Are index fund investors rational?

The effect of fund characteristics on performance and cash flows

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Abstract

This study analyzes the S&P 500 index fund industry and its trends between 2003 and 2012. In addition, the fund characteristics that determine performance relative to the index and fund flows are looked at. No evidence of fund proliferation after 2008 is found, while category proliferation and fee dispersions are confirmed. Of the fund characteristics that determine fund flows, all are found to be determinants of fund performance. This is congruent with rational investors rewarding funds with characteristics that are related to better performance. Surprisingly, the typically labeled non-performing return since inception variable is found to be an important determinant of both. There is some evidence of institutional investors being more performance-driven in their cash flow allocation decisions, as well as of fund performance being more important in determining fund flows during recessions.

Content

1. Introduction

By index funds, this study refers to the subgroup of mutual funds that aim to replicate the movements of a financial index. In particular, this study looks at S&P 500 index funds. Even though 1/3 of US mutual fund investors hold at least one such fund (Investment Company Institute, 2012), academics do not pay much attention to them. In the academic literature, index funds (and the Vanguard 500 in particular) are mostly mentioned as a benchmark for passive fund returns when evaluating active fund performance. For example, see Grubber (1996). Unfortunately, further analysis of index funds is limited to a handful of studies.

The problem with applying the current broad industry literature to index funds is that it defines performance as Jensen's alpha, which is not the optimal measure when funds face extremely similar risks (as their portfolios track the same underlying index) and do not have the objective of out-performing. This means that regular mutual fund studies do not have much to say about index funds, because they tend to focus on active equity funds.

Having identified this problem in the literature, the motivation of this study is to draw from the focal topics in mutual fund research to extend the body of knowledge surrounding index funds. In addition, this presents a good chance of updating and consolidating a somewhat stale literature. This is especially important because the fund proliferation that previous studies found in the industry results in more data being available than ever before. Not only are more observations available, but there are also new fund characteristics in the CRSP database that can be used to try to explain index fund performance and fund flows.

Given the broad goal of this study, the following three questions are posed: 1) What are the determinants of S&P 500 index fund performance?, 2) What are the determinants of fund flows?, and 3) Do the determinants differ between: institutional/retail funds and expansion/recession quarters? In addition, a thorough description of the industry and the trends that have developed is given to gain a better understanding. In particular, fund characteristics such as age and size (along with 14 others) will be explored as determinants.

Given that S&P 500 index funds all offer similar performance profiles (in other words performance is homogenous in expectation), such that the average quarterly spread is 35 basis points, one would expect that non-performance competition is more important in this industry. If funds compete outside the fee dimension, this competition could be captured by fund characteristics. Observing this characteristics is costly for the investor (search costs), and this imperfect information allows dominated products to survive (and thus explaining why there are so many funds offering the same product). This is because it is not possible to go short on an inferior fund and set up an arbitrage trade.

When looking at the data for the funds between 2003 and 2012, the broad industry trend of fund proliferation is not found after 2008 in the S&P 500 index fund industry. Category proliferation for fund families that have at least one such fund is found, as well as evidence of fee dispersion at the top of the expense ratio distribution (confirming the findings of Hortaçsu & Syverson, 2004).

The following fund characteristics are found to be determinants of performance: size, family size, 12b1 fee, management fee, return since inception, restricted sales dummy, rear load dummy, institutional dummy, and the 3rd lag of performance. The following fund characteristics are found to be determinants of fund flows: 12b1fee, restricted sales dummy, rear load dummy, age, return since inception, lagged net cash flow, aggregate industry net cash flow. Unfortunately, some of the effects found disappeared when controlling for fund and time-specific effects.

When comparing the two lists, it seems that the vast majority of the determinants of fund flows are also determinants of performance. This is congruent with rational investors rewarding with transfers funds with characteristics that are related to higher performance. In the theoretical model developed throughout this paper, these are labeled performance-determinants of fund flows. The only possible non-performance determinant of flows found is age; however the econometric technique used does not allow concluding it is not related to performance. Unfortunately, most of the coefficients found were of little economic importance.

Another important finding is that of long term persistence in index fund performance and short term persistence in fund flows. This trend has also been found in the broad industry, where funds with good performance tend to continue doing well. This is explained by the persistence found for certain fund characteristics that determine expenses and vary little over time. Similarly, when the industry has a positive flow then funds tend to receive more money too. This suggests investors of different funds act similarly at the same point in time.

The spread of fees in the cross-section of S&P 500 index funds is similar to that for whole industry (Halling, Cooper, & Lemon, 2012), despite the fact that a homogenous product should result in harsher competition in expenses. This is interpreted as evidence that non-product differentiation is especially important in this industry.

Unfortunately, no clear findings in the performance-flow relationship are made. This is disappointing but similar to Del Guercio & Tkac (2002). Only during recessions a significant relationship is found, suggesting that investors pay more attention to performance in rough economic environments.

On the other hand, remarkable differences are found between institutional and retail investors, as the former's fund flows are harder to predict but more determined by performance-characteristics. This lies in agreement with the ideas of investors of these two types differing in complexity of decisions and sophistication.

Given the evidence found of fund characteristics being determinants of fund flows, the fact that dominated products survive in this market, and the persistence found for both performance and glows; the fund characteristics associated with better performance could benefit investors who select funds that rank highly (or lowly depending on the sign of the relationship) in those. Similarly, the characteristics related to larger cash flows for investors could be used by fund managers to try and attract cash flows by changing some of them (though some, like return since inception, are harder to change).

In the next section, the main mutual fund trends will be examined with a focus on index funds. In Section 3, the data and methodology used to answer the research questions will be described. In the fourth section, the sample will be described looking for key industry characteristics and trends. In section 5, the results of the determinants of performance and fund flows will be analyzed. Finally, in the last section the conclusions of this paper and recommendations for future research in the topic will be given.

2. Literature review

The academic literature researching mutual funds, *en masse*, can mostly be divided into three different topics: performance and its persistence (for example: Sharpe 1966; Jensen 1967; Grinblatt & Titman 1992; Carhart 1997; Wemers 2000, Fama & French 2010), fund flows (Sirri & Tufano 1998; Barber, Odean & Zheng 2005; Cooper, Gulen & Rau 2005), and manager/investor behavior (Grinblatt, Titman & Wermers 1995; Pollet & Wilson 2008; Elton, Gruber, Blake, Krasny & Ozelge 2010). Sometimes two of these topics can intersect; such as in Chevalier & Ellison (1999), where manager characteristics are used to explain manager behavior and fund performance.

Guided by these focal topics, Section 2.1 of this study continues by concentrating on the academic literature regarding the subgroup of index funds. After a brief overview of the state of literature; studies that make usage of the unique characteristics of index funds are used to explore the industry's structure, performance and fund flows. In addition, studies that compare index funds to either the complete mutual fund industry, or other subgroups of it, are used. In Section 2.2, literature is condensed into the three research questions about index funds that will be answered throughout the upcoming sections.

2.1. Index funds

While the underlying idea of mutual funds originates hundreds of years in the past, it was only in the 1930s that the industry got regulated in the United States. In terms of assets under management, the industry has grown exponentially since the 1950s. As the number (both of funds and of types of funds) and importance of mutual funds increased, so did academic research on the topic.

Actively managed funds represent the majority of mutual funds. Active funds have substantially higher expenses (> 1% of assets) than index funds (.20% for the Vanguard 500 Index), as well as higher management fees. Given this observation, it is vital to know whether the active fund managers have enough stock-picking talents to justify the expenses they burden on their investors.

The salient question in the literature is whether or not professional managers who actively trade stocks generate value for their investors. In other words: does an actively managed fund outperform an appropriate passive benchmark? The majority of studies that tackle this question conclude that this is not the case and that investors are better-off by investing on a passive market index. For example: Grubber (1996) labels the growth of active funds a 'puzzle' given that his study finds that they underperform index funds in terms of risk-adjusted performance (Jensen's alpha).

Chen, Jagadeesh and Wermers (2000) found that when adjusting for stock characteristics, the stocks bought by funds outperform those sold by them by two percent. However, this stock-selection ability is not enough to cover the large trading costs and fees associated with active management. This means that while active funds obtain gross returns that are higher than their benchmark, their net returns are smaller. This result is in line with the findings of studies that analyze mutual fund holdings to estimate gross returns, such as Grinblatt & Titman (1993) and Wermers (2000).

While many studies have been made on different aspects of actively managed mutual funds, the literature analyzing index funds is small in comparison. Other than mentioning the returns of passive funds as a benchmark, the majority of the literature does not go further into the analysis of the performance, fund flows and manager/investor behavior of index funds. In addition, studies about index funds have become less popular with the passage of time. One possible explanation for the latter is researchers being more interested in a similar but more innovative product: exchange traded funds (ETFs).

Mutual funds had US$ 11.6 trillion in net assets held by the end of 2011 in the US; of which 11.2% were held by index funds, with positive and significant growth in the industry (for example, equity index funds grew 67% in the last decade). Alternatively, 33% of households that owned mutual funds were part of at least one index fund in 2011 (Investment Company Institute, 2012). Given the scale and growth of the industry, as well as the evidence suggesting that passive funds outperform active funds, it is paramount for investors and researchers to study index funds as more than a benchmark.

2.1.1. Industry description

Mutual funds are open-end investment companies that have their investment policies described in their prospectus. These investment policies differ greatly between funds, as they can invest on different asset classes: equities, bonds, money market securities, or combinations. Furthermore, funds also can choose to invest only in specific products within an asset class: foreign equities, equities from a specific industry, single/multi-state municipal bonds or mortgage-backed securities, amongst several others.

Constrained by the investment policy outlined in their prospectus, these funds use different strategies to try to achieve the highest possible performance. Index funds are different in that their policy is not to maximize risk-adjusted returns under a set of constraints (maximize alpha), but to replicate the performance of a broad market index such as the S&P 500 or the FTSE 100. Traditional indexing is a simple way of achieving this: by holding all the securities that are included in the index in proportion to each security's weight in the index, the fund's performance would match that of the index in a frictionless world.

A weak version of the efficient markets hypothesis where the marginal gain from acting on information is smaller than the marginal cost associated with gathering that information, such as that proposed by Jensen (1978), can explain why index funds appeared in the late 1970s and early 1980s (a period of important developments in the field of finance). They circumvent the inefficiencies of stock selection that are experienced by active funds, a concept which had gained notoriety at that point in time.

Because their investment strategy is markedly different from that of other mutual funds, index funds have a unique property: they offer a homogenous product in terms of performance. While index funds can differ on what index they track and on their fees, all the funds that track the same index are offering the same performance profile. This is markedly different from active funds, where funds with similar investment policies can have very different performances due to managers choosing different investment strategies. The implication of this is that competition in this subgroup of the industry has a smaller degree of product differentiation.

Nonetheless, index funds do compete in another dimension: fees. While in expectation funds should have the same gross return, the net return that investors experience depends on the expense ratio of the fund (the sum of all expenses such as administrative, management and advertising). From the perspective of portfolio theory; as funds offer the same risk and expected gross return, to maximize utility the investor should simply select the fund that has the lowest expense ratio as this maximizes expected net return.

This situation resembles a market under perfect competition, where given a homogenous product the demand is perfectly elastic at a minimal price. For the case of index funds, all investors should choose the fund with the lowest fees and none of the others. However, Hortaçsu and Syverson's (2004) find that non-portfolio characteristics and imperfect information also play a role when investors select an index fund. This observation is used in section 2.1.2 to explain some unlikely characteristics of the industry's structure.

The previous result explains how index funds that are not the cheapest survive in a market for a homogenous product. This result bears negative consequences for investors because they get smaller net returns due to the larger fees. On the other hand, it also has positive consequences for fund managers: they can charge larger fees (which depending on the price-elasticity of fund flows could lead to larger income) and not be pushed out of the market by cheaper competitors.

2.1.2. Industry structure

Gubber (1996) observes that in the decade following the formation of the first index fund (1985-1994), more than 100 index funds covering many types of securities were created. He also observes that while the expense ratio started the decade at 1.24% per year, it ended it ranging between 21 and 147 basis points with an average of 75. These two trends are also present for the whole universe of mutual funds. The first trend is labeled by literature as fund proliferation, while the second is labeled fee dispersion. A third trend labeled category proliferation (the increase in the number of categories of mutual funds that are offered) is observed; but is not relevant for this study, as no research comparing different categories of index funds was found.

Stepping aside of mutual funds for a moment, and looking at industrial organization, in their analysis of monopolistic competition Shaked and Sutton (1982) found that price competition can be reduced through product differentiation. When firms can choose both price and specification for a differentiable product, equilibrium exists where firms choose different products and prices. In this equilibrium, both firms have positive profits. This result validates the observed trends of fund proliferation and fee dispersion, but does not explain them. To delve deeper into the causes of this result, the next step is to look into the characteristics of mutual funds.

Fund proliferation and category proliferation are explained by Massa (2003) as a consequence of the strategies used by mutual fund families. By offering investors the ability to switch between different categories of funds within the family for free, they cater to investors with heterogeneous investment horizons. Differentiating one of their product's non-performance characteristics allows fund families to decrease the importance of performance competition. As the degree of product differentiation increases, so does the number of funds. This explanation is especially appealing if one considers that by the end of 2011; 40% of total net assets in the mutual fund industry belonged to the 5 largest fund families, and 73% to the largest 25 (Investment Company Institute, 2012). As fund families expand their offerings, they are likely to offer an increasing number of index funds. Additionally, as performance competition becomes less important due to non-performance differentiation, fee dispersion becomes easier to understand.

However, the previous explanation does not take into account the unique characteristics of index funds. Hortaçsu and Syverson's (2004) use S&P 500 index funds to propose a model where investors choose between index funds taking into account extra-portfolio characteristics. Their model is able to recreate the observed trends of fund proliferation and fee dispersion despite the financial homogeneity in terms of gross performance.

Their model uses loads, difference between fund and index returns, and the standard deviation of monthly returns as performance variables; with the latter two having positive and significant effects on investor utility. Non-performance variables include fund age, manager tenure, number of funds in family and tax exposure; with the latter two having significantly positive and negative effects on investor utility respectively. Non-performance variables affecting investor utility can explain fund proliferation as a result of product differentiation.

They also find that, against intuition, as the number of S&P 500 index funds increases the average expense ratio increases. This can be explained by the use of search costs in their model: if it is costly for investors to acquire information on the fees charged by different funds, then they are less likely to choose funds that have the lowest fees. Returning to the industrial organization analogy: if clients have imperfect information and perceive differences in the products, this resembles monopolistic competition more than perfect competition. Under this scenario, fee dispersion is comprehensible.

This explanation for fee dispersion is in line with Barber et al. (2005) who find no relation between operating expenses and fund flows. Instead, they suggest that investors pay more attention to more "salient and attention-grabbing" information that has a smaller impact on performance, such as front-end loads and commissions when choosing what fund to invest in.

2.1.3. Performance

When measuring fund performance in the broad mutual fund industry the measure of choice is most often alpha in Fama & French's (1992) 3-factor model, sometimes adding a momentum factor like in Carhart's (1997) 4-factor model. While this measure illustrates a fund's risk-adjusted performance, given that index funds attempt to replicate and not outperform a benchmark this measure is of little help.

The three studies that focus on index fund performance, Grubber (1996) and Frino and Gallagher (2001, 2002), agree with Roll (1992) in that since returns are not chiefly important for index funds then portfolio managers will focus on minimizing tracking error. Thus, tracking error (how closely the fund's portfolio follows the index against which it is benchmarked) is the preferred measure to evaluate the performance of index funds. This is because tracking error represents the implicit cost of investing in an index fund for an investor. Furthermore; while it is crucial to risk-adjust performance for active funds, this is not the case when comparing index funds that replicate the same index as they all face very similar risks.

A market index represents a mathematical calculation (or paper portfolio), but the existence of market frictions implies that index funds will have difficulty in perfectly replicating an index. For example, index funds must incur in costly physical transactions that take time to process; while the calculation of an index assumes that there are no trading costs and that re-balancing is instantaneous at prevailing market prices.

The causes of tracking error are as important as its consequences. Chiang (1998) finds that the following market frictions affect the tacking error of index funds: transaction costs, index composition changes, fund cash flows, index volatility and reinvestment of dividends. Frino & Gallagher (2002) start with these factors and split transaction costs into explicit (commissions to broker) and implicit (bid-ask spread), as well as adding replication strategy (full replication vs. synthetic replication). The mechanics through which each of these factors affect tracking error are discussed below, following the order in which they were listed.

Even though index funds implement a passive strategy, they may still have reasons to trade. When they trade, they pay their broker a commission and this explicit trading cost directly results in tracking error. Additionally, while an index assumes instantaneous re-adjustment at prevailing market prices, it takes time for funds to respond and when they trade there is not a single prevailing price but bid and ask prices. These implicit trading costs also result in tracking error. In both cases, higher trading costs result in higher tracking error.

When the composition of an index changes, index funds must incur in costly trading which in turn increases tracking error. This problem is furthered by the empirical observation that when a stock gets included into an index it experiences positive abnormal returns and a high volume. Similarly, when a stock gets excluded from an index it experiences negative abnormal returns and a high volume (Lynch & Mendenhall, 1997). This can negatively affect index funds due to 'front-running' (Beneish & Whaley, 1996) and thus further increase tracking error.

When an index fund gets or loses a client, these cash flows will result in trading. Either the new cash will be spent across the securities in the index or part of the fund's portfolio will be liquidated. In either case, there will be transaction costs which will result in tracking error. Additionally, a time delay in the fund adjusting its portfolio can also result in higher tracking error as security prices change. Chiang (1998) and Frino & Gallagher (2002) find that the relation between cash flows and tracking error is positive, meaning higher fund flows are related to worse performance.

If an index fund's portfolio perfectly matches the index in terms of composition and stock weights, a change in the value of the index will be perfectly matched by the change in the value of the portfolio. However, there are reasons why these two are unlikely to be perfectly matched. An example of this is given by Frino & Gallagher (2002): if a security in the index is highly illiquid then an index fund might have to proxy it with a similar security. In this case, non-systematic movements in the price of either security will result in tracking error. Under the assumption that a fund's portfolio does not perfectly match the index, higher index volatility will result in larger tracking error.

When a firm listed in an index goes ex-dividend, the index assumes that the dividends are immediately re-invested in the stock. Nevertheless, investors do not receive the dividends until a later date (around a month in the US). This causes both transaction costs and a time delay for reinvestment. Thus, a higher level of dividends in the stocks that compose an index will result in a higher tracking error.

There are different replication strategies that can be used to track an index. For example: stratified sampling involves holding only a representative fraction of the securities in the index, synthetic replication involves using derivative instruments and bonds, or more complex and highly quantitative methods such as Focardi and Fabozzi's (2004) time-series clustering method. Olma (1998) finds that, *ceteris paribus*, non-replication strategies (in other words, strategies that are not traditional indexing) result in a larger tracking error. While they might be related to poorer performance, alternative index replication methods can have advantages too depending on both regulation (for example taxes) and market conditions (low liquidity).

While it is not mentioned in the literature, the amount of cash held by a fund could also positively affect tracking error. Given that funds require some liquidity to quickly service coming/leaving clients, a higher weight in cash by the fund will result in a larger difference between the fund's portfolio and the index's composition and thus lead to larger tracking error. This affects performance through the index volatility mechanism. It is important to note that while the studies quoted use underlying index characteristics mostly, fund characteristics can also be important determinants of performance.

Another possible factor, fund characteristic in specific, that is not mentioned in the literature is the size of the fund (or family of funds). It is reasonable to conjecture that larger funds can have more bargaining power *vis-à-vis* market makers. This, together with economies of scale, means larger funds can trade at a lower cost and better price, and thus experience lower tracking error. This hypothesis is supported by Cooter & Landa's (1984) personal vs. impersonal trade model, where larger trading group size facilitates contracts under uncertainty. The idea behind this is that a trader will prefer to avoid uncertainty and offer better conditions to an 'insider' instead of an 'outsider'; and larger funds, especially those that belong to large families, are more likely to be insiders.

