.386	-0.087	-0.251	-0.219		-0.095	-0.281	-0.061	0.029	-0.072	-0.088	
		(-0.24)	(-0.97)	(-1.48)	(-0.29)	(-0.92)	(-1.01)		(0.32)	(-1.44)	(-0.41)	(0.42)	(-0.25)	(-0.49)	

Table 13 continues to report the alphas obtained by each of the 25 portfolios (5x5) sorted by Constant Selectivity and normalised net fund flows over the subsample based on recessions signalled by the S&P500 market parameter.

The results under both models point that, controlling for Selectivity in the quintiles 3 and 4, a significant differential outperformance in a range from 0.34% to 0.66% per month is detected for the quintiles with highest positive net inflows and that this pattern holds for other quintiles but not at the significance level required. Even not controlling for activeness, the difference among extreme quintiles sorted by normalised net fund flows exhibit that funds with positive monthly net flows perform better than fund with net outflows by 0.18% under the Carhart 4-factor model and 0.33% under the Fama-French 5-factor model plus momentum. Controlling for flow in the Carhart 4-factor model, a higher degree of Selectivity enhances performance for all quintiles, however this pattern is only significant for the mid-flows quintile and is not robust to the Fama-French 5-factor model plus momentum. However, both models point that the worst performers are, again, present within the most negative quintiles per normalised net fund flows, intercepting with low Selectivity values in the case of the Carhart 4-factor model and low and medium Selectivity values for the Fama-French 5-factor model plus momentum. In terms of the outperforming portfolios, they tend to be towards the more positive quintiles by flow in both models but they are considerably dispersed among activeness levels and are not statistically significant at the level required.

In the final part of this section, conditional and relative mutual fund performance during recessions has been tested trying to find evidence of the “Smart Money” effect described by Gruber (1996) and Zheng (1999) and its relationship with the degree of active management as catalysts of superior performance.

After contrasting the results over different subsamples, benchmark models and variables, some general conclusions can be drawn: controlling for both Minimum Active Share and Selectivity, funds with more positive normalised net fund flows experience a better performance accounting for a yearly difference up to 10.82% against funds receiving large negative net outflows, dependent on quintiles, subsample and activeness measure. This is robust across subsamples and models and can be explained by the potentially harmful effect of withdrawals during distressed states of the economy when high outflows can force portfolio managers to liquidate position that they would not under normal circumstance. Moreover, without controlling for the level of active management, funds within the highest quintile of monthly normalised net fund flows earn 3.91% to 6.93% more on a yearly basis than fund within the most negative quintile by normalised net fund flows. Therefore, the “Smart Money” effect seems to be present in the one-month lagged period chosen in this study rather than immediate diseconomies of scale as described by Berk and Green (2004) in their rational equilibrium model.

There are some eye-catching repetitive patterns that are worth to be highlighted. One of them is that the worst performing funds are mainly concentrated among the quintiles with more negative normalised net fund flows and low Minimum Active Share and Constant Selectivity in the S&P500 recessionary sample, signalling some degree of influence on performance. Nevertheless, this premature inference quickly fades away when tested under the NBER sample. As a consequence, there is no evidence of robust interaction of the level of active management with the normalised net fund flows and its relationship with performance.

Even though the only portfolios able to outperform their benchmark tend to be among the medium and high quintiles of active management as measured by Minimum Active Share, not a single positive alpha is statistically significant in the results. While it has been demonstrated that investors are able to predict performance to a certain degree rebalancing their portfolios on a monthly basis based on fund flows, these funds do not manage to consistently beat their passive counterparts. Overall, no evidence was found to support the hypothesis that mutual funds with higher levels of active management and positive net inflows show significantly higher abnormal returns during recession periods. Hence, H03 must be rejected.

TABLE 13

Portfolio Approach: Constant Selectivity and Normalised Net Fund Flows according to S&P500 Recession Subsample

This table displays the *alphas (α)* obtained from the time-series regression of the average excess returns of 25 portfolios derived from funds sorted into quintiles based on their 1-month lagged level of active management (Constant Selectivity) and fund flows (Normalised Net Fund Flows). The sample period corresponds to a subsample of all monthly observations classified as recession by the S&P500 market parameter between January 1988 and December 2015. Panel A illustrates the results of the regressions under the Carhart 4-factor model. Panel B presents the results of the portfolio implementation under the Fama-French 5-factor model plus momentum. *All* category represents each independent quintile over one dimension only. *Difference 1-5* exhibits the alpha range between the extreme portfolios on a certain level of active management or fund size. Numbers in parentheses represent the t-statistics of the coefficients. Those denoted with * are significant at 10% level, with ** are significant at 5% level and with *** are significant at 1% level.