After looking at the effects and then causes of tracking error, its reported magnitude is analyzed: Grubber (1996) finds that the average yearly tracking error is 21.9 basis points Furthermore, he regresses index fund returns on index returns to find an average beta of 0.999 (ranging from .991 to 1.004) and an annualized alpha of -20.2 basis points. This alpha represents risk-adjusted performance and is significantly smaller for passive funds than for active funds, while the beta is in line with their objective of replication. Using a larger sample and more recent data, Frino & Gallagher (2001) find that annualized tracking error ranges between 17.7 and 72.1 basis points. Furthermore, they find that tracking error is significantly larger every third month when stocks go ex-dividend (February, May, August and November) and significantly smaller the month after when dividends are received. They explain this quarterly seasonality with the dividend effect that was previously discussed.

Finally, Elton, Grubber and Busse (2004) find evidence of persistence in yearly tracking error and alpha for S&P 500 index funds: there is a high rank correlation between past performance and future performance. To illustrate this: buying the top decile funds in terms of past performance results on 97 basis points less tracking error in the next year than the bottom decile funds. For alpha, this difference is 107 basis points. They also find evidence for persistence in expenses, as funds with low expenses last year tend to continue having low expenses and vice-versa. In checking robustness they use alpha and the expense ratio as alternative measure of performance.

2.1.4. Fund flows

While the majority of the early literature surrounding mutual funds relates to its performance, the analysis of their fund flows has gained importance over time. Fund flows are the net of all cash inflows and outflows that a fund has in a given period, ignoring the fund's performance and focusing on the amount of cash from clients entering/exiting the fund. The importance of a fund flow is that it acts as an indicator or signal of the prevailing trend in the market for a product; as such, it proxies investor sentiment towards the product. For example: if recent data shows that a fund has had positive fund flows, this is a signal that the product is 'hot' and the demand for it is on the rise.

Although it is a potentially useful indicator of the market's sentiment towards a product, fund flows are not directly related to performance and should be interpreted in that way. For example: increased flows to money market funds can be interpreted as a signal that equities are underperforming (and thus investors are moving to other asset classes), instead of a signal of investors anticipating a good performance by these funds.

In the previous section about index fund performance, it was mentioned that fund flows were a determinant of tracking error. Reversing the situation, researchers have also found a strong and significant relation between fund past performance and current growth (Ippolito, 1992). This suggests that funds that have performed well in the past have positive fund flows, and vice-versa. However, this relationship is not linear as transaction costs for investors (selling is more expensive than buying) make funds that have a better performance perceive this effect more strongly. A more recent study by Sirri & Tuffano (1998) confirms that the sensitivity of fund flows to performance is very high for the funds in the top percentiles of performance, and smaller as one goes down the performance ranking. This result is robust to different measures of performance such as average return and alpha, so that extending this conclusion to tracking error is possible even though this measure is not risk-adjusted (like alpha). One may note that studies like Del Guerico & Tkac (2002) find no relationship between tracking error and fund flows for mutual funds, but this result may be driven by the use of other performance measures in the same regression. Additionally, tracking error should work better for index funds than for the broad industry as in their study.

Related studies have also found that fund flows affect manager behavior. For example, given the convex shape of the fund flow-performance relationship, Chevalier & Ellison (1995) find that fund managers have incentives to adapt the riskiness of their fund depending on the funds year-to-date performance: taking more risk can improve performance and thus rank, which in turn would improve fund flows and thus managerial fees; while if the increased risk worsens performance, there will be less punishment due to the convexity of the relationship. However, this effect should be negligible for index funds as their investment objective is replication and not outperformance.

Information costs are also extremely important in determining fund flows: as much as other variables can affect fund flows, the net flow of cash to a fund hinges on the decisions of investors to join or leave the fund. To make these choices, investors need information. Hortaçsu & Syverson (2004) highlight that to decide, investors need to acquire information on the existence and characteristics of mutual funds. This information is limited and costly to acquire, and the term used to describe it in the context of investors selecting a fund is search costs. One factor was whether the fund has a front/back load or not, and this is related to search costs: load fund investors are less educated, less wealthy, more likely to use a financial intermediary, and thus have larger search costs. The puzzling fact that expensive funds with loads grew in the late 1990s is explained in their study by an influx of high search cost investors. This is supported by the investor profile of load fund investors (Investment Company Institute, 2001).

One problem with search costs is that they are an investor characteristic that is hard to measure, instead of a fund characteristic. As such literature focuses on creating models for it and testing it against the data *à la* Hortaçsu & Syverson (2004). Nonetheless some of the influence of search costs can be captured by measuring fund fees, which Sirri & Tuffano (1998) link to marketing effort. They find that the fund flow-performance relationship is stronger for funds with higher fees, which could be explained by higher fees representing larger efforts in marketing which reduce search costs. As recently explained, front/back loads could fit this role too as they are also a type of fee. Additionally, they find that the size of the fund family and the media coverage of a fund also affect search costs.

In Section 2.1.2, search costs were used to explain fund proliferation and fee dispersion, and some fund characteristics that are valued by investors were listed. Since investors value these characteristics (as utility depends on them), they should also determine fund flows. Following convention in research on the determinants of fund flows, fund characteristics were split into performance and non-performance variables. The typical regression of this type has fund flows (normalized by fund size) as the dependent variable, and fund characteristics as independent variables. For an extensive list of independent variables that can be used for this regression (although it includes some performance variables that apply for active funds more than index funds), see Elton et al. (2004).

Unlike listing the determinants of performance; doing so for fund flows is more complicated, because theoretically it includes any and every variable that the investor uses to decide his/her money transfer to a mutual fund. It is very hard to distinguish an exhaustive list of which variables are used by the investor to make an investment decision, as psychology would suggest a myriad of factors affect the cognitive process of making a decision. For example: funds that change their name to a currently ‘hot’ investment style experience an average abnormal cumulative flow of 28% despite no improvements in performance (Cooper, Gulen & Rau, 2005). While this example does not directly apply to index funds (which are homogenous in investment style), it does suggest that unexpected factors that connote popularity can have an impact on fund flows.

A similar conclusion was reached by Elton et al. (2004) who use the homogenous product of index funds to test investor rationality: they found that “in a market where arbitrage is not possible, dominated products can prosper”, meaning that funds with high costs can have positive fund flows due to search costs and many degrees of non-performance product differentiation.

As hinted earlier, psychology is important in answering a question regarding the cognitive process of decision making by investors. In particular, behavioral finance in the form experiments has been used to solve this problem of apparent investor irrationality. Borrowing from psychology, Choi, Laibson and Madrian (2006) do an experiment to understand why investors do not all choose the index fund with the lowest fees (as the law of one price would suggest for a homogenous product). They find that, even after unbundling non-portfolio services a fund might give, "subjects overwhelmingly fail to minimize fees". When increasing the saliency of fees, investors shift to cheaper funds but still give importance to an irrelevant variable: return since inception. This suggests that investors fail to realize the nature of the product offered by index funds (even though the sample includes Harvard staff, MBA students and college students only), as historical returns are mostly a function of fund age and index returns and do not reflect future performance. Interestingly, education has little to no effect in an individual's ability to minimize fees and ignore historic returns. The following variables are found to matter in the fund selection decision: quality of prospectus, brand recognition, fees, loads, expenses, performance since inception, performance over current year, performance over different horizon, desire to diversify. Another experiment by Beshears, Choi, Laibson and Madrian (2009) finds that giving an investor a full or summarized prospectus of a mutual fund makes no difference, and that investors demonstrated poor understanding of loads (as investors with very short horizon were as likely to select a load fund as the rest).

It can be noted from looking at experimental data that factors outside the typical fund flow determinants regression can affect the decision making process. Some of these factors cannot be explained in terms of the financials surrounding mutual fund investments. Beshears et al. (2008) distinguish between the factors that the subject is actually interested in (*normative preferences*) and the factors that rationalize the subject's observed actions (*revealed preferences*). They explain that in many circumstances these preferences do not coincide. As experiments (such as questionnaires) can only help to identify revealed preferences, factors that affect fund flows (normative preferences) could be nearly impossible to identify exhaustively.

2.2. Research questions

Compared to the broad mutual fund family, index funds have received little attention in terms of academic literature. In section 2.1 the different focal topics of research about index funds were described; in cases where it applied, studies from the broad industry where used. One important observation is that most of the studies about index funds referenced have small sample sizes and small time windows. Studies usually start their windows in the early 1990s, and: for performance studies latest data is from 2001, while for fund flow studies the most recent data is from around 2005.While there are newer studies in the fund flow field, these use investor-level data instead of fund-level data.

One additional observation is that the majority of recent studies on index funds focus on the subset of S&P 500 index funds. One important reason for doing this is that it simplifies fund identification: in earlier studies it had to be done by analyzing fund names, while more recently it is done by fund classification codes in the database used. In both cases identifying S&P 500 index funds is simpler and less bound to errors than identifying any other type of index funds. In addition the S&P 500 index fund industry is the largest within index funds, with 78% of assets in the index fund industry invested in stock index trackers and 34% in S&P 500 index trackers (Investment Company Institute, 2012). The rest of the assets in stock index trackers are divided as follows: 33% other domestic equity, 11% world equity, 22% bond and hybrid.

As the trend of fund proliferation suggests, the number of index funds has increased over time. In addition, the time window for this study can extend until 2012. This results on a larger sample, in terms of both funds and observations per fund, than any previous similar study. This study has the opportunity to replicate previous studies of both performance and fund flows with more and more recent data, to see if previous findings persist or change.

The focus of this study is to compare the effect of different fund characteristics in determining fund flows. The sub-sample of S&P 500 index funds is chosen, in accordance to most literature in index fund flow determinants. Beshears et al.'s (2008) distinction between normative preferences (the factors that the subject is actually interested in) and revealed preferences (the factors that rationalize the subject's observed actions) in decision making, and the large number of determinants of fund flows found in the literature determine this study's first research question:

(Q.1) What are the factors that determine S&P 500 index fund performance?

To answer (Q.1) all the distinguishable fund characteristics that can be found (including both those motivated by the literature review, as well as others) are tested as determinants of fund performance. The factors used include the determinants of fund flows, as the same list of variables will be used for the upcoming question on that topic. The answer to this first question allows this study to find which fund characteristics affect performance.

With this distinction in fund characteristics, this study then proceeds to test the fund characteristics used in the previous questions as determinants of fund flows. The second research question of this study is:

(Q.2) What are the factors that determine S&P 500 index fund flows?

To answer (Q.2), the effect of the fund characteristics on fund flows is tested. Comparing the answers of the first two questions it is possible to see if the determinants of fund flows are also related to performance. If investors are rational, they should reward characteristics that are positively related with performance.

Finally, this study does two sub-sample analyses to observe the differences in the answer of (Q.2). The third research question is:

(Q.3) Does the effect of performance and non-performance fund characteristics on fund flows differ between: (a) institutional and retail funds, and (b) recession and expansion periods?

To answer (Q.3) the analysis done for (Q.2) will be repeated for each category in the sub-sample. Each of the two conditions in the question is motivated by existing literature. Together with economic intuition, this type of analysis helps to confirm (or mold new) theories about why and how the effect of fund characteristics changes in a specific sub-sample. For example: it is expected that institutional investors, who are more sophisticated, pay more attention to performance characteristics and less to non-performance characteristics. Finding this in the data would corroborate previous studies (the studies that motivate the choice of these sub-samples are discussed in section 3.4), while the opposite finding would motivate looking for an alternative explanation.

3. Methodology

3.1. Data

This study collects data from CRSP survivor-bias-free US mutual fund database. Given that many relevant variables are available since between 1998 and December 2002, observations will begin at the start of 2003. They will span to the most recently published information: June 2012.

S&P 500 index funds will be identified using Lipper Objective Code: this variable looks at a fund's prospectus language to identify the investment objective of the fund into one of over 200 types of objective. It reports in quarterly frequency. Unlike studies before the introduction of this variable, which relied in Wiesenberger investment fund types (this only offered 28 types, in yearly frequency, and did not identify index funds), it is not necessary to identify funds by name *à la* Grubber (1996). This reduces the chances of errors in the process of identifying funds. It also allows moving away from using yearly data, like Sirri and Tuffano (1998), into using quarterly data. The funds that are used by this study are described as 'S&P 500 index objective funds' and are: passively managed, committed in their prospectus language to replicate the S&P 500 index (including reinvested dividends), and have a small advisor fee (< 0.5%).

The fund characteristics (variables such as asset composition, management company, age, 12b1 fee, management fee, expense ratio, turnover, and identifiers for: merged, dead, restricted sales, institutional and retail funds) are available at quarterly frequency. The funds returns and total net assets (TNA) are available at monthly frequency. This creates a dilemma in terms of selecting a frequency, as it is possible to: transform the returns into a quarterly frequency and merge the returns into the fund characteristics, or transform the characteristics into a monthly frequency by assuming every three months in a quarter have the same values for all characteristics. The first method is chosen, as the second would lead to 'stale' observations with repeated values which could lead to dependence in error terms in a regression situation. This forgoes the advantage of the second method which is a quadrupled sample size.

To transform the returns from monthly to quarterly, the following formula is used: $r_{i,q,t} = (1 + r_{i,m,t}) * (1 + r_{i,m,t-1}) * (1 + r_{i,m,t-2}) - 1$. Where: $r_{i,q,t}$ is the return in quarterly frequency at time t for fund i, and $r_{i,m,t}$ is the return is the return in monthly frequency at time t for fund i. Quarter's dates are set at the end of March, June, September and December. The TNA require no transformation, $TNA_{i,q,t} = TNA_{i,m,t}$, meaning that the quarterly TNA is the TNA in the month that matches the quarterly date and that TNA data for months that do not match is not used.

Few observations are lost due to monthly data and quarterly dates not matching, resulting on a sample of 356 S&P 500 index funds with 9,236 quarter-fund observations. Because CRSP calculates fund returns in terms of changes in TNA, there are some extreme returns that far exceed the S&P 500 index performance. These observations are excluded by setting a threshold of $\pm .5 \times \sigma_{S\&P500}$ around each quarter's S&P 500 index performance, where $\sigma_{S\&P500}$ is the standard deviation of the quarterly returns on the S&P 500 index. An example of a situation where an extreme return in terms of TNA might occur is if a fund absorbs another, where TNA could increase significantly and a large return would not reflect the performance of the securities held by the fund. Less than 40 extreme observations were dropped this way.

Using the cleaned merged dataset, the following variables of interest for this study are directly available from the database: return differences between fund and S&P 500 index (derived from the quarterly fund returns and underlying index returns), expense ratio, percentage of fund invested in cash, total net asset value (measure of size), 12b1 and management fees, age in years (derived from date fund was first offered), fund turnover, and dummy variables for if the fund: is open to investors, has restricted stock sales, has been absorbed by another fund due to a merger, is a retail fund, and is an institutional fund (of the latter two, only the last is kept after confirming no overlap).

In order to calculate how well the funds track the S&P 500 index (return differences), monthly data on the index's returns including reinvested dividends is obtained from CRSP. This is transformed to quarterly data so to match the quarter dates on the merged dataset. On the next section, quarterly fund minus index returns will be used to measure fund performance.

The rest of the variables of interest have to be derived from related variables available in the database, or computed from the available observations. The following variables are constructed: fund net cash flows, fund family size, performance since inception, and dummy variables for front and rear loads. In addition, the natural logarithm of TNA is used as a measure of size. The latter is in accordance to similar studies, and is explained by the fact that the distribution of size is strongly skewed due to few very large funds dominating the industry.

Net cash flows are defined as the net of cash inflows and outflows into a fund over a period of time. These can be calculated from the quarterly fund TNA and return data, and in accordance to literature they are also scaled by fund size. The calculation is done using the following formula: $CF_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \times (1 + r_{i,t})}{TNA_{i,t-1}}$, where $CF_{i,t}$ is the normalized net cash flow for fund i at time t, $TNA_{i,t}$ is the net asset value for fund i at time t, and $r_{i,t}$ is the return for fund i at time t.

Family size is calculated for each fund and in each quarter by counting the number of funds that share a management company, for this the entire CRSP mutual fund database is used for the time window of this study. The logarithm of the number of funds in family is also calculated in case the variable is positively skewed and has important outliers (like un-transformed size). Fund return since inception is calculated as the average quarterly return for a fund, from the fund's creation until the current quarter. For this, returns of all the S&P 500 index funds in the sample since the creation of each fund are used (the first fund appeared in the 1970s, so data will span from there).

From the records of front and rear load policies used by funds over time, we generate dummy variables for both loads. While it is possible to derive measures of magnitudes of the loads, this study follows the literature in, for simplicity, only using dummy variables indicating the presence and absence of a load of each type. The dates of load policy changes are rounded to the nearest quarter, to allow merging into the panel data structure.

To clean the data sample, all observations that are missing data on any of the variables of interest are dropped. This drops funds that did not report information on all the variables, as well as funds that reported for less than three consecutive quarters. Abnormal observations such as extremely negative cash holdings (-57%) or management fees (-37%) are also removed. In particular the top and bottom 1% of management fees and cash holdings are dropped due to extreme values. The resulting sample size is 5,823 quarter-fund observations, for 213 funds. The 140 funds that are lost are either: funds that existed for a short time period, funds that are less than a year old, funds that did not report all the variables of interest, and fund-quarters with extreme values (as previously described).

One last adjustment that is often present in the literature of mutual fund studies is adjusting the data for mergers: when two funds in the database merge, this can generate repeated observations due to double entries. These can happen because when two funds with unique codes merge, it is possible that post-merger data for the fund that ceased to exist continues to appear in the database. Using the merger identifier, the cases where two funds inside the sample merge are checked to avoid this problem.

The resulting data structure is a panel where the cross-sectional dimension is the different funds, and the time-series dimension is the quarters between March 2003 and June 2012. This panel is unbalanced because funds can die and new ones can enter the sample.

3.2. Performance analysis

In order to answer the first research question (what are the factors that affect fund performance?), variables that represent both fund performance and fund characteristics that might affect performance are used. The goal of this question is to classify some of the available fund characteristics into performance factors, the rest possibly being and non-performance factors. This means that the independent variables that are included in the regression represent not only variables suggested by literature, but also other variables that could possibly affect performance (for example cash holdings or turnover), and others that will probably not and are labeled non-performance in the literature (for example fund family size or age).

The reason for including variables that are unlikely to affect performance is that it is interesting to know if determinants of fund flows are related to performance. From a theoretical perspective, many fund characteristics (for example size or age) could affect performance through the channel of reputation: an older and larger fund might have more bargaining power with market makers and have transaction lower costs and thus higher performance. For robustness, different measures of fund performance are used.

3.2.1. Performance measurement

In Section 2.1.3 the case is made for using tracking error as the relevant measure of performance for index funds. There are various ways of measuring tracking error in the literature (see for example: Roll, 1992), as measures of tracking error over multiple time periods are important for investment managers to measure how far off a portfolio manager has been from a relevant benchmark's performance. However, in this case, the simplest measure of tracking error is used which is the return differences: $rd_{i,t} = r_{i,t} - r_{S\&P\ 500,t}$, where $rd_{i,t}$ is the return difference for fund i in quarter t, $r_{i,t}$ is the return for fund i in quarter t, and $r_{S\&P\ 500,t}$ is the return for the S&P 500 index in quarter t.

This is the same measure used by Frino & Gallagher (2002) to measure performance of Australian index funds, and preferred to alpha which is the measure of choice when comparing active funds. To test if the results obtained are robust the expense ratio of the fund is used, as suggested by Elton et al. (2004).

3.2.2. Performance regression

Frino & Gallagher (2002), using a panel data structure like the one used by this study but at monthly frequency, propose the regression specification in equation [1] below to explain return differences for index funds:

$$[1] \qquad \left|e_{i,t}\right| = \alpha_i + \beta_1 \times CF_{i,t-1} + \overrightarrow{\beta_2}' \times \overrightarrow{SP_t} + \varepsilon_{i,t} \ ,$$

where $e_{i,t}$ is the return difference as defined in the previous subsection for fund i in quarter t, α_i represents fund-level fixed-effects (FE), $CF_{i,t-1}$ is the cash flow for fund i in quarter $t-1$, β_1 is the sensitivity of the absolute value of return differences to lagged cash flows, $\overrightarrow{SP_t}$ is a vector with characteristics of the S&P 500 index in quarter t (transaction costs, index composition changes, fund cash flows, index volatility and reinvestment of dividends), and $\overrightarrow{\beta_2}$ is a vector with the sensitivities of return differences to each index characteristic.

When using quarter-level FE, all of the index characteristics in $\overrightarrow{SP_t}$ can no longer be used. This is because in any quarter t the values of all of these variables will be the same for every fund in the sample. This means that it is no longer possible to distinguish which of the index characteristics are determinants of the performance of funds that follow the same index, but is not a problem because this study is interested on the effect of fund and not index characteristics on performance. The time FE will capture the effect of the variables that can no longer be used, and in turn reduce the concern of endogeneity.

Fixed effects are chosen (by them and in upcoming regression specifications for this study) because of their prevalence in mutual fund literature. The Hausman test is used to confirm that FE is preferred to random effects (RE) for this sample. For the multiple regressions specifications that will be tested in Section 5 in all of this study, differences are found between the coefficients for FE and RE and the Hausman statistic is large and significant and allows to reject the hypothesis that both work. This allows rejecting that RE as inconsistent, because the assumptions needed for that statistical technique to work are not met.

This regression specification is modified in the following ways: two dependent variables are tested in return differences and expense ratio, time FE are added and thus S&P 500 index characteristics are removed, fund FE are replaced by clustering error by fund to allow inclusion of fund characteristics that do not vary over time, the other factors that determine performance from the literature review are added, the factors that determine fund flows are added, and other factors from the database that could affect either performance or fund flows are added. The approach is similar to a backwards regression, where as many as possible variables are tested as independent variables to determine what the actual determinants of performance are. From this analysis, it is possible to then label these variables as performance determinants for section 3.3.

While increasing the number of independent variables reduces the likelihood of finding statistically significant results, the sample size is larger than previous studies and definitely large enough to support tens of independent variables. Additionally the use of time FE helps to account for any time-specific differences in performance, and clustering errors by fund helps to reduce the likelihood of violating the ordinary least squares (OLS) assumptions that errors are serially uncorrelated. Indeed, it might not be safe to assume that the errors (after fitting the model) for one fund over consecutive quarters are uncorrelated.

The following fund characteristics are found in the performance literature review section: lagged fund cash flows, cash holdings, fund size, fund family size. The following additional fund characteristics are found in the fund flow literature review section: front and back loads, fees (which are divided into 12b1 fee and management fee), performance since inception. The following fund characteristics are all the other reported characteristics that were found relevant: fund age, institutional dummy, open to investors dummy, restricted sales dummy, merger dummy, and turnover ratio. The resulting regression specification is given in equation [2] below:

$$[2] \qquad DV_{i,t} = \alpha_t + \beta_1 \times CF_{i,t-1} + \beta_2 \times Cash_{i,t} + \beta_3 \times Size_{i,t} + \beta_4 \times FamS_{i,t}$$
$$+\beta_5 \times FL_{i,t} + \beta_6 \times RL_{i,t} + \beta_7 \times Fee12_{i,t} + \beta_8 \times FeeM_{i,t} + \beta_9 \times HisP_{i,t} + \beta_{10} \times Age_{i,t}$$
$$+\beta_{11} \times Turn_{i,t} + \beta_{12} \times Op_{i,t} + \beta_{13} \times Res_{i,t} + \beta_{14} \times Mer_i + \beta_{15} \times Ins_i + \varepsilon_{i,t} \ ,$$

where: $DV_{i,t}$ is either return difference or expense ratio for fund i in quarter t, α_t captures the time FE, $CF_{i,t-1}$ is the one quarter lagged cash flow for fund i, $Cash_{i,t}$ is the percentage of fund assets held in cash for fund i in quarter t, $Size_{i,t}$ is the logarithm of the total net value of fund assets for fund i in quarter t, $FamS_{i,t}$ is the family size or the number of funds in the mutual fund family that a fund belongs to for fund i in quarter t, $FL_{i,t}$ is a dummy variable that indicates if there was a front load for fund i in quarter t, $RL_{i,t}$ is a dummy variable that indicates if there was a rear load for fund i in quarter t, $Fee12_{i,t}$ is the 12b1 fee (for marketing expenses) for fund i in quarter t, $FeeM_{i,t}$ is the management fee (for professional management skills) for fund i in quarter t, $HisP_{i,t}$ is the historic performance or the average quarterly return since fund inception for fund i in quarter t, $Age_{i,t}$ is the age of the fund in years for fund i in quarter t, $Turn_{i,t}$ is the asset turnover ratio for fund i in quarter t, $Op_{i,t}$ is a dummy variable that indicates if the fund is open to investors for fund i in quarter t, $Res_{i,t}$ is a dummy variable that indicates if the fund's stock sale is restricted for fund i in quarter t, $Mer_{i,t}$ is a dummy variable that indicates if a fund has at any point in time been absorbed by another fund (through a merger) for fund i and has no time-variation, and Ins_i is a dummy variable that indicates if it is an institutional fund (it is otherwise a retail fund) for fund i and has no time-variation. The errors in this regression are clustered by fund (so they are robust), since fund FE would not allow to test the last two independent variables.

Of the fifteen independent variables in equation [2], it is likely that some variables will have a relatively high correlation with others. For example: larger funds (higher TNA) could be related to a larger family size, or 12b1 fee to management fee. At the upcoming data description section, the correlations between the factors will be estimated to evaluate cases where it could be of benefit to use only 1 of 2 (or more) highly correlated factors that capture a similar fund characteristic.

An alternative specification to equation [2] is also tested where fund FE are used. The result of changing the method in this way is that variables 14 and 15 can no longer be used as the model accounts for all fund-specific characteristics that do not change over time and affect performance. This second specification allows to test whether the effect of certain determinants of performance survives when controlling for fund FE.

By looking at the results of testing this regression specification in the sample using OLS, this study's first research question will be answered: all the fund characteristics that have a significant coefficient are labeled determinants of performance. In the next section, if they also determine fund flows then the characteristics are labeled performance determinants of flows. If not, the method used does not allow to conclude that they are non-performance determinants.

3.3. Fund flow analysis

In order to answer the second research question (what are the determinants of S&P index fund flows?) the variables from the previous regression are used. They are split by how directly they affect returns from the perspective of the investor (such that fees affect directly, while size indirectly) for reference.

It is important to remark that the procedure of labeling variables performance or non-performance is not straightforward. The reason for this is that finding that a characteristic is not a significant predictor of performance (in the regression discussed in the previous section) only allows inferring that the null hypothesis that there is no effect cannot be rejected. This means that the results obtained will not be grounds for a definite categorization of fund characteristics, but will be used as an aid.

Elton et al. (2004), using a panel data structure like the one used by this study but at annual frequency, propose that four different types of index fund characteristics affect cash flows. A simplified version of their regression specification is shown in equation [3] below. This specification is the base from which the model used in this study will be built:

$$[3] \qquad CF_{i,t+1} = \alpha + \overrightarrow{\beta_1}' \times \vec{A} + \overrightarrow{\beta_2}' \times \vec{B} + \overrightarrow{\beta_3}' \times \vec{C} + \overrightarrow{\beta_4}' \times \vec{D} + \varepsilon_{i,t} \ ,$$

where: $CF_{i,t+1}$ is period $t+1$'s net cash flow for fund i, α is a constant, $\overrightarrow{\beta_1}$ to $\overrightarrow{\beta_4}$ are vectors containing the sensitivities of cash flows to factor groups A to D respectively, $\vec{A}$ is a vector containing predictors of performance, $\vec{B}$ is a vector containing determinants of management performance, $\vec{C}$ is a vector containing determinants of risk, and $\vec{D}$ is a vector containing determinants of tax efficiency for investors.

From the findings of Elton et al. (2004): good measures of fund performance ($\vec{A}$) are return differences or expense ratio, while determinants of risk and tax efficiency ($\vec{C}$ and $\vec{D}$) have no significant effect of fund flows. The next step is then to remove the latter two vectors so that only two types of fund characteristics are left, and re-label the $\vec{B}$ vector so that it includes all non-performance variables. All of the fund characteristics that were used in equation [2], except fund flows which is now the dependent variable, are put into these vectors. In addition, time FE are used (as in most models of this type) and errors are clustered by fund. The resulting specification is show on equation [4] below:

$$[4] \qquad CF_{i,t+1} = \alpha_t + \overrightarrow{\beta_1}' \times \vec{A} + \overrightarrow{\beta_2}' \times \vec{B} + \varepsilon_{i,t} \ ,$$

where: $CF_{i,t+1}$ is period $t+1$'s net cash flow for fund i, α_t captures the quarter FE, $\vec{A}$ is a vector containing fund characteristics that affect its performance (return differences, and all other variables that are significant predictors of performance from [2]), and $\vec{B}$ is a vector containing fund characteristics that do not affect its performance (all other fund characteristics that are not in $\vec{A}$). Additionally, squared returned differences are added into $\vec{A}$ to see if the flow-performance relationship is convex or concave. Furthermore, the following two variables are also tested: aggregate net cash flow to industry is tested as a replacement for time FE, and lagged fund flow is used to control for a fund's reputation. We remark that for practical purposes the division of characteristics into the vectors is rather arbitrary since the performance determinants regression cannot conclude a factor does not affect performance.

3.4. Subsample analysis

In order to answer the third research question (Does the effect of performance and non-performance fund characteristics on fund flows differ in sub-samples?), the following two variables are used to split the data: a dummy for institutional funds, and a dummy for recession periods.

Then, the regression specified in equation [4] is adapted so that it is possible to compare the sensitivities of cash flows to the independent variables between the previously specified two conditions. While the specification described in section 3.2 has a dummy variable that identifies institutional funds; the interpretation of its coefficient being significantly different from zero is that institutional funds have significantly different net cash flows than retail funds. This means that this method does not allow analyzing how the coefficients of the other independent variables differ between institutional and retail funds. It is fundamental to see how sensitivities, such as the performance-flow relationship, differ too.

Splitting the sample in two and running two separate regressions (one for institutional and one for retail funds) would allow obtaining one coefficient for each independent variable for the two types of funds. However, the two coefficients for one independent variable will not be comparable because the variance of residuals will be different in each regression. Thus the chosen method is that of Brav (2009) where a pooled regression is done with the panel data, but the institutional fund dummy variable (and its complement) are multiplied by each independent variable so to produce institutional and retail categories for each. Thanks to this method, it is then possible to use an F-test to see if there are significant differences between the coefficients for an independent variable between institutional and retail funds.

The theoretical motivation for repeating the analysis of determinants of fund flows but splitting the sample by institutional and retail funds is nested in research on the differences between the two types of funds. Literature suggests that retail funds investors and institutional investors are different in three key aspects: sophistication, investment objectives, and search cost (Alexander, Jones and Nigro, 1998). In an analysis of determinants of fund flows for mutual and pension funds, Del Guercio and Tkac (2002) find that pension clients punish poorly performing funds more than others. This evidence of shape in the flow-performance relationship is interpreted as a sign of notable differences in what factors influence fund flows for different types of clients. Given that institutional investors are more sophisticated, one would expect that the coefficients of performance variables in equation [4] are larger and more significant for institutional funds. Likewise, the coefficients for non-performance variables in equation [4] are expected to be smaller and less significant.

The same method is then used to compare the determinants of fund flows between time periods of economic expansion and those of economic recession. The theoretical motivation for this split comes from Boyer and Zheng (2008), who find a significant relationship between domestic market returns and mutual fund flows. This is interpreted as evidence that market conditions affect mutual fund flows, and opens the possibility of fund flow determinants differing between good and bad economic times. This idea is supported by Avramov and Wermers (2006) who find that manager skills have an important impact on fund performance, and in particular that skilled managers outperform momentum benchmarks in timing industries over the business cycle. If skilled managers perform better during expansion periods and/or investors expect this to happen, the determinants of fund flows can differ between the two conditions. While the latter result comes from the broad mutual fund industry (where manager skills are more important as the fund's goal is to outperform), it is interesting to test whether these effects are also present for index funds. Evidence of no differences would suggest that index fund investors are different from regular mutual fund investors, which could be caused by the smaller degree of performance competition in the index fund industry.

To test this, a dummy variable is created where every quarter on the time-series dimension is assigned to either expansion or recession conditions. This process is fallible because it can be hard to call a quarter recessionary or expansionary, and the classification can therefore be unreliable. So that the results of this study can be replicated by other researchers, the National Bureau of Economic Research's business cycle dating committee data is used (NBER, 2010). The data only spans until the first quarter of 2010, which means the most recent observations are lost. This reduces concerns of unreliably calling quarters during 2010-2012, where the US economy was very volatile following the late-2000s recession. A recession is defined as three quarters (or more) of negative GDP growth, thus there is one recession in the sample: Dec 2007 to Jun 2009.

4. Data description

4.1. Industry outline

After dropping outliers, funds with missing data, and short-lived funds (to see a detailed description of the data trimming process see section 3.1), 216 S&P 500 index funds remain with 5,823 quarter-month observations between July 2003 and June 2012. Table 4.1 shows descriptive statistics for the variables of interest.

This table paints a static picture of the S&P 500 index funds industry; which matches industry characteristics of low expense ratios (and fees), low turnover, small and on average negative return differences against the index, and most funds belonging to relatively large families. Furthermore, the aggregate TNA of the selected funds in the end of 2011 is around US$ 400 billion in the sample, while the size of the industry was reported to be around US$ 375 billion (Investment Company Institute, 2012). This suggests that the sample used in this study excludes only small funds in the outliers dropped, and is highly representative of the industry.

Instead of a static view on the industry, it is more interesting to look at some of these fund characteristics over time so to explore the important trends of fund proliferation and fee dispersion. Chart 4.1 shows the number of funds over time as well as the sum of TNA of all funds.

The number of S&P 500 index funds increases until 2008 and then decreases afterwards. This goes against the idea of fund proliferation (particularly after 2008), but could be affected by the fact that funds with very short histories are excluded (if the funds that were created late 2011 are included, the shape of the curve changes and the slope is positive in the last quarters). It can be seen that the recent financial crisis has decreased the number of funds in an industry that had been growing since its inception in the late 70s.

On the other hand, the industry's TNA has an increasing trend except for the drop around 2008. The increasing value of total TNA could be driven more by the market (via changes in the value of their portfolio) than by the fund clients: fund assets change value with the securities in the underlying index, which increased from 2004 to 2008, decreased until 2009, and then continued increasing. To test the latter, total TNA is compared with the cumulative returns of the S&P 500 index. The results can be seen in Chart 4.2.

It can be seen that the changes in TNA are highly related to the changes in the value of the S&P 500 index, and thus that neither the number of funds nor the total TNA in the industry show evidence of fund proliferation. This is especially true after 2008.

Alternatively, it is also possible to test for category proliferation: if present, one would expect that the number of funds in family variable increases over time as fund families continue to offer more new types of funds. The average and median number of funds per family (excluding the 4 funds that are not part of a family) are plotted over time and shown in Chart 4.3.

Table 4.1: Descriptive statistics

The table shows the unit of measurment and descriptive statistics for the fund characteristics that will be used throughout this study. The sample includes US S&P 500 index funds between 2003 and 2012.

Variable	Unit	Mean	Standard deviation	Median	Minimum	Maximum
Expense ratio	% of assets	.0062	.0043	.0050	.0002	.0229
Cash holding	% of assets	.0145	.0351	.0065	-.0376	.4967
12b1 fee	% of assets	.0024	.0034	.0000	0	.0100
Management fee	% of assets	.1702	.1414	.1630	-.4270	.7500
Turnover	% of assets	.1075	.2188	.0600	.0100	3.9600
Cash flow	% of assets	.0085	.5302	-.0116	-1.0908	2.8552
Age	Years	9.9004	5.1444	9	1	37
Funds in family	Funds	223.92	175.46	178	0	1081
Log (Funds in F.)	Log(funds)	5.0212	1.0819	5.1818	0	6.9856
Log (TNA)	Log($ mill.)	4.8343	2.4311	4.9200	-2.3026	11.5676
Return difference	%, Quarterly	-.0015	.0025	-.0014	-.0158	.0165
Historic return	%, Quarterly	.0042	.0051	.0044	-.0254	.0506
Open to investors	Dummy	.9274	.2596	1	0	1
Restricted sales	Dummy	.0153	.1227	0	0	1
Institutional	Dummy	.4532	.4978	0	0	1
Merged	Dummy	.1154	.3195	0	0	1
Front load	Dummy	.1796	.3839	0	0	1
Rear load	Dummy	.1956	.3967	0	0	1
Observations	5796					

Chart 4.1: Number of funds & aggregate TNA over time

The chart shows the time-series of two variables measuring industry size (number of funds and industry size in millions US%) at quarterly frequency.

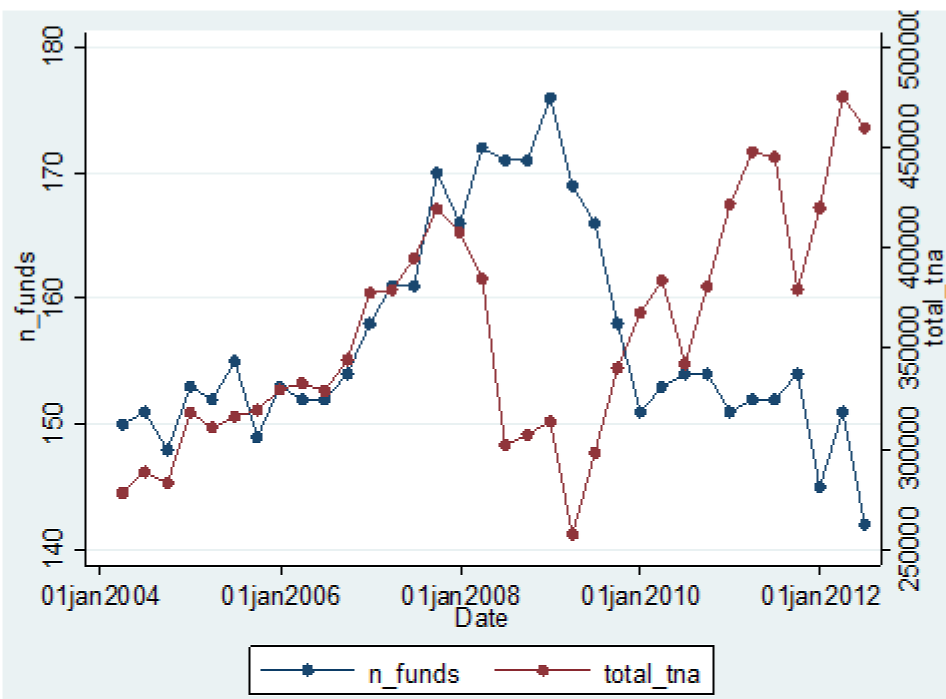


Chart 4.2: Aggregate TNA and S&P 500 index returns over time

The chart shows the time-series of industry size (in million US$) and relative index performance (2003=1) at quarterly frequency.