Alpha (α)		Normalised Net Fund Flow Quintiles													
		Panel A: Carhart 4-Factor Model							Panel B: Fama-French 5-Factor Model + Momentum						
		(Negative) 1	2	3	4	(Positive) 5	All	Difference 1-5	(Negative) 1	2	3	4	(Positive) 5	All	Difference 1-5
Constant Selectivity	(Low) 1	-0.248	-0.247	-0.239	-0.163	-0.101	-0.192	-0.107	-0.321	-0.314	-0.218	-0.162	-0.110	-0.214	-0.211
		(-2.00)**	(-2.15)**	(-2.77)***	(-2.65)***	(-0.86)	(-3.06)***	(-0.68)	(-2.95)***	(-2.48)**	(-2.19)**	(-2.13)**	(-0.82)	(-3.08)***	(-1.22)
	2	0.023	-0.164	-0.199	-0.123	0.009	-0.106	0.014	-0.203	-0.228	-0.118	-0.009	-0.020	-0.095	-0.123
		(0.12)	(-1.05)	(-1.29)	(-0.92)	(0.07)	(-0.86)	(0.08)	(-0.71)	(-1.32)	(-0.70)	(-0.07)	(-0.14)	(-0.69)	(-0.62)
	3	-0.307	-0.166	-0.145	-0.143	0.037	-0.148	-0.343	-0.391	-0.121	-0.121	-0.117	0.021	-0.142	-0.402
		(-1.51)	(-0.79)	(-0.84)	(-1.01)	(0.21)	(-0.96)	(-1.94)*	(-1.68)*	(-0.51)	(-0.62)	(-0.76)	(0.11)	(-0.83)	(-2.05)**
	4	-0.244	-0.050	-0.046	-0.015	0.184	-0.017	-0.428	-0.355	-0.101	-0.114	0.107	0.265	-0.039	-0.660
		(-0.88)	(-0.18)	(-0.24)	(-0.07)	(0.89)	(-0.09)	(-1.68)*	(-1.29)	(-0.33)	(-0.54)	(0.51)	(1.21)	(-0.18)	(-2.42)**
	5 (High)	-0.137	-0.066	0.256	-0.018	0.120	0.021	-0.257	-0.294	-0.154	0.119	-0.234	0.098	-0.106	-0.422
		(-0.46)	(-0.31)	(1.00)	(-0.06)	(0.41)	(0.08)	(-1.06)	(-1.00)	(-0.65)	(0.42)	(-0.72)	(0.30)	(-0.39)	(-1.58)
	All	-0.168	-0.121	-0.063	-0.114	0.012	-0.075	-0.180	-0.314	-0.168	-0.069	-0.091	0.012	-0.105	-0.326
		(-1.34)	(-0.71)	(-0.45)	(-0.86)	(0.60)	(-4.14)***	(-1.74)*	(-1.54)	(-0.88)	(-0.44)	(-0.62)	(0.07)	(-5.30)***	(-1.88)*
	Difference 1-5	-0.071	-0.182	-0.465	-0.215	-0.221	-0.212		0.003	-0.159	-0.288	0.021	-0.208	-0.108	
		(-0.27)	(-1.06)	(-1.96)**	(-0.76)	(-0.82)	(-0.98)		(0.01)	(-0.84)	(-1.12)	(0.07)	(-0.71)	(-0.46)	

Chapter 5: Conclusion

Since the popularisation of open-end mutual funds in the 1960s in North America, the mutual fund performance has been a widely document topic in finance literature. Multiple researchers such as Jensen (1968), Malkiel (1995), Carhart (1997), Wermers (2000) and Fama-French (2008, 2010) have demonstrated that the average actively managed mutual is not only uncapable to beat its passive counterparts after fees but also generates a negative net alpha that destroys relative value for individuals who trust their wealth to active portfolio managers. While the passive management industry has gained considerable ground over the last decade, 52% of investors still decide to choose actively managed mutual funds to optimise their portfolios despite its apparent relative weakness. This financial anomaly, commonly known as Gruber's puzzle (1996), signals that either investors do not act rationally or they are able to predict which funds will outperform in future or they find other reasons to compensate their losses in profitability. Elaborating on the latter argument, a major flaw in the abovementioned studies about mutual fund performance is that they assume constant risk under unconditional methods which may understate manager's skill during period of high volatility such as market crashes.

In this thesis, I investigate into feasible explanations to solve the puzzle. Specifically, I revisit a discrepancy in the previous literature between Kosowski (2006) and Sun, Wang and Zheng (2009) regarding the existence of an overlooked counter-cyclical performance in the average actively managed mutual fund that would encourage investors to sacrifice overall performance in exchange for protection of their capital during recession periods. Furthermore, I disaggregate mutual funds by its level of active management and interact them with fund characteristics that play a role in performance such as fund size and net flows hoping to find a relationship that may help investors in their financial decision-making during bear markets.