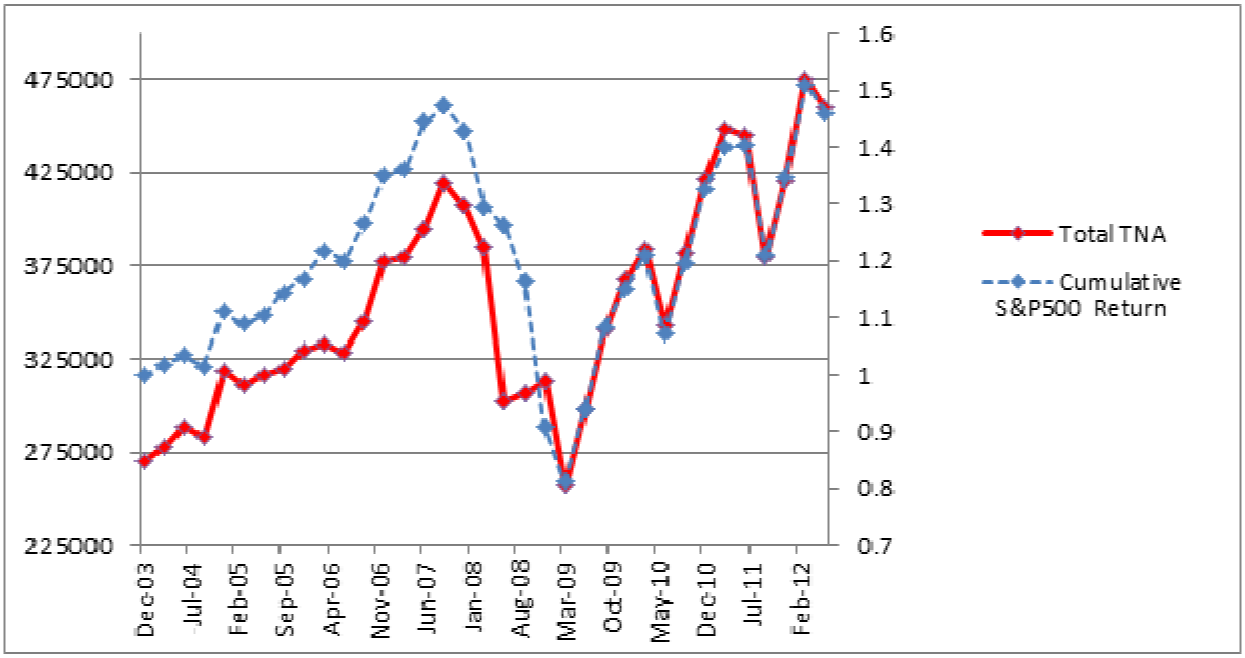
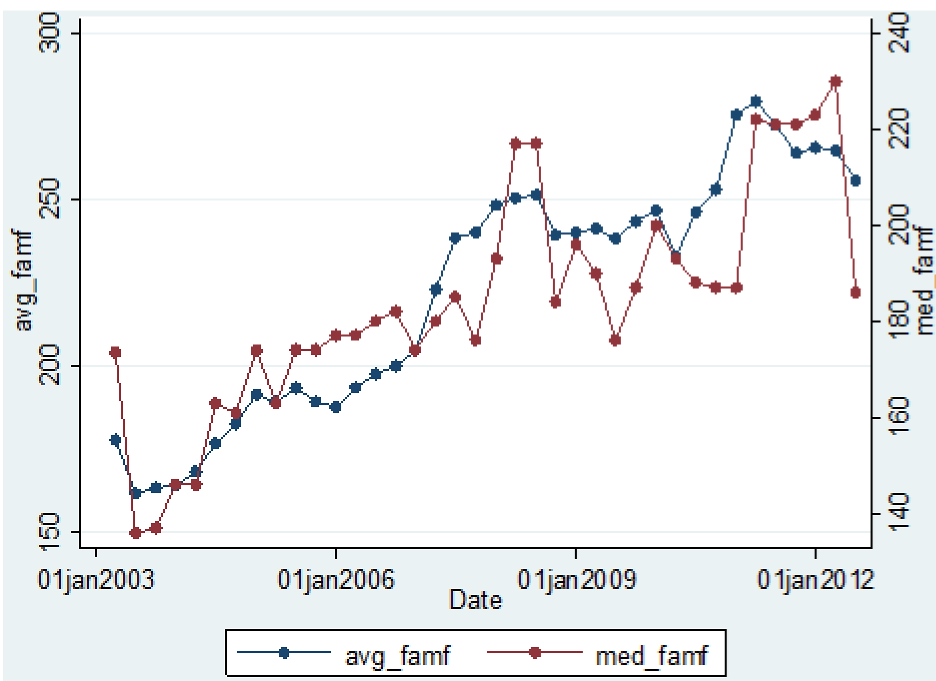


Chart 4.3: Mean & median funds per family over time

The chart shows the time-series for two measures of family size (average and median number of funds) at quarterly frequency.



Both the mean and median number of funds in family increase over time. While this graph only represents fund families that have at least one S&P 500 index fund, it can be said that the number of funds per family has increased and thus that there is some evidence of category proliferation in the sample. Given that non-product competition is one of the *raisons d' être* of fund families, category proliferation was to be expected.

Finally, to look for evidence of fee dispersion the year-end expense ratio is chosen. The reason for choosing this variable is that the expense ratio is the sum of all expenses levied on the investor (divided by TNA) by the fund, and thus captures the 'cost' of investment. Box plots are used and data is summarized at yearly frequency for clarity. The results are shown on Chart 4.4.

It can be seen that the median expense ratio remains steady over time, while the 75th percentile and upper adjacent value increase from 2005 onwards. More outliers with very high expense ratios appear as time goes on. This is labeled as evidence of fee dispersion in the industry, and supports the findings of Hortaçsu and Syverson (2004) for the S&P 500 index fund industry who find that the number of high-fee funds is increasing. This finding is economically un-intuitive but could be seen as evidence of: increased non-product differentiation, investors facing large search costs, or both.

Given that the average and median expense ratios do not increase over time, it seems that the fee dispersion phenomenon is confined to the upper tail of the distribution. The latter can be seen on Chart 4.5 where the average, median, and 5% and 1% largest expense ratios are shown.

The phenomenon of fee dispersion can only be observed when looking at the top 1% of funds with highest expense ratios, while other statistics with more observations do not show evidence of this trend. The fact that the sample has been trimmed (over 100 funds were lost in the process) supports this findings because extreme observations have been removed from the sample yet the trend persists. It is important to note that differences between Charts 4.4 and 4.5 (both with expense ratio on the vertical axis) could be driven by data being compounded to an annual frequency in the first.

Halling, Cooper and Lemmon (2011) find systematic differences in fund fees and expenses across US equity funds. The spread of 2.30% they find is almost identical to the 2.27% found in this sample. Chart 4.5 then supports their finding of fee dispersion in the S&P 500 index fund industry, despite the investment product offered being homogenous. They label this as evidence against the industry being a competitive market.

Chart 4.4: Expense ratio over time

The chart shows box plots showing the spread of the expense ratio (as % of TNA) across funds at yearly frequency.

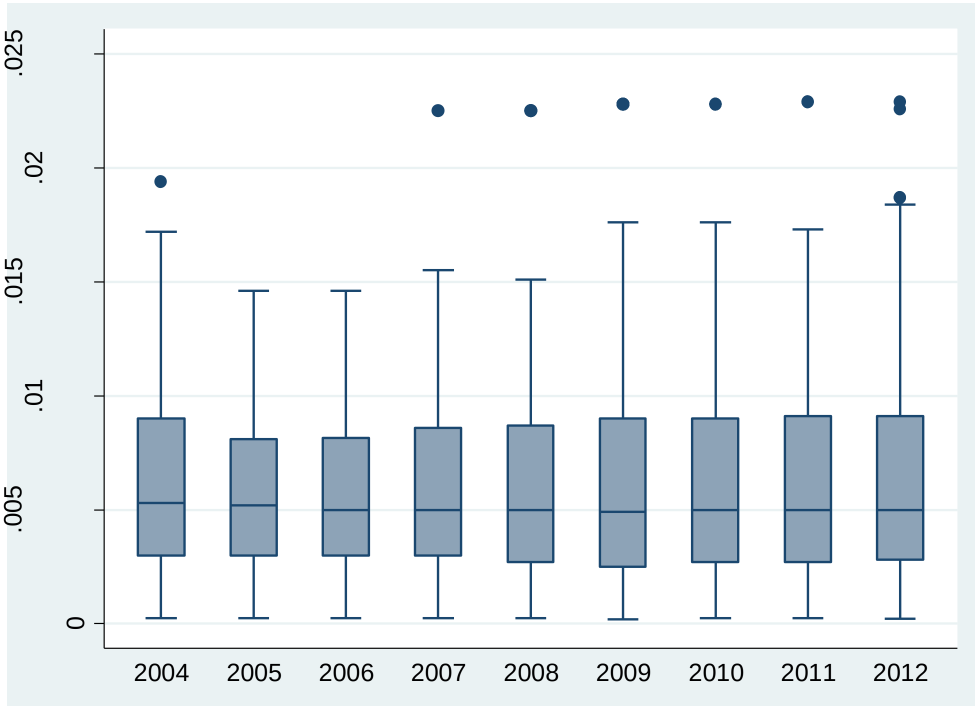
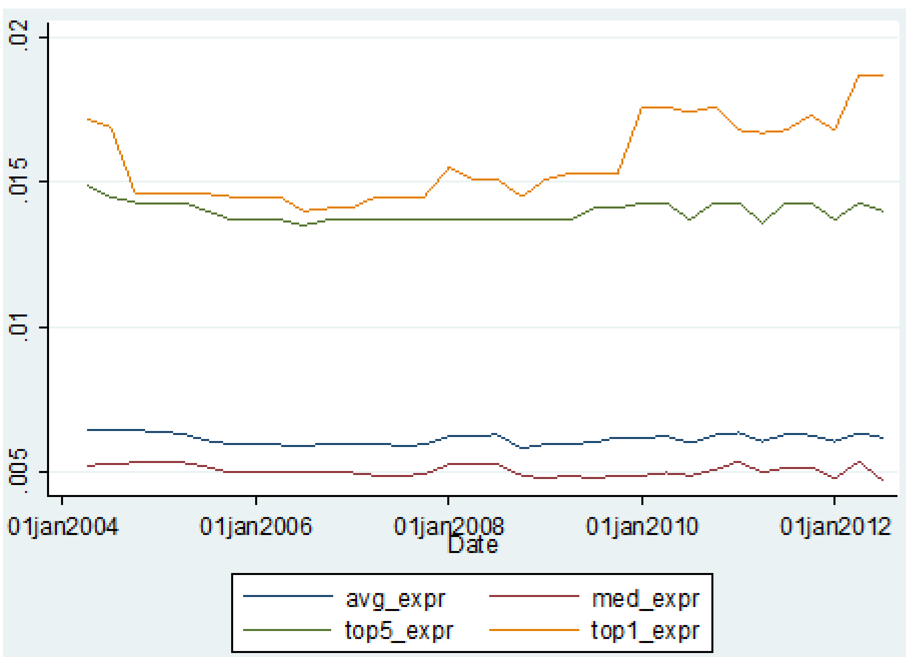


Chart 4.5: Different expense ratio statistics over time

The chart shows time-series for 4 expense ratio measures (average, median, 5th and 1st percentiles) at quarterly frequency.



4.2. Performance

The return differences between the funds and the S&P 500 index (calculated fund minus index returns so positive numbers mean outperformance and negative underperformance) over time are plotted in Chart 4.6. Box plots are used to see how the performance is spread over time. The motivation for this measure instead of the more traditional alpha is argued in section 2 and 3.

It can be seen that, after removing outliers, all the funds' return is less than 2% away from the index return every quarter. The average height of the linwa (the distance between the upper and lower adjacent values) shows that, ignoring outliers, performance in the industry is rather homogenous as fund returns differ an average of less than 35 basis points every quarter. It can also be noted that the vast majority of observations show funds that underperform the index, but that there is also evidence of few funds outperforming the index in some quarters. It is also interesting to note that more than half the funds outperform the index in only two periods: quarters 2 and 3 of 2009 and quarters 1 and 2 of 2012. This is evidence of seasonality.

Given that box plots only show the 75^{th} percentile, a histogram of return differences squared (unreported) would show that 99% of observations are smaller than 58 basis points in absolute value of return difference. This confirms that after removing outliers fund performance is homogenous as expected.

Some studies have conjectured that there is persistence in fund performance and that funds that have a good performance this quarter are more likely to have a good performance the next quarter. While these broad industry studies use alpha, given similar risks return differences should work too. To look for evidence of this, the return difference over time for funds in the top 10 percentile at the end 2004 is shown in Chart 4.7. The overall return difference (full sample) is also plotted for comparison, as Chart 4.6 suggested trends over time in that variable (an effect also found by Frino & Gallagher, 2001)

It can be seen that the funds that were in the top 10^{th} percentile at the end of 2004 (first blue bar) did continue having superior performance when compared to the whole sample. While the magnitude of the difference gets smaller as years pass, this can be interpreted as evidence of persistence in performance. The finding that mutual funds that performed well in the past do well in the future has been found many times in the broad industry.

To delve into the persistence of fund performance, current return differences are regressed on the variables most recent lagged quarter (robust standard errors are used). This is repeated for 4, 8 and 12 lags to confirm findings ($AR(\#)$ models); though including a larger number of lags in the model reduces the number of usable observations. The results are presented in Table 4.2.

Chart 4.6: Return differences over time

The chart shows box plots showing the spread of return differences (fund minus index return) across funds at quarterly frequency.

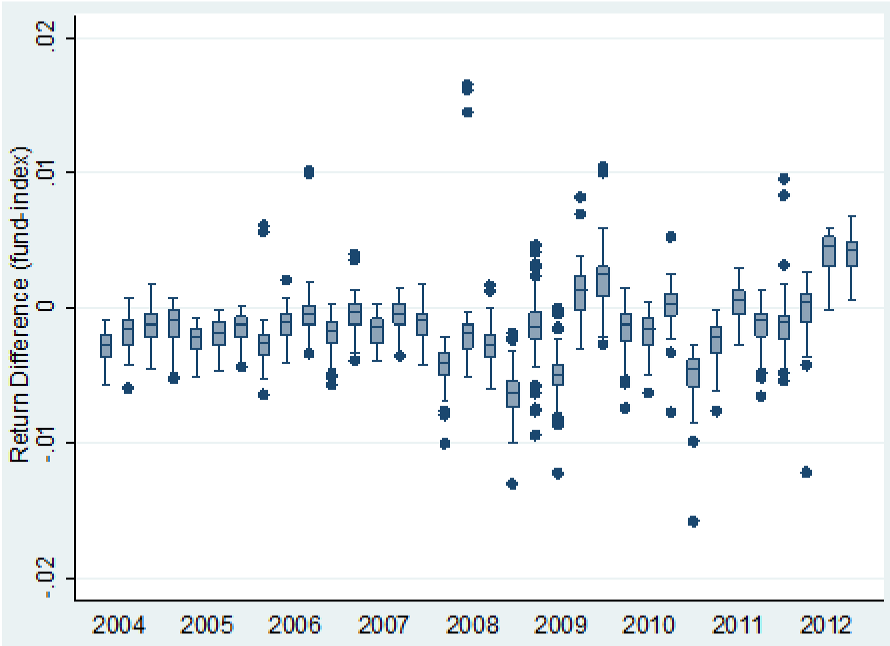


Chart 4.7: Return differences over time for top 10% 2004 funds and whole sample

The chart shows box plots showing the spread of return differences (fund minus index return) across funds at yearly frequency, where blue is the top 10% performing funds at the end of 2004, and red is the full sample.

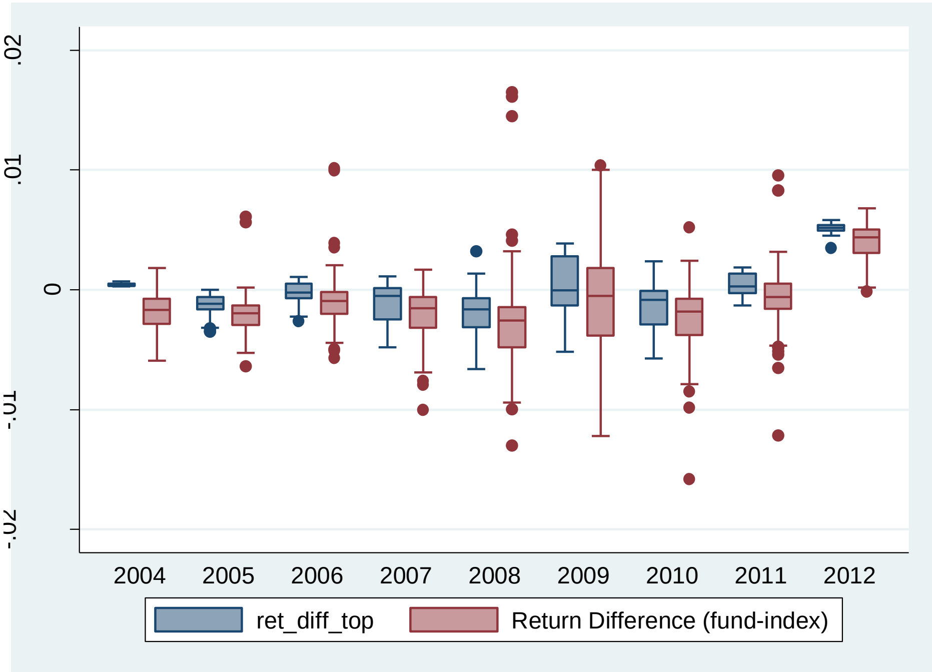


Table 4.2: Auto-regression of return differences

The table below presents the results of AR(#) models of return difference. Coefficient [t-value] are reported.

Specification	(1)	(2)	(3)	(4)
1st lag	.37 [18.25]	.34 [16.68]	.32 [14.83]	.24 [10.99]
2nd lag	-	.18 [9.62]	.13 [5.47]	.03 [1.15]
3rd lag	-	.25 [11.03]	.28 [13.27]	.23 [9.30]
4th lag	-	-.11 [-4.99]	-.14 [-6.08]	-.14 [-6.88]
5th lag	-	-	-.06 [-2.93]	-.13 [-6.36]
6th lag	-	-	.00 [0.04]	.05 [2.07]
7th lag	-	-	.01 [0.41]	-.01 [-0.29]
8th lag	-	-	.29 [8.10]	.25 [9.75]
9th lag	-	-	-	-.11 [-4.18]
10th lag	-	-	-	.25 [9.75]
11th lag	-	-	-	.35 [11.11]
12th lag	-	-	-	-.01 [-0.20]
Observations	5607	4963	4155	3405
R^2	.1218	.2182	.2706	.3660

It can be seen that the return difference in the past quarter is a statistically significant determinant of the return difference in the current quarter ($p < .001$), and 12% of the variance of the latter is explained by the former. The subsequent specifications that include more lags show that as more lags are included, a greater proportion of the variance in return differences is included. In other words, as suggested by looking at the top performers in 2004 over time, there is persistence in return differences. The memory of said auto-regression seems to be long as observations that are many quarters away are still largely significant. Most coefficients are positive (as one would expect: high performance this quarter related to high performance the next one, and vice-versa), but a few lags are negative and significant. For regression purposes in the future, only the first 3 lags can be included without sacrificing sample size because the threshold was set at a minimum of 3 consecutive observations.

Halling, Cooper and Lemmon (2011) also find evidence that the initial expense ratio of a fund is an important determinant of its contemporaneous expense ratio. If there is persistence in fund expenses, it is possible that this persistence is found because both variables measure performance from the perspective of the investor. Indeed, an auto regression of the expense ratio in the sample (on a yearly frequency, given data constrains that will be discussed in Section 5.4) would also reveal very strong persistence.

4.3. Fund flows

The fund net cash flows scaled by fund size (as defined in section 3.1) over time are shown in Chart 4.8. The reason for not plotting the mean is that it is highly sensitive to outliers such as mergers (where cash flows can easily exceed $\pm$100% of TNA). The median shows that there is a small trend for negative cash flows in the S&P 500 index fund industry (average cash flow shows a similar trend, except it is very high in years with outliers such as 2005 and 2011). When looking at the top and bottom 10 percentiles; it can be seen that while there is variation over time, there is a slight trend of decreasing cash flows. Given that the cash flow calculation controls for fund performance, this could be seen as evidence of investors moving their money away from S&P 500 index funds. The fact that the sample average net cash flow is slightly positive (while the sample median and most quarterly medians are slightly negative) suggests that most funds have negative flows but few funds at the top have large positive flows that make the average positive.

Some studies have conjectured that there is persistence in fund flows and that funds that have a positive flow this quarter are more likely to have a positive flow the next quarter. To look for evidence of this, the cash flow for funds in the top 10 percentile at the end 2004 is show in Chart 4.9.

It can be seen that the majority of funds that were in the top 10^{th} percentile at the end of 2004 (first bar) continued to have positive cash flows in the short run. This trend disappears as more time passes, as the box plots become smaller and move towards the variable's mean (close to zero). This can be interpreted as short-run persistence in fund flows. Given that persistence was found in fund performance too, it is possible that persistent performance is the driver of persistent fund flows (as higher performance is related to higher cash flows in the literature).

As it was done for return differences in the previous subsection, cash flows are regressed on its values in past quarters too. In addition, the analysis is repeated for observations where the cash flow a time t is positive (so to see the regression results only for observations where the current cash flow is positive). The results are presented in Table 4.3.

The first and most important observation is that there seem to be important differences in the auto-correlation of cash flows between funds with positive and negative flows. Following positive fund cash flows, the first lag has a significant coefficient. On the other hand, for the complete sample no significant relationship is found (the three models are rejected using an F-test at the 5% level). From these observations, it is possible to conclude that there is evidence of an asymmetric auto-correlation in cash flows between funds with positive and negative flows. The memory of said auto-regression seems to be very short as only the first lag is significant.

Chart 4.8: Different net cash flow ratio statistics over time

The chart shows time-series for 3 measures (median, top and bottom 10th percentiles) of net fund flow scaled by TNA at quarterly frequency.

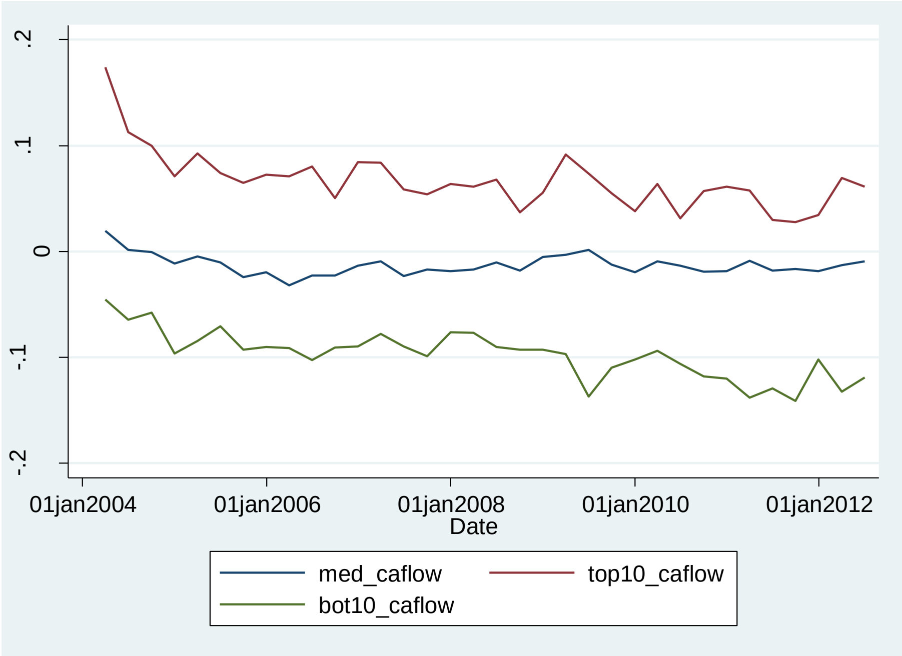


Chart 4.9: Net cash flow ratio over time for top 10% 2004 funds

The chart shows box plots showing the spread of net fund flows scaled by size across funds at quarterly frequency.

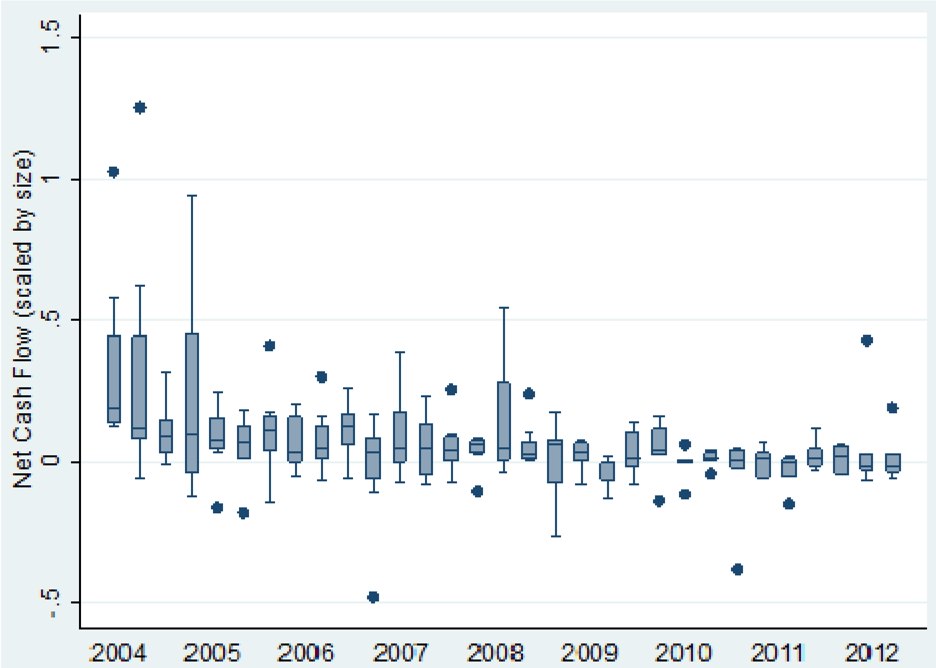


Table 4.3: Auto-regression of net cash flow ratio

The table below presents the results of AR(#) models of net fund flows scaled by size. Coefficient [t-value] are reported. In the second column, only observations where $CF(t) > 0$ are included.

	Full sample			After positive cash flows only		
Specification	(1)	(2)	(3)	(1)	(2)	(3)
1st lag	.02 [1.33]	.02 [1.31]	.02 [1.24]	.08 [3.81]	.08 [5.26]	.08 [6.25]
2nd lag	-	.01 [0.75]	.01 [0.81]	-	-.01 [-0.17]	.00 [0.03]
3rd lag	-	.01 [0.67]	.01 [0.72]	-	-.01 [-0.49]	-.01 [-0.25]
4th lag	-	.01 [1.28]	.01 [1.20]	-	.03 [1.20]	.02 [0.83]
5th lag	-	-	.01 [1.51]	-	-	.00 [0.11]
6th lag	-	-	-.01 [-0.98]	-	-	-.00 [-0.13]
7th lag	-	-	.02 [1.74]	-	-	.00 [1.01]
8th lag	-	-	.02 [1.55]	-	-	.01 [1.04]
Observations	5607	4963	4155	2155	1750	1374
R^2	.0005	.0008	.0034	.0010	.0010	.0028

Compared to the auto-regression for return differences, cash flows have a shorter memory. Furthermore, the R^2 for the latter variable is orders of magnitude smaller which suggests higher persistence in performance than fund flows. This is consistent with economic intuition as fund characteristics that could affect performance (like size, family and age) are relatively easy to predict, while fund flow ratios are the outcome of human decisions and thus harder to explain using fund characteristics.

4.4. Other characteristics

After individually analyzing the two dependent variables of this study (return differences and fund net cash flows), the next step is to examine the relationship between the two. This performance-flow relationship is important for mutual funds because there is both theory and evidence linking higher fund performance to higher funds flows. The economic intuition is clear too, because it makes sense for funds that provide a better performance to have larger net cash flows from investors. The situation is analogous to a regular firm selling a product that works better than its competitors', and faces a higher demand.

To compare the two variables, funds are divided into deciles after ranking by cash flow (fund net cash flow) for each quarter, and the average performance (return difference, and expense ratio to confirm results) over all quarters is reported for each decile. The results are shown in Table 4.4.

There are important industry characteristics that are revealed this way: there seems to be a positive relationship between return differences and fund flows such that higher flows are associated with less negative return differences. Conversely, there seems to be a negative relationship between expense ratios and fund flows such that higher flows are associated with

Table 4.4: Performance for funds grouped by cash flow rank

The table below shows the average quarterly return difference and expense ratio over time for groups of funds ranked by their scaled net cash flow. The groups are rebalanced every quarter.

	Net Cash Flow									
Decile	Bottom	2nd	3rd	4th	5th	6th	7th	8th	9th	Top
Return difference (%)	-.182	-.179	-.176	-.150	-.120	-.123	-.111	-.134	-.132	-.148
Expense ratio (%)	.812	.785	.737	.631	.522	.508	.480	.535	.547	.615

smaller expense ratios. Putting the two together, it seems to be that when performance is better (less negative return difference or smaller expense ratio) fund net cash flow is larger. This is in line with fund flow studies that find a positive and important performance-flow relationship.

Given that the sample consists of only S&P 500 index funds, it is interesting that the top cash flow decile observations do not conform to the previously described relationships. One possible explanation is that fund characteristics other than performance predict cash flows better for the funds with the largest flows every quarter. For example, a fund that offers many non-portfolio services that investors value (at the expense of performance) and is consistently bringing in new clients due to them would defy the relationship found. This explanation is rejected because the funds in the top cash flow decile change consistently over time, such that the fund present the most quarters had 10 appearances in 39 possible quarters.

Instead, the data suggests that abnormal events such as mergers or fee policy changes drive many of the cash flows that are in the top decile: when excluding fund-quarters with mergers the top cash flow decile's average return difference becomes larger (expense ratio smaller), and the same is true to a larger extent when analyzing only funds with no load fees (and thus no ability to change them).

While percentile analysis for each of the independent variables listed in the methods section's relation with performance/flows would be interesting, the large number of fund characteristics would make this cumbersome and extensive. Instead, to summarize the relationships between all the variables in the sample, a table of correlations between them is shown in Table 4.5.

As one would expect when using such as exhaustive collection of fund data (performance and characteristics), the correlation matrix is large and has 136 ($\frac{17\times16}{2}$) correlations between different variable pairs ($\rho_{ij}, i \neq j$) between the 17 variables. Many of these ρ_{ij} are statistically significant but small, this is a positive finding because it suggests that many of these variables are related to fund performance/flows and are good candidates to be tested as determinants.

Setting the threshold at $|\rho_{ij}| > .40$, there are 7 cases where high correlations could be problematic (in bold in Table 4.5). The reason why a high correlation between two independent variables in a regression could be problematic is that they could both be measuring the same construct, making it difficult to assess their relative importance as a determinant of a dependent variable.

Table 4.5: Correlation matrix for all variables

The table below presents the pair-wise correlations of all the available variables. The rho coefficient is reported, with a * given when the coefficient is significant at the 5% level.

	Expense ratio	Cash holdings	12b1 fee	Management fee	Turnover	Net c.flow	Age
Expense ratio	1	-	-	-	-	-	-
Cash holdings	.0806*	1	-	-	-	-	-
12b1 fee	**.8949***	-.0084	1	-	-	-	-
Management fee	.2289*	.1522*	-.0250	1	-	-	-
Turnover	.1833*	.3067*	.0269*	.2990*	1	-	-
Net c.flow	-.0344*	.0392*	-.0306*	.0027	.0532*	1	-
Age	-.3158*	-.1348*	-.2668*	-.0683*	-.1146*	-.0389*	1
Log (family size)	.1017*	-.0477*	.1277*	.1542*	.0076	.0054	.1511*
Log (TNA)	**-.6122***	-.0754*	**-.5037***	-.0823*	-.1163*	.0052	**.4101***
Return diff.	**-.4145***	-.1079*	-.3888*	-.0848*	-.0205	-.0027	.2596*
Historic return	-.2062*	-.1339*	-.1789*	-.0198	-.0886*	-.0292*	.4390*
Open to investors	-.1279*	.0525*	-.1573*	.0595*	.0588*	.0257*	-.1012*
Restricted sales	-.0540*	-0.0238	-.0643*	-.0560*	.0034	.0011	-.0675*
Institutional	**-.4715***	.0321*	**-.4904***	.0339*	-.0121	.0352*	.0686*
Merged	-.0152	.0316*	-.0338*	-.1068*	-.0116	-.0058	-.0472*
Front Load	.1617*	.0031	.0872*	.0667*	.0117	-.0128	.0202
Rear Load	.2004*	-.0421*	.2134*	-.0542	-.0855*	-.0308*	.1259*

	Log (fa. size	Log (TNA)	Return diff.	Historic return	Open to investors	Restricted sales	Institutional	Merged	Front Load
Log (family size)	1	-	-	-	-	-	-	-	-
Log (TNA)	.1409*	1	-	-	-	-	-	-	-
Return diff.	-.0443*	.2618*	1	-	-	-	-	-	-
Historic return	.1441*	.2232*	.1409*	1	-	-	-	-	-
Open to investors	-.1716*	.1340*	.0265*	-.0632*	1	-	-	-	-
Restricted sales	-.3162*	-.0497*	.0144	-.0971*	.0349*	1	-	-	-
Institutional	-.0674*	.1573*	.1971*	.0213	.1232*	-.1134*	1	-	-
Merged	-.0234	-.0602*	-.0453*	.0301*	-.0107	.0163	-.0287*	1	-
Front Load	.0439*	-.0903*	-.0634*	-.0147	.0207	.0000	-.3469*	-.0136	1

Rear Load	.0767*	-.0886*	-.0512*	.0923*	-.1355*	-.0367*	-.2063*	.0428*	.0557*

The first 4 cases are for expense ratio. This measure of performance is: a linear function of the 12b1 fee (explaining their correlation of .89), a known proxy for performance (explaining high and negative correlation with return difference), and highly determined by fund size and institutional dummy. These high correlations could be a reason why the index fund literature prefers using return differences as a measure of performance: it has no problematically high correlations with the other independent variables. Nonetheless, when the expense ratio is used to verify the robustness of the results obtained for return differences, it will be important to keep in mind that as a dependent variable the expense ratio will be highly determined by the 12b1 fee, size and institutional dummy.

The next two cases are between 12b1 fee and size and institutional dummy. The 12b1 fee is for marketing and distribution expenses, and both larger funds and institutional funds are expected to spend a smaller percent of assets on trying to get more clients (compared to smaller/retail funds) due to the nature of their business. The last case is the correlation between size and age, which is the result of over two decades of large growth in the S&P 500 industry. Given that distinguishing the determination of the dependent variable between these 3 independent variable pairs will be difficult, multiple regression specifications will be provided in Section 5 that exclude some of them.

Additionally, the correlations between return difference and independent variables are as expected: the largest correlation is with expense ratio (both being proxies for performance), factors that induce costs (like fees, holding cash, more trading) have a negative correlation, and factors that boost performance (like size, age, and institutional via the reputation hypothesis in section 3.1) have a positive correlation. The correlations between fund flows and independent variables are different: they are much smaller (probably due to cash flows being much harder to predict than performance), and some of them have signs that go against common sense (for example funds with restricted sales having higher net cash flows). The latter should be paid little attention given the small magnitude of the coefficients. Overall, all the characteristics are a significantly correlated with either (or both) of the dependent variables.

As one would suspect in such an exhaustive collection of fund characteristics, many of the measures have small but statistically significant correlations. Given this finding, the relationship between performance and fund flows found in Table 4.4 (which is not supported by the insignificant and small correlation between return differences and fund flows) could be driven by any of the variables in Table 4.5 that is significantly correlated with those measures. To look deeper in to the performance-flow relationship, multivariate regression will be used in the upcoming section so to control for the effects of the independent variables on one another, and then asses their fit as determinants of the dependent variables.

Before analyzing the regression outcomes in the upcoming section, the data is checked to see if the assumptions required for OLS to be unbiased are met by the variables that will be used. In particular, the Gauss-Markov assumptions are used: linear parameters, expected error term of zero ($E(\varepsilon_i) = 0$), homoscedasticity ($V(\varepsilon_i) = E(\varepsilon_i) = \sigma_\varepsilon^2 =$ constant), independent and uncorrelated errors ($Cov(\varepsilon_i, \varepsilon_j) = E(\varepsilon_i \varepsilon_j) = 0, i \neq j$), independent variables are deterministic. The first is not a problem given the nature of the analysis and variables (and ample evidence in the literature), while the second is imposed by OLS when using an intercept in the regression. The third is checked using the modified Wald test, which reveals problems of group-wise heteroskedasticity. For the fourth (and to solve the third), standard errors are clustered by fund to allow for correlation of errors within a fund's observations as persistence is observed is performance and flows (which would mean errors for consecutive quarters are likely to be correlated for a given fund, or serially correlated).

Given that many independent variables will be included in the regression to reduce the likeliness of endogeneity (including FE), this could be related to a problematic trade-off in terms of multicollinearity. The correlation coefficients in Table 4.5 were used to identify cases were this could be a problem (no collinearity is required for BLUE estimators).

5. Analysis and results

5.1. Performance

Given that many of the fund characteristics that will be tested as determinants of performance and fund flows are small in magnitude (due to being small percentages of assets or in quarterly basis), return difference is scales times 100 to be measured in basis points. Because the values of some independent variables were so small (see Table 4.1), the regression coefficients would be small too. This trick allows making the coefficients larger and thus easier to work with. Similarly, the number of funds in family is replaced by its logarithm because it is positively skewed and has large outliers. The outcomes of the regression for multiple specifications are shown in Table 5.1.

The first specification uses the most salient fund characteristics in the literature to predict return differences. It can be seen that lagged fund net cash flow, size, family size, age and institutional dummy are statistically significant predictors of performance in a pooled regression. However, not including time FE means important determinants of index fund performance (such as index volatility, or dividends of stocks in index) that affect all funds equally on each quarter are excluded. The second specification shows that the percentage of the variance of return differences that is explained by the model triples to 40.16%, greatly improving the model given that adjusted R-squared increases almost as much despite 38 quarter dummies being added. After controlling for fund characteristics that vary only over time and not per fund, the coefficient for lagged cash flow is no longer statistically significant. This means little can be said about the performance-flow relationship.

Table 5.1: Results of performance regressions

The table below shows the determinants of quarterly fund return differences (fund minus index returns) for S&P 500 index funds between 2003 and 2012. The first row of determinants has the previous 3 quarter's lagged return difference. The second row has fund characteristics that vary over time: lagged cash flow scaled by size, logarithm of Total Net Assets, logarithm of number of funds in family, turnover scaled by size, cash holdings scaled by size, 12b1 and management fees, and average quarterly return since inception. The third row has fund characteristics that are dummy variables: open to investors, presence of sales restrictions, institutional (as opposed to retail), presence of any front and rear loads. The fourth row shows whether quarter Fixed Effects (FE) and fund FE are included in the regression. OLS is used for this S&P 500 index fund panel, and errors are clustered by fund. Coefficient and [t-statistic] are reported below for 9 different specifications.