Using a survivor-bias-free CRSP sample of 2,078 actively managed U.S. mutual funds between January 1988 and December 2015 in which standard and enhanced index trackers are erased, I first conduct unconditional and conditional panel regressions under the Carhart 4-factor model and Fama-French 5-factor model plus momentum to test the performance of the average active mutual fund both assuming constant and time-varying risk based on NBER and S&P500 binary indicators for expansion and recession and analyse the excess return differences.

The unconditional results confirm the traditional findings of the literature and accounts for an annualised negative alpha between -0.91% and -1.06% depending on the multifactor model applied. When time-varying risk is considered, the outcome fails to find superior performance of the average mutual fund during recessions, contradicting the conclusions of Kosowski (2006) and providing support to the findings of Sun, Wang and Zheng (2009). The evidence reveals that the average annualised alpha during recession varies between -1% and -1.76% for the NBER indicator and between -0.54% and -1.14% according to the market parameter.

Next, I analyse two different recessionary subsamples based on NBER and S&P500 binary indicators and sort the active mutual funds in quintiles by its level of active management, fund size and normalised net fund flows. Then, I construct 25 portfolios (5x5) interacting the aforementioned fund characteristics with its Minimum Active Share and Constant Selectivity values several times under different subsamples, benchmark models and variables. Even though some interesting patterns are found, my thesis fails to find an exploitable relationship between the level of active management and the studied fund characteristics during recession periods. In fact, there is weak evidence supporting that any group of funds with common characteristics is able to consistently beat the market as not a single statistically significant positive alpha was found among the constructed portfolios.

The implications of this results partially align with Berk and Green (2004) theories and seriously undermine the presence of highly skilled managers in the small funds by demonstrating that they are not able to successfully weather the storm during bear markets. As a consequence, the resolution to the Gruber's puzzle (1996) remains largely unexplained.

Chapter 6: Limitations and Future Research

The development and conclusions of this study must be carefully considered as, similarly to most research out there, it suffers from several limitations which may affect the outcome of the results.

Primarily, the research focuses on the actively managed mutual fund performance during recession periods but the data sample only includes three downturns of the economy according to the NBER indicator and two according to the market parameter. A longer sample, including more economic cycles, would definitely help to establish a clearer and repeated pattern of performance during declines of the economy. Unfortunately, a wider range of data could not be used due to the lack of reliable monthly observations on both returns and fund characteristics prior to 1988. On the other hand, lengthy time-series data is known to generate bias due to the changing conditions of the market. For instance, the composition of the market participants and availability of near real-time information has dramatically changed over the last two decades so old data may not be fairly comparable to the current conditions and vice versa. One suggestion for future research is to include more recessionary periods in the near future while focusing only on the XXI century distressed periods which will share more similar features.

Secondly, as recently exposed by Cederburg, O'Doherty, Savin and Tiwari (2018), Active Share and Selectivity are not perfect measures of active management but mere approximations and its predictive power over performance must be cautiously evaluated, specially under conditional performance models. Moreover, the Constant Selectivity variable applied in this study is not time-variant as the one used in Amihud and Goyenko (2013) and, while allowing time variation would certainly be more adequate in most cases, the limited number of time-series observations during recession periods made me choose a constant measure rather than drastically reducing the sample and obtaining meaningless results.

Thirdly, the variable net normalised fund flows may depict different results by taking different lags and rebalancing the portfolios on different timeframes. Future research could investigate further on the performance relationship involving a comparison of several portfolio rebalancing intervals in both flows and activity over a wider range of periods. However, this testing is out of the scope of this study.

Another limitation worth to highlight is the fact that widely recognised benchmark models such as the ones used in this research are not perfectly fitted to explain the excess returns of the market. Indeed, Cremers, Petajisto, and Zitzewitz (2013) tested both the acclaimed Fama-French 3-factor model and Carhart 4-factor model against the S&P500 and Russell 2000 indices and found statistically significant results signalling that their alphas were large and different than zero, being positive for the S&P500 and negative for Russell 2000. The authors point that the lack of explanatory power is related with an excessive weight allocated to the SMB and HML factors and that amended benchmark model weights might considerably reduce the anomaly in the constant term. Future research could investigate the weights that make alpha to be zero for a passive index and apply this modification of the standard factor model to ensure total accuracy of the constant when evaluating performance.

Last but not least, the results on this study are subject to model misspecification due to the chosen conditional methodology regarding the state of the economy. According the Kosowski (2011), a binary model based in NBER to distinguish between expansion and recession periods is not optimal as it fails to capture transition stages such as economic growth slowdowns. The same reasoning could be applied to the S&P500 market parameter used for robustness purposes. While the objective of a binary dummy approach is to simplify the real-world situation and derive clear conclusions from it, a more sophisticated model accounting for higher degrees of variation in the economic cycle could certainly help to extract some aspects which may be otherwise overlooked. Therefore, subsequent research could revisit the conclusions of this study and test the same hypothesis under a non-binary model to corroborate the results.

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