DV	Return Differences								
Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lag. DV	-	-	-	-	-	-	-	-	.0098
									[0.35]
Lag2 DV	-	-	-	-	-	-	-	-	-.0044
									[-0.21]
Lag3 DV	-	-	-	-	-	-	-	-	.1523**
									[5.74]
Lag. cash flow	-.0002**	-.0000	.0000	-.0000	-.0001	-.0003**	-.0002**	-.0002**	.0089
	[-3.20]	[-0.40]	[0.50]	[-0.61]	[-1.86]	[-5.46]	[-2.83]	[-2.85]	[0.30]
Log (TNA)	.0172**	.0227**	-	.0236**	.0059**	.0176**	.0098	-	-
	[6.61]	[8.32]		[10.04]	[3.42]	[3.34]	[1.87]		
Log (family size)	-.0200**	-.0241**	-.0194**	-.0242**	-.0103**	-.0242	-.0301	-.0329	-.0270
	[-3.58]	[-4.07]	[-3.51]	[-4.06]	[-2.63]	[-1.13]	[-1.38]	[-1.51]	[-1.22]
Age	.0093**	.0013	.0071**	-	-	-	-	.0677**	.0692**
	[7.49]	[1.12]	[5.88]					[6.45]	[5.99]
Turnover	-.0205	-.0183	-.0393*	-.0191	.0174	.0672	.0851	.0811	.0543
	[-1.21]	[-1.10]	[-2.35]	[-1.14]	[0.53]	[1.44]	[1.89]	[1.76]	[1.26]
Cash holdings	-	-	-	-	-.0047**	-	-.0051**	-.0046**	-.0042**
					[-6.53]		[-4.28]	[-4.14]	[-3.28]
12b1 fee	-	-	-	-	-24.47**	-	-16.41*	-16.47*	-16.71*
					[-20.53]		[-2.46]	[-2.52]	[-2.21]
Management fee	-	-	-	-	-.1214**	-	-.0526	-.0658*	-.0381
					[-5.72]		[-1.72]	[-2.10]	[-1.07]
Historic perf.	-	-	-	-	2.090**	-	11.58**	12.29**	14.88**
					[2.62]		[7.47]	[7.71]	[8.18]
Open to inv.	-	-	-	-	.0117	-	-.0005	.0019	.0131
					[0.84]		[-0.02]	[0.09]	[0.61]
Restricted sales	-	-	-	-	-.0198	-	-.2619**	-.2796**	-.1439**
					[-0.82]		[-21.69]	[-22.05]	[-12.57]
Institutional	.0779**	.0755**	.0909**	.0752**	.0056	-	-	-	-
	[7.00]	[7.25]	[7.44]	[7.23]	[0.71]				
Front load	-	-	-	-	-.0146	-	.0064	.0065	.0242
					[-1.82]		[0.25]	[0.26]	[0.69]
Read load	-	-	-	-	.0024	-	.0254**	.0005	-.0046
					[0.32]		[3.06]	[0.05]	[-0.58]
Quarter FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	No	No	No	Yes	Yes	Yes	Yes
R^2	.1341	.4016	.3642	.4013	.4720	.5069	.5206	.5270	.5516
Adj. R^2	.1332	.3970	.3594	.3968	.4673	.4840	.4976	.5043	.5272
N	5796	5796	5796	5796	5796	5796	5796	5796	5796

* p<.05, ** p<.01

The adjusted R-squared obtained under the second specification is over four times larger than that obtained by Frino & Gallagher (2002) of 9% for S&P 500 index funds between 1994 and 1999, confirming that quarter FE successfully captures the effect of S&P 500 volatility, average bid/ask spread, dividends, and other characteristics. This comparison allows one to conclude that predicting a fund's return difference from fund characteristics only (as done in specification 1) yields better model fit than from index characteristics (as done by Frino & Gallagher, 2002); although index characteristics (like its future volatility or dividends) might be easier to forecast than fund characteristics (like future fund size) making the latter preferable.

The next step is to use specifications 3 and 4 to see whether including age and size on their own (instead of together like in specification 2) changes the results obtained: given the high correlation between the two variables found in section 4.4, this is a possibility. On their own, both age and size are significant predictors of return difference. However, it can be seen that size on its own provides a better model fit that is very close to that when both are included. From this it follows that the effect of age on return differences (in specification 3) is captured by the size variable (in specifications 2 and 4). Given the high correlation between the two, size is used in further specifications and age is not.

In specification 5, the rest of the available fund characteristics are added to specification 4. It can be seen that the fit of the model increases, as now 47.20% of the variance of return differences is explained by the independent variables. All of the dummy independent variables have statistically insignificant coefficients, which suggest that the previously found outperformance of institutional funds (positive and highly significant coefficients in specifications 1 to 4) is explained by the newly included variables (some of which are significant predictors of return difference).

Specification 6 is analogous to 4, but it also includes fund FE (which means the institutional dummy cannot be included because it is constant for every fund and thus collinear with fund FE). Controlling for all fund-specific characteristics makes the family size insignificant, suggesting that the effect of family size on return difference is explained by fund-specific characteristics.

Specifications 7 and 8 are analogous to 5, but also include fund FE. Size and age are used independently and respectively, the latter providing a model with slightly better fit. The opposite was the case before including fund FE, the difference being a result of the effect of size on performance being statistically insignificant (in regression 7) when controlling for fund-specific characteristics. This finding could be caused by the high correlations between 12b1 fee and fund size, giving a second reason to choose specification 7 which uses age instead.

Given the evidence for persistence in return differences found in in section 4.2, the first 3 lags of return differences are also be tested as determinants. While a long-term persistence was found in the data, including more than 3 quarters per fund would sacrifice observations and change the sample used to estimate the model. The first two lags have insignificant coefficients, which suggest that in the short run performance persistence can be explained by the fund characteristics. However, performance three quarters ago is positively and significantly related to current performance: a 25 basis point higher return difference three quarters ago (1 standard deviation) is related to an increase in current return difference by 3. From the mean return difference of minus 15 basis points per quarter, this would be an improvement of 20%.

When controlling for past return difference, the goodness of fit of the model increases marginally. Compared to specifications 5 and 8 (which use very similar independent variables), many of the same variables are found to have significant coefficients: age and historic performance (or performance since inception) have a positive effect on return difference, while cash holdings, 12b1 fee and restricted sales dummy have a negative effect. When controlling for past return difference, the effect of the net cash flow is no longer statistically significant: this could be explained by the fact that past performance is a determinant of net cash flow.

Given that the coefficients for most independent variables are small and have different orders of magnitude, the impact of a 1 standard deviation increase in an independent variable compared to the dependent variable's mean (economic impact) will be calculated for all the significant determinants of fund flows. A 5 year older fund has a .35 basis points higher return difference, an improvement of 2%. A fund with .51 basis points higher average quarterly return since inception has an 8 basis point higher return difference, and improvement of 53%. A fund with 3.51% of assets higher cash holdings has fewer than .1 basis points lower return difference, an improvement of less than 1%. A fund with 0.34% higher 12b1 fee has .1 basis point lower return differences, an improvement of less than 1%. A fund with restricted sales (since this is a binary variable, it makes no sense to use the standard deviation) has a .2 basis points lower return differences, an improvement of 1%.

From the analysis of the economic significance of the factors with statistically significant coefficients it can be said that: while they are all statistically significant, only historical quarterly return has an economically meaningful impact. The other 3 variables have the signs predicted by economic theory (older funds bargain with more power to achieve higher performance, funds that hold more cash face more trouble replicating a paper index, funds with higher marketing fees perform worse because fees act like expenses on the investor), while the return since inception has a strong and positive effect on performance. This could be for the same reason as initial expense ratio is a predictor of current expense ratio.

5.2. Fund flows

The outcomes of the fund flow determinants regression for multiple specifications are shown in Table 5.2. The variables in the table are organized as follows: controls for reputation and industry performance, factors that (possibly) affect investment return from the viewpoint of an investor, factors that (possibly) affect costs and thus performance from the viewpoint of a mutual fund, and other controls. The reason for splitting the fund characteristics is that: some of them are directly related to performance from the viewpoint of the investor (higher return difference or larger fees would immediately translate into lower returns), some of them are indirectly related to performance from the viewpoint of the investor because they could only affect investment returns if they are determinants of performance, and the rest are either important controls for this type of regression that a rooted in the literature.

As a consequence of this split, it becomes possible to interpret results by group: fund characteristics that directly affect investment performance and are significant are labeled performance determinants of scaled fund flows, factors that affect performance indirectly and significantly affect fund flows are labeled performance determinants if found significant in the performance regression (see Table 5.1) and otherwise non-performance determinants, and the other factors are controls suggested by literature. This allows insight for the classification of fund characteristics into performance determinants of fund flows.

Unlike the regressions for return difference, it can be immediately seen that future net cash flows scaled by fund size are harder to predict from fund characteristics. When not using time and fund FE, around 5% of the variance is explained; while for a comparable specification with return differences, it was almost 13%. When using time and fund FE, around 22% of the variance of the dependent variable is explained by the model; while for a comparable specification with return differences, it was almost 55%.

The first two regression specifications use a limited number of fund characteristics as independent variables, and comparing the two it can be seen that using fund age instead of size leads to better model fit. In both cases, the 12b1 fee and the rear load dummy are significantly and negatively related to next period’s net fund flow. The coefficient for age is negative and significant while that for size is not. The third regression specification is based on the first (which shows age works better than size), but including all other available fund characteristics. Even though there is also a large correlation between the 12b1 fee and age, when put together in a regression they are both significant so there seems to be no problem.

Table 5.2: Results of fund flow regressions

The table below shows the determinants of next quarter's fund net cash flow for S&P 500 index funds between 2003 and 2012. The first row of determinants has the lagged flow and the aggregate industry flow. The second row has fund characteristics that directly affect performance for an investor: return differences and its square, 12b1 and management fees, front and rear load dummies, and restricted sales dummy. The third row has fund characteristics that affect performance for the fund: cash holdings, turnover, age, log (total net assets), log (number of funds in family), and institutional fund dummy. The fourth row shows returns since inception and open to investors dummy. All independent variables are lagged one quarter unless noted. The fifth shows whether quarter Fixed Effects (FE) and fund FE are included in the regression. OLS is used for this panel, and errors are clustered by fund. Coefficient and [t-statistic] are reported below for 8 different specifications.

DV	Net cash flow (t+1)							
Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Net cash flow	-	-	-	-	-	-	.0005**	.0005**
							[5.40]	[5.55]
Industry net	-	-	-	-	-	-	-	.0001**
cash flow (t+1)								[2.67]
Return diff.	-.0115	-.0244	-.0123	-.0087	-.0089	-.0143	-.0141	-.0091
	[-0.85]	[-1.92]	[-0.89]	[-0.49]	[-0.53]	[-0.69]	[-0.68]	[-0.54]
Return diff. ^2	-3.327	-4.458	-4.066	-4.783	-2.238	-3.064	-3.029	-2.112
	[-1.18]	[-1.67]	[-1.31]	[-1.34]	[-0.62]	[-0.76]	[-0.75]	[-0.58]
12b1 fee	-4.320**	-3.590**	-4.608**	-4.045**	6.914	5.612	5.591	6.806
	[-3.74]	[-2.91]	[-3.88]	[-3.42]	[0.72]	[0.55]	[0.55]	[0.69]
Management	-.0168	-.0113	-.0223	-.0220	.0041	.0055	.0054	.0057
fee	[-1.02]	[-0.63]	[-1.42]	[-1.41]	[0.13]	[0.18]	[0.18]	[0.19]
Front load	.0015	-.0022	-.0012	.0013	-.0149	-.0022	-.0029	-.0133
	[0.024]	[-0.31]	[-0.18]	[0.19]	[-0.75]	[-0.11]	[-0.15]	[-0.68]
Rear load	-.0153*	-.0252**	-.0139*	-.0126*	.0002	-.0008	-.0009	.0005
	[-2.51]	[-4.01]	[-2.30]	[-2.03]	[0.05]	[-0.16]	[-0.17]	[0.12]
Restricted sales	-	-	-.0178	-.0113	-.0776**	-.0802**	-.0806**	-.0789**
			[-1.00]	[-0.64]	[-7.42]	[-6.67]	[-6.65]	[-7.53]
Cash holdings	-	-	.0002	.0000	.0003	.0002	.0361	.0003
			[0.59]	[0.10]	[1.07]	[0.74]	[1.19]	[1.08]
Turnover	-	-	.0088	.0101	.0410	.0377	.0361	.0379
			[0.45]	[0.52]	[1.41]	[1.23]	[0.75]	[1.31]
Age	-.0042*	-	-.0037**	-.0029**	-.0063**	.0004	.0002	-.0059**
	[-5.82]		[-5.06]	[-3.50]	[-5.76]	[0.06]	[0.04]	[-5.49]
Log (TNA)	-	-.0031	-	-	-	-	-	-
		[-1.71]						
Log (family	.0115	.0065	.0135	.0153	-.0044	-.0024	-.0024	-.0038
size)	[1.41]	[0.82]	[1.41]	[1.71]	[-0.41]	[-0.21]	[-0.22]	[-0.35]
Institutional	-	-	-.0053	-.0026	-	-	-	-
			[-0.74]	[-0.36]				
Historic perf.	-	-	-1.014	-1.083	-2.547*	-1.756	-1.678	-2.256
			[-1.49]	[-1.47]	[-2.11]	[-1.37]	[-1.30]	[-1.81]
Open to inv.	-	-	.0167	.0155	.0129	.0131	.0131	.0129
			[1.20]	[1.13]	[0.94]	[0.98]	[0.98]	[0.94]
Quarter FE	No	No	No	Yes	No	Yes	Yes	No
Fund FE	No	No	No	No	Yes	Yes	Yes	Yes
R^2	.0470	.0203	.0508	.0627	.2041	.2112	.2117	.2057
Adj. R^2	.0456	.0190	.0485	.0543	.1713	.1731	.1736	.1728
N	5796	5796	5796	5796	5796	5796	5796	5796

* p<.05, ** p<.01

From all of the characteristics, when not controlling for time nor fund-specific effects the following are found to be determinants of next period's net cash flow: 12b1 fee, rear load dummy, and age have a negative and significant coefficient. Higher marketing expenses and the presence of a front load both negatively affect fund flows as they directly reduce investor returns: investors will give less money to funds that are higher in characteristics which reduce their return. The negative and statistically significant coefficient for age suggests that older funds have smaller scaled cash flows. This could be explained by the significant and positive correlation between size and age: older funds are also larger, and since fund flows are scaled by TNA it is harder for larger funds to increase at large rates in terms of percentage of assets.

The negative and significant coefficient for age remains when moving to specification 4, where specification 3 is repeated adding quarter FE. This makes the adjusted R-squared increase marginally, while the regression coefficients keep their sign and significance. Fund FE are added instead of quarter FE for specification 5, which makes the percentage of variance explained by the model more than triple to 20.41%. While controlling for fund-specific characteristics makes the coefficient for 12b1 fee insignificant, it also makes that for historic performance negative and statistically significant. It is surprising that the coefficient for quarterly return since inception is negative and significant; given that experimental evidence on this variable suggests a positive relationship with fund flows, alternative regression specifications will be used to confirm or reject this finding. Additionally, the coefficient for the restricted sales dummy also becomes negative and significant. Specification 6 repeats 3 but using both quarter and fund FE, where only the restricted sales dummy is a significant predictor. The interpretation of this is that controlling for all quarter and fund-specific characteristics absorbs the explanatory power of the other determinants found in earlier specification.

Specification 7 repeats 6 but adds the lagged fund net cash flow as a predictor. The reason for this is that; given the short-term persistence found in fund flows, last quarter's fund flow should have an impact on this quarter's fund flow. While the goodness of fit only improved marginally, the coefficient for lagged net cash flow is negative and significant meaning that a higher flow last quarter is related to a lower flow this quarter (keeping all others constant): an increase in cash flow last quarter by 1 standard deviation (+12%) is related to an increase in cash flow this quarter by 0.6% of TNA, which is 67% of the mean of minus 0.9% of TNA.

Specification 8 is like 7, but quarter FE are removed so to be able to control for the aggregate cash flow in the industry (which is the same for all funds at each quarter but changes over time, so is collinear with quarter dummies). While the goodness of fit is only marginally better than the very similar specification 5, the aggregate industry flow has a positive and significant coefficient. This means that an increase in aggregate industry flow by 1 standard deviation (158 million dollars) is related to an increase of 1.6% of TNA, which is more than 100% of the mean. The interpretation of this economic implication is that the current net flow of the aggregate S&P 500 index fund industry is a significant and important determinant of the current net fund flow. In other words: when the industry grows the individual funds' scaled fund flows increase.

The fact that neither the return difference nor its square is statistically significant means that it is not possible to make conclusions about the shape of the flow-performance relationship: literature suggests that performance has a positive effect on flows, and that the relationship is convex. Neither of those two trends is found in the data as the two coefficients are not significantly different from zero. While this is unexpected, Del Guercio and Tkac (2002) also find no effect when controlling for other fund characteristics.

5.3. Subsample analysis

The literature review section found ground for expecting differences in the determinants of net fund flows to differ in two cases: retail and institutional funds, and expansion and recession periods. The reason why the coefficients of the fund flow regression in Table 5.2 may differ between these groups lies on palpable differences between how each group in the two categories would decide to give or take away money to a fund.

Given that Boyer and Zheng (2008) found that market conditions affect mutual fund flows, comparing the determinants of fund flows between expansion and recession periods could yield to the confirmation of that finding in the S&P 500 index fund industry. Three of the more complete fund flow determinant regression specifications used in the previous section are repeated for each subsample, and the result can be seen on Table 5.3. Specifications 5 and 8 of Table 5.2 are included to the left for comparisons between the full sample and subsamples.

Of the 5796 fund-quarter observations in the full sample; 4610 belong to the 33 quarters classified as expansion, and 1186 belong to the 6 classified as recession. Comparing the regression results between the two types of funds, some differences in the determinants of net cash flow can be distinguished.

The R-squared values for the different specifications show that in all cases the fund flows can be better explained by the models during recessions: up to 41% of the variance of fund flows can be explained by the most complete model during recessions, while only 22% of the variance can be explained during expansions. This difference could be driven by the variance of the dependent variable being different for the subsamples: the volatility of fund flows is 11.97% during expansions and 10.46% during recessions, even though sample volatility decreases with sample size and expansion periods have four times more observations. Fund flows are less volatile during recession periods because they are mostly negative (average -1.42% of assets and smaller standard deviation), while the spread is larger during expansion periods (average -0.81% and larger standard deviation).

Table 5.3: Results of fund flow regressions for expansion and recession periods

The table below is similar to Table 5.2, divides the sample into recession (at least 3 consecutive quarters of negative GDP growth according to NBER (2010) data) and expansion quarters. OLS is used for this panel, and errors are clustered by fund. Coefficient and [t-statistic] are reported below for 3 different specifications.

Condition	Full Sample		Expansion			Recession		
Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Net cash flow	-	.0005**	-	.0005**	.0005**	-	-.0129	-.0240
		[5.55]		[4.76]	[4.62]		[-0.32]	[-0.59]
Industry net cash flow (t+1)	-	.0001**	-	.0001**	-	-	.0000	-
		[2.67]		[2.78]			[0.61]	
Return diff.	-.0089	-.0091	.0093	.0101	.0093	-.1039*	-.1040*	-.1075*
	[-0.53]	[-0.54]	[0.77]	[0.83]	[0.63]	[-2.00]	[-2.00]	[-2.01]
Return diff. ^2	-2.238	-2.112	4.696	4.722	4.553	-13.95*	-13.92*	-14.69*
	[-0.62]	[-0.58]	[1.89]	[1.91]	[1.64]	[-2.11]	[-2.10]	[-2.21]
12b1 fee	6.914	6.806	15.16	14.80	13.52	-30.63	-31.06	-27.17
	[0.72]	[0.69]	[1.38]	[1.34]	[1.17]	[-1.87]	[-1.91]	[-1.77]
Management fee	.0041	.0057	.0240	.0243	.0245	-.1383	-.1375	-.1023
	[0.13]	[0.19]	[0.76]	[0.77]	[0.80]	[-1.28]	[-1.28]	[-0.93]
Front load	-.0149	-.0133	-.0218	-.0203	-.0098	.1341	.1341	.1377
	[-0.75]	[-0.68]	[-1.24]	[-1.17]	[-0.54]	[0.99]	[0.99]	[0.91]
Rear load	.0002	.0005	.0001	.0005	.0012	-.0015	-.0014	.0010
	[0.05]	[0.12]	[0.01]	[0.10]	[0.20]	[-0.16]	[-0.15]	[0.09]
Cash holdings	.0003	.0003	.0003	.0003	.0004	.0002	.0001	-.0004
	[1.07]	[1.08]	[0.39]	[0.39]	[0.44]	[0.08]	[0.03]	[-0.21]
Turnover	.0410	.0379	.0499	.0443	.0403	.1384	.1421	.1477
	[1.41]	[1.31]	[0.92]	[0.82]	[0.74]	[1.65]	[1.64]	[1.72]
Age	-.0063**	-.0059**	-.0070**	-.0067**	-.0058	-.0013	-.0019	-.0158
	[-5.76]	[-5.49]	[-6.68]	[-6.43]	[-1.02]	[-0.12]	[-0.18]	[-1.17]
Log (family size)	-.0044	-.0038	.0056	.0061	.0072	.0067	.0085	.0160
	[-0.41]	[-0.35]	[0.37]	[0.40]	[0.47]	[0.28]	[0.34]	[0.90]
Historic perf.	-2.547*	-2.256	-3.367*	-2.980*	-2.026	.5380	.3878	4.424
	[-2.11]	[-1.81]	[-2.59]	[-2.24]	[-1.50]	[0.18]	[0.13]	[0.97]
Open to inv.	.0129	.0129	.0088	.0087	.0099	.0208*	.0204*	.0274*
	[0.94]	[0.94]	[0.50]	[0.50]	[0.58]	[2.08]	[2.08]	[2.25]
Quarter FE	No	No	No	No	Yes	No	No	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	.2041	.2057	.2140	.2157	.2243	.3801	.3810	.4054
Adj. R^2	.1713	.1728	.1737	.1751	.1771	.2558	.2553	.2653
N	5796	5796	4610	4610	4610	1186	1186	1186

Evidence suggests that this difference is not the only driver. Another explanation for the higher model fit during recessions, despite only 3 of the fund characteristics tested having significant coefficients, is that fund-specific characteristics are better explanatory variables during recessions.

During expansions, age and historic return have negative and statistically significant coefficients. The lagged net cash flow and industry cash flow have positive and significant coefficients. On the other hand, during recessions the return difference and its square have negative and significant coefficients. The open to investors dummy has a positive and significant coefficient. In all cases fund FE are used, which means that the relationships found are robust to controlling for fund-specific characteristics.

No relationship between return differences and fund flows was found in the full sample, even though performance was predicted to be an important determinant of flows. This relationship is found during the recession periods in all three specifications, in all cases with negative and statistically significant coefficients. The same is true for return differences squared. During a recession, an increase in return difference by 0.25% (1 standard deviation) is related to a decrease in fund flows of 0.03% of TNA (using the coefficient from specification 7) which is almost 2% of the variables mean during recessions. In addition, this increase is related to an increase in return difference square which further decreases fund flows by almost 0.01% of TNA. Together the effects are of little economic importance, but its sign for the first is unexpected: rational behavior would suggest that in *ceteris paribus* investors reward their index fund outperforming the underlying with positive cash flows. The negative and significant coefficient for the second suggests that extreme performance is punished with lower fund flows during recessions.

Unlike recessions, expansion periods have positive and significant coefficients for the lagged net cash flow and the industry cash flow. The first is consistent with the results of the auto-regression of fund flows, which found persistence in flows only to be a trend for positive fund flows (which are more abundant in expansion quarters). The second suggests that growth in the overall S&P 500 index fund industry leads to a positive change in fund flows during expansions, while no effect is found during recessions. Otherwise, the results are similar.

The differences between institutional and retail investors could also lead to differences in the criteria they use for deciding to give or take away money to an index fund. To test this, the sample is split into retail and institutional funds and the fund flow regression is repeated. Table 5.4 shows how the determinants of fund flows change between institutional and retail funds.

Of the 5796 fund-quarter observations in the full sample; 3173 belong to 131 retail funds, and 2623 belong to 94 institutional funds. Comparing the regression results between the two types of funds, important differences in the determinants of net cash flow can be distinguished.

The R-squared values for the different specifications show that in all cases the fund flows can be better explained by the models for retail funds: up to 27% of the variance of retail fund flows can be explained by the most complete model, while only 18% of the variance of institutional fund flows can be explained by that same model.

For retail fund flows, age and historic performance have negative and statistically significant coefficients. The open to investors dummy has a positive and significant coefficient. On the other hand, for institutional fund flows, age and the open to investors and front load dummies have negative and significant coefficients. The squared return difference, lagged net cash flow and industry cash flow have positive and significant coefficients.

Table 5.4: Results of fund flow regressions for retail and institutional funds

The table below is similar to Table 5.2, divides the sample into institutional and retail funds. OLS is used for this panel, and errors are clustered by fund. Coefficient and [t-statistic] are reported below for 3 different specifications.

Condition	Full Sample		Retail			Institutional		
Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Net cash flow	-	.0005**	-	.0248	.0193	-	.0005**	.0005**
		[5.55]		[0.63]	[0.51]		[4.45]	[4.02]
Industry net cash flow (t+1)	-	.0001**	-	.0000	-	-	.0004**	-
		[2.67]		[1.16]			[3.03]	
Return diff.	-.0089	-.0091	-.0186	-.0198	-.0301	.0110	.0109	.0137
	[-0.53]	[-0.54]	[-0.71]	[-0.77]	[-0.96]	[1.04]	[1.02]	[1.05]
Return diff. ^2	-2.238	-2.112	-4.895	-5.225	-5.927	5.330**	5.562**	4.471
	[-0.62]	[-0.58]	[-1.01]	[-1.14]	[-1.20]	[2.83]	[2.95]	[1.94]
12b1 fee	6.914	6.806	-3.124	-3.117	-5.550	25.38	25.39	25.56
	[0.72]	[0.69]	[-0.57]	[-0.58]	[-1.04]	[1.08]	[1.08]	[1.10]
Management fee	.0041	.0057	.0161	.0181	.0135	.0007	.0016	.0079
	[0.13]	[0.19]	[0.38]	[0.43]	[0.33]	[0.01]	[0.03]	[0.15]
Front load	-.0149	-.0133	-.0004	.0016	.0131	-.1083**	-.1051**	-.0938**
	[-0.75]	[-0.68]	[-0.02]	[0.08]	[0.65]	[-7.23]	[-6.65]	[-4.85]
Rear load	.0002	.0005	.0007	.0006	-.0035	-.0020	-.0011	-.0004
	[0.05]	[0.12]	[0.15]	[0.13]	[-0.59]	[-0.16]	[-0.09]	[-0.03]
Cash holdings	.0003	.0003	.0004	.0004	.0003	-.0000	-.0000	-.0002
	[1.07]	[1.08]	[0.92]	[0.78]	[0.59]	[-0.05]	[-0.08]	[-0.48]
Turnover	.0410	.0379	.0414	.0336	.0316	.0666	.0558	.0534
	[1.41]	[1.31]	[1.07]	[0.71]	[0.64]	[1.21]	[1.05]	[0.99]
Age	-.0063**	-.0059**	-.0068**	-.0064**	.0083	-.0074**	-.0069**	-.0110
	[-5.76]	[-5.49]	[-4.41]	[-4.71]	[1.08]	[-4.77]	[-4.37]	[-1.15]
Log (family size)	-.0044	-.0038	.0472	.0464	.0442	-.0178	-.0167	-.0165
	[-0.41]	[-0.35]	[1.03]	[1.04]	[0.94]	[-1.39]	[-1.31]	[-1.23]
Historic perf.	-2.547*	-2.256	-3.615**	-3.520**	-2.650	-1.143	-.6889	-.5070
	[-2.11]	[-1.81]	[-2.81]	[-2.73]	[-1.93]	[-0.52]	[-0.31]	[-0.22]
Open to inv.	.0129	.0129	.0288*	.0284*	.0288*	-.0504*	-.0512**	-.0541**
	[0.94]	[0.94]	[2.38]	[2.37]	[2.44]	[-2.41]	[-2.62]	[-3.25]
Quarter FE	No	No	No	No	Yes	No	No	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	.2041	.2057	.2590	.2604	.2736	.1655	.1691	.1772
Adj. R^2	.1713	.1728	.2243	.2253	.2296	.1307	.1337	.1294
N	5796	5796	3173	3173	3173	2623	2623	2623

While a larger percentage of the variance of net fund flows is explained for retail funds, the number of variables with significant coefficients is smaller. This suggests that fund and quarter FE explain a larger part of the variance of retail fund flows. In other words, factors that do not vary for a given fund over all periods (fund-specific) or that do not vary between funds in every period (time-specific) have more predictive power for retail funds. This observation is congruent with institutional investors being more sophisticated and having lower search costs: a larger proportion of the fund characteristics tested as independent have significant coefficients for institutional funds, and many of these characteristics are significantly related to fund performance (see Table 5.1). A sophisticated investor is predicted to give performance determinants of flows more importance when choosing to give or take away money from a fund.

Del Guercio and Tkac (2002) find that pension clients punish poorly performing funds more than others. The coefficient for lagged fund return difference is not significantly different in either sample for neither of the regression specifications, but the squared return difference has a positive and significant coefficient for institutional funds on the specifications that do not use fund FE. A positive coefficient suggests a U-shaped flow-performance relationship, where funds with extreme performance have comparatively more fund flows. An increase in return difference of 0.25% (1 standard deviation) is related to an increase in return difference for institutional funds (decrease for retail), but neither of those two coefficients are significantly different from zero. However, for retail funds that increase is related to an increase in net fund flow scaled by TNA of 0.003% (using the coefficient from specification 7), which is about one third of a percent of that variables mean. While statistically significant, this effect is of little economic impact.

Given that this study does not find the positive and significant coefficient for lagged return difference, it is not possible to confirm their finding that more sophisticated investors punish underperformers more. One explanation for this could be that this phenomenon does not present itself in the S&P 500 index fund industry. Perhaps the pattern they found is constricted to the manager characteristic and fund product data they use, or the time period which spans from 1985 and 1994.

5.4. Robustness check

For the models for return differences and net fund flows scaled by TNA to be robust, they should remain valid under different assumptions, parameters and conditions. After presenting the two models in the first two subsections, the third one looked for changes in the coefficients of the regressions under two salient conditions. In addition, several specifications of the models are tested in each case to see if the coefficients change when controlling for different things. In particular; the use of fund and quarter FE and controlling for lagged terms in the dependent variable for different specifications, allow seeing if the significance, sign, and magnitude of the relationships found change when controlling for different fund characteristics, and fund and quarter-specific effects. These procedures reduce the likelihood of endogeneity problems.

The next step for this study is to see if the relationships found in the return difference and fund flows regressions are also present when performance is measured by the expense ratio instead of return differences. Finally, the fund flow regression will be repeated using the fund net cash flow (not scaled by fund size) to see if the relationships found change.

Firstly, the model for the determinants of performance with dependent variable return differences has to be adapted when changing the dependent variable to the expense ratio. The reason for this is that the expense ratio is highly correlated to 12b1 fee (correlation coefficient of 89%) because the first is a linear function of the second and the management fee. The management fee is the plug variable on the aggregation of itself, the 12b1fee, and other expenses into the expense ratio. It can also have negative values when clients are given exemptions from paying fees, which starts to explain its low but significant correlation with the expense ratio (correlation coefficient of 23%). In both cases it is positive because the expense ratio is the sum of the three types of expenses burdening of the investors of the fund. The two variables are excluded as determinants due to the 12b1 fee's high correlation, and the management fee's lack of information content as a plug variable despite its linear relationship with expense ratio.

Additionally, the value for the expense ratio in the quarterly mutual fund CRSP database is the year end reported value from the latest year-end report. This characteristic of the data means that there will be an extremely high autocorrelation in that variable. Indeed, an auto regression reveals that a single lag can predict over 99% of the variance in the dependent variable. This high persistence in the data, accentuated by the reporting frequency mismatch with this study's quarterly frequency, means that past performance is not controlled for.

A higher expense ratio means lower performance for an investor due to expenses widening the gap between the gross and net return offered by his fund, while a higher return difference means higher performance for an investor because it would mean the fund has obtained a higher return compared to the S&P 500 index. This means that one would expect the coefficients of the determinants of performance (excluding the ones discussed previously) to change signs. The results are presented on Table 5.5.

It can immediately be seen that the model fit is better when the measure of performance is the expense ratio, as the simplest specification which is a pooled regression explains 56% of the variance in the expense ratio. This is more than four times the percentage of variance captured by the same specification for return differences. The difference becomes smaller but is present in all the specifications.

In the first specification, most of the coefficients change sign as predicted and remain statistically significant compared to the regression of the determinants of return differences. Turnover has a significant coefficient (and continues to do so until fund FE are added), unlike with the other dependent variable. The coefficient for lagged cash flow is negative and significant, meaning that a larger fund flow is related to a lower expense ratio. This goes against the idea that larger net cash flows result on higher trading costs and thus expenses, and the result persists across multiple specifications. A possible explanation is that the persistence in fund performance creates a reverse causation problem where a large net flow last quarter could be caused by low expense ratio this quarter (which was also low on previous quarters).

In the second specification quarter FE are added, and the model barely improves in terms of R-squared. Given that 39 quarter dummies are added to the regression, the adjusted R-squared of the model decreases. Otherwise, the coefficients do not change in terms of magnitude and significance. On Section 5.1, the correlation between size and age prevented both being used as

Table 5.5: Results of performance regressions using expense ratio

The table below is similar to table 5.1, but the dependent variable is now the expense ratio. Some fund characteristics cannot be included due to problems with this variable. OLS is used for this S&P 500 index fund panel, and errors are clustered by fund. Coefficient and [t-statistic] are reported below for 5 different specifications. Like the return difference, the dependent variable is scaled to basis points for larger coefficients.

DV	Expense Ratio				
Specification	(1)	(2)	(3)	(4)	(5)
Lag. cash flow	-.0013**	-.0013**	-.0014**	-.0001**	-.0000
	[-8.21]	[-8.40]	[-9.20]	[-3.04]	[-1.24]
Log (TNA)	-.0923**	-.0919**	-.0903**	-.0059	-.0096
	[-11.29]	[-10.43]	[-9.83]	[-0.98]	[-1.63]
Log (family size)	.0627**	.0621**	.0552**	-.0325*	-.0315*
	[3.34]	[3.23]	[3.20]	[-2.34]	[-2.40]
Age	-.0069**	-.0077*	-.0042	.0007	.0012
	[-2.59]	[-1.99]	[1.05]	[0.19]	[0.27]
Turnover	.2249**	.2265**	.2305**	-.0002	.0011
	[2.70]	[2.71]	[3.10]	[-0.02]	[0.11]
Cash holdings	-	-	.0009	-	-.0002
			[0.37]		[-0.51]
Historic perf.	-	-	-8.149	-	2.258
			[-2.53]		[1.49]
Open to inv.	-	-	.0139	-	.0351
			[0.22]		[1.49]
Restricted sales	-	-	-.3209**	-	-.2011
			[-2.71]		[-21.70]
Institutional	-.3210**	-.3209**	-.3248**	-	.0357**
	[-8.55]	[-8.49]	[-7.72]		[2.86]
Front load	-	-	-.0344	-	-.0412**
			[-0.63]		[-2.85]
Read load	-	-	.0992**	-	-.0012
			[2.88]		[-0.33]
Quarter FE	No	Yes	Yes	Yes	Yes
Fund FE	No	No	No	Yes	Yes
R^2	.5617	.5627	.5849	.9841	.9845
Adj. R^2	.5612	.5594	.5813	.9833	.9838
N	5796	5796	5796	5796	5796

* p<.05, ** p<.01

predictors in the same regression; in this case, it is not necessary as the high correlation does not confound the effects with the two coefficients being significant.

The third specification is like the second, but also includes the other control variables that were available in the data set. Those determinants that are deemed problematic, such as the 12b1 fee, are not included. The coefficient for cash holding is not significant in this case (compared to the return difference regression), while that of the restricted sales, institutional, and rear load dummies are now significant.

A 12% larger scaled net cash flow (1 standard deviation) on the previous quarter is related to a .02 basis point lower expense ratio, less than a percent of the average expense ratio.

A 243% larger TNA (the standard deviation for the logarithm of TNA is 2.43) is related to a decrease of the expense ratio of .23 basis points, which is less than 1% of the dependent variable's mean. A 108% larger family of funds (the standard deviation of the logarithm of number of funds in family is 1.08) is related to a .6 basis point higher expense ratio, around one percent of the mean. It seems that funds with larger families charge their investors higher expenses, perhaps taking advantage of non-product differentiation. A 22% of assets higher turnover is related to an increase in the expense ratio of .5 basis points, almost one percent of the mean.

Funds with restricted sales have an expense ratio which is .32 basis points smaller. Institutional funds have a similarly lower expense ratio, and funds with a read load have a .10 basis point higher expense ratio. In all the cases, despite their statistically significance the coefficients are not economically important. Even less so than those for the model with return difference as the dependent variable, even though this model does have a better goodness of fit without using FE.

The fourth specification introduces fund FE to specification 2, which increases the percentage of variance explained by the model to over 98%. In this case, and also in specification 5 where more controls are added to this model, the coefficients for many of the variables of interest become insignificant. It seems that controlling for fund-specific characteristics takes away the explanatory power of some of the variable of interest, but does significantly boost goodness of fit.

Given these findings and how they compare to the return differences regression results, it can be said that most of the relationships found before persist when using a different dependent variable. While the expense ratio provides a model with better fit, its high persistence (and yearly change) makes it un-appealing as a measure of performance for the fund flow regression.

Re-stating the scaled net cash flow scaled by fund TNA regression is much simpler, as the value of the flow in millions of dollars is used as the dependent variable instead. No other changes are necessary, and the results are presented on Table 5.6. For reference, the average fund flow is 25 million dollars, with a standard deviation of 1.08 billion dollars, a minimum of -16 billion and a maximum of +37 billion. While the average un-scaled net cash flow is positive, the average for its scaled counterpart is negative. This is explained by the impact of large positive outliers in the un-scaled variable's distribution. In both cases the median net fund flow is negative, reflecting the fact that overall S&P 500 index funds have been losing money over the period studied.

Table 5.6: Results of fund flow regressions using non-scaled dependent variable

The table below is similar to table 5.2, but the dependent variable is non-scaled fund net cash flows. OLS is used for this S&P 500 index fund panel, and errors are clustered by fund. Coefficient and [t-statistic] are reported below for 5 different specifications.

DV	Net cash flow (t+1)				
Specification	(1)	(2)	(3)	(4)	(5)
Net cash flow	-	-	-	-	.0223
					[1.34]
Industry net cash flow (t+1)	-	-	-	-	-.0020
					[-0.03]
Return diff.	-2001	-57.64	-6838	1034	-6879
	[-0.32]	[-0.01]	[-1.01]	[0.13]	[-0.97]
Return diff. ^2	$1.2*10^6$	$.6*10^6$	$.4*10^6$	$.3*10^6$	$.4*10^6$
	[1.72]	[1.20]	[0.81]	[0.56]	[0.74]
12b1 fee	7637	7454	-5250	$1.2*10^4$	-5941
	[0.69]	[0.72]	[-1.27]	[-1.12]	[-1.41]
Management fee	-176.9*	-144.7*	-41.74	-57.72	-54.21
	[-2.42]	[-2.15]	[-1.46]	[-1.12]	[-1.70]
Front load	39.52	40.39	-6.293	22.25	-8.613
	[0.96]	[1.00]	[-0.49]	[1.17]	[-0.46]
Rear load	15.34	4.721	-3.233	-20.95	-4.367
	[0.44]	[0.13]	[-0.55]	[-0.79]	[-0.76]
Restricted sales	-105.9	-129.5	-20.28	-28.23	-34.34
	[-1.04]	[-1.10]	[-0.94]	[-0.77]	[-1.14]
Cash holdings	-1.691	-.1372	-.1818	.2542	-.0482
	[-1.68]	[-0.18]	[-0.26]	[0.46]	[-0.07]
Turnover	26.44	24.68	22.07	8.650	27.16
	[0.98]	[0.99]	[0.61]	[0.24]	[0.69]
Age	-.17.02	-28.20*	-2.052	21.69	.1384
	[-1.68]	[-2.00]	[-0.52]	[0.76]	[0.04]
Log (TNA)	42.89	48.19*	-20.11	-17.50	-20.27
	[1.93]	[2.15]	[-1.87]	[-1.67]	[-1.71]
Log (family size)	-134.5	-154.7	242.4**	226.5**	143.8*
	[-0.98]	[-1.11]	[2.82]	[3.36]	[2.23]
Institutional	80.31	65.38	5.903	-.0754	7.966
	[1.19]	[1.08]	[0.25]	[-0.00]	[0.36]
Historic perf.	3698	7702	3645	6299	5123
	[0.94]	[1.46]	[1.54]	[1.78]	[1.60]
Open to inv.	194.2	-55.20	13.91	2.435	16.03
	[1.10]	[-1.58]	[1.00]	[0.15]	[1.13]
Quarter FE	No	Yes	No	Yes	No
Fund FE	No	No	Yes	Yes	Yes
R^2	.0103	.0189	.0625	.0684	.0631
Adj. R^2	.0077	.0098	.0237	.0232	.0241
N	5796	5796	5796	5796	5796

* p<.05, ** p<.01

It can immediately be seen that in all cases the goodness of fit worsens, with one fourth of the variance being explained by the simplest model compared to when the dependent variable was scaled (1% and 4% respectively). Given that funds are largely heterogeneous in terms of size, a possible explanation for the worse model fit observed could be that not scaling the net fund flow makes it harder to explain that variable. The distribution of the un-scaled fund net cash flows has a skewness of 18 and kurtosis of 557, while for net cash flow scaled by size the skewness is .5 and the kurtosis 22.8. In other words, the scaling by size transformation seems to be making it easier to find linear relationships between the variables using OLS (explaining why the transformation is ubiquitous in the literature).

Other differences are that the 12b1 fee, age, and rear load dummy are no longer significant, compared to the scaled net fund flows. This could be due to the overall worse model fit. The only fund characteristics with a statistically significant coefficient is the management fee, sign being negative as expected (the sign does not change compared to scaled flows). A 14% increase in management fee (1 standard deviation) is related to a 25 million decrease in net cash flow, which is the same size as the average cash flow. This effect is then economically important, unlike in the un-scaled case when the coefficient was not significantly different from zero.

Then, for specification 2 the regression is repeated including quarter FE. This new model produces significant coefficients for size and age, positive and negative respectively. The average fund size is around 2 billion dollars; heavily biased by the top 5% funds with over 12 billion dollars, as the median is only 137 million. This makes the standard deviation large (one standard deviation is a 243% increase in TNA). An increase in the logarithm of TNA of 1 standard deviation is related to an increase in net fund flow of 117 million. This is very close to the the median, but much smaller than the mean. The directionality is in accordance to expectations too, as larger funds have are more visible which would lead to lower search costs for investors and inhibit positive cash flows. On the other hand older funds having lower flows, despite the positive and large correlation between age and size, suggests that when controlling for many other fund characteristics age has a negative impact. A 5 year older fund has all others constant, a 145 million smaller net cash flow. This is larger than the median, but much smaller than the mean net cash flow. Given the positive correlation between size and age (around 40%), these two effects should net each other out to some extent when the *ceteris paribus* assumption is abandoned.

For the third specification, fund FE are added to specification 1. When controlling for all fund-specific characteristics, the explanatory power increases significantly but is still much lower than when the dependent variable was scaled by size. With these additional controls, the only fund characteristic in the sample that has a significant coefficient is the logarithm of the number of funds in the family, the sign of which is positive. An increase in the number of funds in family of 108% is related to an increase in net fund flow of 262 million dollars. This is almost twice the median, but barely over 10% of the mean net cash flow. This effect is economically important and was not found when using the scaled dependent variable. The positive and significant coefficient suggests that a larger number of funds in the family is related to larger cash flows, in agreement with the idea of non-product differentiation (more options for investments within the mutual fund family) being rewarded by investors.

In the fourth specification, both quarter and fund FE are included. The results are very similar to those obtained in specification 3 with only fund FE. Given that the adjusted R-squared is higher for specification 3 than it is for 4, quarter FE are not included in subsequent specifications.

In the fifth and final specification, only fund FE are included. Additionally, the lagged net cash flow is included to control for reputation and the aggregate industry net cash flow is also included. The coefficients for the latter two controls are not statistically significant. Again, only the number of funds in family has a significant coefficient. The sign remains the same, while the magnitude decreases. The relationship between the numbers of funds in family and fund flow is present across multiple specifications, controlling for several other fund characteristics.

In all cases, the coefficient for the historic quarterly return is positive but not significantly different from zero. When the dependent variable was not scaled, a negative and significant coefficient was found in certain specifications. The negative sign is unintuitive, as experimental research suggests investors reward funds for its time of inception's alignment with S&P 500 index returns even though this does not affect performance. Unfortunately, the small t-statistics (and negative coefficients when t-values were large enough) do not permit to translate this finding from experimental investor-level data to fund-level data. The explanation to the negative coefficient of return since inception for scaled cash flow could lie in the scaling transformation, which offers a better model fit and finds more significant coefficients for determinants.

6. Conclusion

6.1. Answers to research questions

To start, the findings of important broad industry trends in the S&P 500 index fund industry will be discussed. After that, the three research questions will be answered in order.

The number of S&P 500 index funds decreases after 2008, while the total net asset value of all the funds in the industry only increases in line with changes in the underlying index over the whole period. These two findings give little support to the presence of fund proliferation for S&P 500 index funds between 2004 and 2012, and oppose previous studies that use the same sub-sample of the index fund industry. Nonetheless, in accordance to current broad industry studies (which find the number of funds continues to increase), it is found that the number of funds in family consistently increases over the sample period. This is evidence of category proliferation in the fund families that own at least one S&P 500 fund, and hints at the possibility that the number of funds elsewhere in the mutual fund industry is growing.

While the lowest expense ratios in the industry have not changed much (research in the 80s and 90s found decreases in them as the industry went from 1 to 100 funds, explained by economies of scale and competition) and remain steady around 50 basis points per year, there is evidence of fee dispersion in the upper tail of the distribution of the expense ratio. Since 2005 the

99th percentile increase from under 1.5% to 1.8% of assets and the number of outliers with large expense ratios increases too. This finding is congruent with Hortaçsu and Syverson (2004) who find that the search costs for S&P 500 index fund investors increase over time, and that since the late 90s there had been an increase in the number of high search-costs investors.

The first research question of this study is about the determinants of fund performance. When defining fund performance as the return difference (fund return – index return), the following fund characteristics are found to have a statistically significant relationship with performance: size (positive), family size (negative), 12b1 fee (negative), management fee (negative), return since inception (positive), restricted sales dummy (negative), rear load dummy (positive), institutional dummy (positive), and 3rd lag of performance (positive).

The approach of using quarter FE to control for time-specific variables such as S&P 500 index volatility and dividend level (which are important determinants of index funds returns) leads to a good model fit. It also allows reducing the omitted variable bias by controlling for any shock that would affect all S&P 500 index funds equally in every quarter (fund-invariant). The fund characteristics approach used in this study allows explaining 40% of the variance in return differences in a model with 5 key characteristics, while the index characteristics approach of Frino and Gallagher (2001) explains only 9%. On the other hand, the model used in this study does not find the negative relationship between lagged net fund flow and performance; not finding evidence of past positive flows resulting on larger expenses through trading and subsequent worse performance.

Fund FE allow controlling for time-invariant factors, such as unique fund attributes that affect performance (for example the ability of a fund’s investment manager). In some cases, controlling for such characteristics turn some of the relationships listed from significant to insignificant (for example size after fund FE). In such cases, it can be speculated that the effect of the fund characteristic on the performance is taken away by controlling for time or fund-specific characteristics. However, it is important to remember that not finding a significant coefficient only means a failure to reject the null hypothesis that the fund characteristic has no effect on fund performance. In other words, no evidence is found that the fund characteristic has a significant effect on performance. This means that no relationship is found, not that it was found that there is no relationship.

Furthermore, all of the relationships found have weak economic implications: a 1 standard deviation change in the determinants leads to a change in return difference of less than 2% of its average. The return since inception is the exception with its effect being 53% of the average return difference. Remarkably this fund characteristic, that has found to be a significant determinant of fund flows in fund selection experiments, is found to have a significantly positive and meaningful impact of fund performance. This effect persists even when controlling for fund age and time-specific factors, both of which are related to return since inception by construction.

The relationships found when using return differences as the dependent variable were also found when using the expense ratio. As was to be expected from the nature of the variables, the signs were reversed (a lower expense ratio and a higher return difference both mean better performance). Even though the latter provided a model with better fit without the need of using quarter FE, its miss-match with the quarterly data frequency used makes it a sub-optimal choice for a measure of performance in the fund flow regression. Other studies using a yearly frequency to study the determinants fund flows should find the expense ratio a good proxy for performance in index funds.

For both measures of performance, there was evidence of long term persistence: past performance is an important determinant of future performance.

The second research question of this study looked at the determinants of S&P 500 index fund flows. When scaling the fund net cash flow by the TNA, the following fund characteristics are found to be significant determinants of scaled fund flows: 12b1 fee (negative), rear load dummy (negative), restricted sales dummy (negative), age (negative), return since inception (negative), lagged scaled net cash flow (positive), and aggregate industry net cash flow (positive).

As was the case during the first research question where no relationship was found between current performance and lagged fund flow, no significant relationship is found between lagged fund performance and fund flows. This is disappointing because across multiple specifications, what the literature labels as the performance-flow relationship cannot be found for the chosen measure of fund performance (return differences).

Of the determinants of performance found when answering the first research question, the following are also determinants of fund flows: 12b1 fee, rear load dummy, restricted sales dummy, and return since inception. That those fund characteristics are determinants of both performance and fund flow allows identifying what was theoretically described in Section 3 as performance determinants of flows.

In the fund flow regression literature, there are two types of variables that have been found to be determinants of fund flows: performance and non-performance fund characteristics. The first are factors that directly affect the investors return via their effect on the fund's performance (for example larger fees are related to worse performance, and larger size related to better performance), which in turn affects fund flows because investors reward funds that perform better by giving them money. The second are factors that affect the investors decision to give money to a fund, but are not via fund performance. Instead, this could be factors that affect fund flows such as its visibility (such as size or age) in an environment where investors face search costs.

Comparing the variables that were found to be significant determinants of performance and fund flows, the only non-performance variables found is age. The rest of the variables that are found to be determinants of fund flows are also found to be determinants of performance. The fact that some variables are found to be determinants of performance but not fund flows could suggest, from a theoretical perspective, that investors are not taking into account some performance-determining fund characteristics when choosing to give or take money from their fund. However, there is another explanation: that a coefficient was significant in the performance but not in the fund flow regression, does not mean that it is not a determinant. The theoretical idea proposed cannot be confirmed, given the statistical testing done.

In theory, age could be a non-performance determinant of fund flows through the visibility and search cost interaction: in a market where investors face search costs, increasing fund age paired with increasing reputation and notoriety could affect the investor's decision to give money to a fund. However, a negative coefficient is found meaning that older funds have smaller fund flows. This could be explained by the positive correlation between age and size (over 40%), and the fact that fund flows are scaled by size: older funds tend to be larger, and the latter have smaller flows as a % of their TNA. When non-scaled fund flows are used in Section 5.4 when testing for the robustness of the model, the goodness of fit is greatly reduced and only family size is a significant determinant of flows. This does not allow making inferences about the alternative explanation's validity. Interestingly, while much model fit is lost when not scaling fund flows, mutual fund family size is found to be a determinant of fund flows. This effect is economically important, and supports the hypothesis that investors give more money to funds that offer more options in their family.

Given that the average number of funds in the family for the funds in the sample is 223 and the maximum is 1081, it seems that the majority of funds in the sample are part of large fund families (only 4 funds were not part of a family). If larger families have a larger size in terms of TNA, not scaling the cash flow made it easier to find a linear relationship using OLS.

Comparing the signs of the coefficients of the performance of fund flows-determining fund characteristics in Tables 5.1 and 5.2, one would expect from economic intuition that factors that have a negative effect on performance will also have a negative effect on fund flows (and vice versa). This is the case for the 12b1 fee and restricted sales dummy, but not for the return since inception and rear load dummy.

For the first two variables, the economic intuition is fulfilled. However, the rear load dummy is related to higher performance and lower fund flows. Given that the rear load dummy signals if a fund has any type of rear load fee in a given quarter, that a fee dissuades investors from giving money to a fund seems right. However, the positive relationship between a fee investors pay when taking away their money of the fund and the fund's performance seems unintuitive. This is because the load is paid to an intermediary and thus does not affect the fund's operating expenses, which means it does not affect TNA. Thus, it does not affect performance measured as return differences. Beshears, Choi, Laibson and Madrian (2009) find that investors have a poor understanding of loads (and will select a fund with a load even with a short investment horizon), and this could be an explanation.

A larger average quarterly return since inception is related to better contemporaneous performance, and in some specifications to lower scaled fund flows.. This result could be explained by the long term persistence of performance found in section 4.2: persistent performance would explain why the fund's average return over many quarters (over 80 for some funds) is related to the fund's current performance. The sign for that relationship is positive as funds that have performed better in the past perform better in the present. Return since inception is not determined by the fund (only as far as their choice of year of creation), but more so by the S&P 500 index performance and expense ratio (or return difference). This does not cloud the effect of return since inception on current performance.

The negative relationship found between return since inception and scaled fund flow is surprising, and goes against the experimental results obtained by Choi, Laibson and Madrian (2006) where a positive relationship is found. Unfortunately, the results for the non-scaled regression have positive but non-significant coefficients for return since inception and it cannot be concluded that this problem is caused by the scaling by fund size. One important difference is that their experiment is done at the investor level, while this study used fund-level aggregate data as well as net cash flows (instead of an investment decision questionnaire). As a result, this experiment controls for many more fund characteristics and has a harder time finding a linear relationship with the dependent variable (which is the net cash flow scaled by size).

Finally, the determinants of fund flows results obtained for the second research question are repeated for two groups: institutional and retail funds, and recession and expansion periods. In both cases, notable differences in the determinants of net cash flow scaled by size are found between each category.

The goodness of fit of the model is better for retail funds, where 26% of the variance of scaled fund flows is explain as opposed to 16% of institutional funds. The following fund characteristics have a significant coefficient as determinants of scaled fund flows for both retail and institutional funds: open to investors (different signs), and age (negative). The following are only significant determinants for institutional funds: squared return difference (positive), and front load dummy (negative). The return since inception is only significant for retail funds (negative), as well as for the full sample in specifications that do not control for time-invariant fund characteristics.

Given that the model fit is better for retail funds and the number of significant determinants is smaller for these funds, it seems that the quarter and fund FE do a better job at explaining how retail investors determine money transfers to retail funds. That institutional fund flows are harder to explain could be due to higher degree of sophistication by investors, which is also supported by more performance-determining fund characteristics being significant determinants of institutional investment flows.

The negative coefficient for front load for institutional funds, while no significant effect was found for retail funds or the full sample, could be explained by more sophisticated investors having a better understanding of flows and thus giving less money to funds with front loads. Investors in institutional funds are also found to reward extreme performance (when fund returns are more different from the underlying index's returns), but the lack of a significant coefficient for non-squared performance does not allow to make further inferences on the shape of the performance-flow relationship.

The return since inception was found to be a significant determinant of scaled net fund flow for the full sample when controlling for fund FE. Similar findings are present for the retail funds, where higher historic performance is related to lower fund flows. The effect is of little economic importance, and its sign goes against experimental results discussed earlier. Nonetheless; evidence of a significant impact of this variable on fund flows is only found for retail funds, which is in accordance to the rationale that institutional investors are less prone to give importance to a variable that is a direct function of the time of fund inception in their fund selection decision.

The determinants of fund flows also differed between economic recession and expansion periods for S&P 500 index funds; as predicted by Boyer and Zheng (2008), who find that mutual fund flows are related to the economic situation of the country. In this case, the division of quarters into expansion and recession based on US GDP growth data allows comparing two the determinants of fund flows under two different general economic conditions.

The following characteristics were significant only during expansions: lagged scaled net cash flow (positive), aggregate industry net cash flow (positive), age (negative), and return since inception (negative). The following were significant only during recessions: return difference (negative), return difference squared (negative), and open to investors dummy (positive).

During expansions, a funds' reputation and the net cash flow of the whole industry both are related to possitive fund flows. This is also observed in the full sample, but not during recessions. Instead, a negative relationships between performance (and its square) and fund flows is found. This is against economic intuition, which suggests that investors would reward funds for good performance by giving them more money. Given that significant coefficients are found for return differences (and its square), it is possible to infer the shape of the performance-flow relationship during recession quarters: downwards sloping (high return difference related to lower flows), and extreme differences between fund and index returns is punished by investors. While the second makes sense, as S&P 500 investors seek to replicate index performance and not for alpha, the first is harder to explain.

The fact that age is significant only during expansions could be explained by the fact that it is possible that this variable is a non-performance determinant of fund flows (although the lack of a significant coefficient does not imply the absence of a relationship). If during recessions fund performance (measured by return differences) has a more significant effect on net fund flow, maybe during expansion non-performance variables are comparatively more important. While this cannot be concluded from this study, the results obtained hint at the possibility of S&P 500 index fund investors paying more attention to performance determinants of fund flows during recessions, and more to non-performance determinants during expansion.

Overall, this study has managed to use the largest and most up to dataset on S&P 500 index funds to update mutual fund literature for this small group of funds. The main industry trends were discussed in the context of this sub-sample of the mutual fund industry, and the determinants of fund performance and fund flows were analyzed. Results were checked for robustness, and compared between different types of funds and economic conditions. In the end a lot of insight was gained into this type of mutual funds, after applying different styles of mutual fund research for this subsample of interest.

To conclude, two practical applications of the findings of this study are given as an example of how this research could affect investors and mutual fund managers. For S&P 500 index fund investors: the performance regression shows that choosing a fund that is larger, has smaller fees, and has performed well in the past is related to higher performance (under the *ceteris paribus* assumption). This result is in the same direction as that of Halling, Cooper and Lemmon (2011), who find that investors that pick funds with lower fees and funds with good past performance earn higher returns. In other words; in a market for a product where shorting is not possible, dominated or inferior products can survive.

For S&P 500 index fund managers: the fund flow regression shows that lower fees are related to larger fund flows (the 12b1 fee is economically small, but statistically very important), such that marketing expenses are penalized by investors with lower fund flows. This is despite the fact that businesses, S&P 500 index funds included, spend in marketing with the goal of increasing sales. It seems possible that in this industry, controlling for other important fund characteristics and in *ceteris paribus*, burdening marketing expenses on investors could be counter-productive.

6.2. Recommendations and limitations

One of the main drawbacks of this study is that it focuses on S&P 500 index funds only, which means less than 40% of the index funds in the US are examined. While it is the largest type of index fund, it is possible that for other index fund categories (for example bond indices) performance and flows are determined in a different way. Therefore, the results obtained cannot be generalized (in other words, they lack external validity). Similarly, the results cannot be generalized to index funds outside the US. In both cases, better identification methods or new sources of data could allow extending the research in either direction. For example, Frino & Gallagher (2002) analyze the performance of Australian index funds to find that they are not very different.

Given the similarities between index funds and exchange-traded funds (ETFs) in terms of the product they offer to investors, it would be interesting to see if they face similar determinants of performance and fund flows. However, Kostovesky (2003) points out that for retail investors index funds have lower costs and are therefore preferable for tracking an index.

In order to compare the determinants of S&P 500 index fund flows to the broad industry, it would also be interesting to use alpha as a measure of performance instead of return differences. This would allow comparing coefficients with many more studies. Using a larger sample period would also allow comparing the results obtained to similar studies that were done in the past, but this comes at the expense of being able to use less fund characteristics.

Two interesting characteristics found in the data were: the average fund beats the index in four quarters (2009-2/3 and 2012-1/2), and return since inception has a negative effect on fund flows. Neither of these results is in line with the existing literature, and it would be interesting to find an explanation. In addition, the performance-flow relationship was not found in the full sample. Further research is required to discover if (and how much) past outperformance by the fund is rewarded by investors with higher fund flows.

Reflecting on what can be concluded from the results obtained, this research does hold important implications for S&P 500 index fund investors (in the performance determinants regression) and for fund managers (in the fund flow determinants). While the relationships found are statistically significant and mostly congruent with other research, the methodology used does not allow concluding how investors and funds will behave in causal statements: this begins to explain why the determinants of fund flows are sometimes studied in experiments, where there is control over the independent variables and less endogeneity/reverse-causation problems (through simplistic designs).

The latter two problems are important in this study. Firstly, the CRSP database does not necessarily include all relevant fund characteristics to use as controls (omitted-variable bias) and therefore raises the concern of endogeneity. This is alleviated by the fact that a large number of fund characteristics and fixed effects are used to control for many types of effects. Secondly, the performance-flow relationship works in both directions: performance and flows are used as determinants of each other, while there is ample evidence that they both cause each other (past performance affects future flows, and past flows affect current performance) which together with the persistence raises reverse-causation concerns.

7. References

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