MUTUAL FUND MANAGEMENT: DOES ACTIVE MANAGEMENT PAY?

by

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ABSTRACT

According to classical portfolio theory, two implications follow when an asset has a positive alpha against some benchmark: (1) the benchmark is mean-variance inefficient; (2) by combining the positive alpha asset with the benchmark, one can improve the mean-variance efficiency of the benchmark. The first implication is well known, but the second is largely ignored in the existing literature. This dissertation tests and applies the second implication. The dissertation has two chapters.

Chapter 1 empirically tests the theory. Specifically, we test whether the alpha of an investment relative to one's existing portfolio can be used to improve out-of-sample performance as measured by Sharpe ratio and four-factor alpha. For the period 2000 - 2014, we confirm this for the Vanguard S&P 500 Index Fund and the Growth and Small Index Fund, which we extend by adding various Exchange Traded Funds.

Chapter 2 applies the theory in the mutual fund context in order to shed light on the relation between active management and fund performance. Recent studies have documented a positive relation between the degree of active management and mutual fund performance. We show that this relation holds only for fund managers who trade in an optimal way. The optimality measure that we develop, "investment alpha," captures whether a mutual fund is trading towards mean-variance optimality, which, we argue, is the first-best choice for mutual fund managers within a mean-variance framework. This investment alpha is similar to previous work using evaluation alphas such as Jensen's alpha, except that our benchmark is the manager's own portfolio. We show that if the investment alpha of a fund's incremental portfolio — defined as the portfolio obtained by collecting the changes in a manager's positions over a given period — is positive then the fund is trading in the "right" direction. We show empirically that managers who do so outperform, and the more so if they are more active, and that investors react to the correct direction through increases in fund flows in the subsequent quarter. Actively managed funds that don't trade toward mean-variance optimality do not outperform.

For my mom

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CHAPTER 1

USING ALPHA TO GENERATE ALPHA

1.1 Introduction

It has long been known (e.g., Blume (1984), Dybvig and Ross (1985a)) that, in principle, alpha can be used to improve the Sharpe ratio of one's portfolio. All one has to do is to *marginally change portfolio weights of individual holdings in proportion to their alphas.* Importantly, the alphas should be computed with one's own portfolio as benchmark, and not some other, arbitrary benchmark. While the approach is mathematically correct, it is not obvious that it will work in practice (although we discuss related work below). To our knowledge, there is no systematic evidence on whether the technique produces economically significant results. This is what we set out to test.

There are a number of reasons why adjusting weights in proportion to alphas may not work in practice. Estimation error immediately comes to mind: alphas are, after all, estimated, and the resulting sampling error may destroy the improvement in the Sharpe ratio that one could obtain if one had known the true alphas. But perhaps the most important reason is that expected returns change over time (e.g., Conrad and Kaul (1988)). By the time alphas are estimated accurately, expected returns have moved, to the extent that the obtained alphas are no longer relevant. One is effectively chasing a moving target (Gârleanu and Pedersen, 2013).

A particularly interesting case to consider, we think, is where an investor holds a broadly diversified index initially, i.e., some proxy of the market portfolio, and then tries to improve the mean-variance efficiency of the held index. That is what we report on here. We shall refer to the improved portfolio that the investor obtains after adjusting weights in proportion to alphas as the *alpha adjusted index.* We think that our case is interesting because of two reasons: (i) we know that broad indices generally are not mean-variance optimal, so that alphas of individual securities are indeed nonzero; (ii) when one takes the index as a proxy of the market portfolio, the emergence of nonzero alphas implies that the csapital asset pricing model (CAPM) fails. If, however, markets constantly move *in the direction of* CAPM, then the alpha adjustment strategy may fail after all. Indeed, prices adjust to ensure that alphas converge to zero (this is what it means for markets to move in the direction of CAPM).

Hence, the index one started from becomes mean-variance optimal, while the alpha adjusted index becomes mean-variance suboptimal. As such, one should have remained invested in the index, rather than adjusting its weights.

The latter remark suggests that this study could be viewed as a test of *whether markets move towards CAPM*. It is well known that CAPM fails empirically (see Fama and French (1992)), but traditional tests assume that one always observes prices when the market is in equilibrium. Common sense instead suggests that markets take a long time to equilibrate, and chances are slim that observations always coincide with equilibrium. Experimental evidence confirms this: even if traditional CAPM tests may fail, markets do have a strong tendency to move towards CAPM (Bossaerts and Plott (2004), Asparouhova et al. (2003)). Of course, real-world financial markets are more complex than laboratory markets, encounter far more friction, and participants know much less than in a controlled setting (e.g., they do not know the true distribution of future payoffs). So, additional forces may be at work which the stylized setting of the laboratory ignores. If we find that our alpha adjusted index does not improve the mean-variance efficiency of our index, one possible cause is that prices adjust in the direction of CAPM. Indeed, in that case, it is beneficial to stick to the original index, even if, based on prior return data alone, the index is inefficient (i.e., there exist nonzero alphas). One effectively lets the markets do the adjustments towards mean-variance optimality.

One way to gauge the economic significance of our exercise is to appeal to a result in Dybvig and Ross (1985a). There, it is shown that, to generate a positive alpha with respect to *any* (necessarily mean-variance suboptimal) benchmark or collection of benchmarks, it suffices to acquire a mean-variance optimal portfolio. Admittedly, our investment strategy does not guarantee full mean-variance optimality. At best, the strategy improves efficiency. Still, one can pose the following question: will improvement in mean-variance efficiency be sufficient to generate a (significantly) positive alpha with respect to benchmarks traditionally used in the academic literature? The benchmarks we have in mind are the Fama-French-Carhart four-factor portfolios (Carhart (1997)). That is, we test whether the alpha adjusted portfolio is capable of generating positive alpha with respect to the traditional Fama-French-Carhart factor portfolios.

Putting everything together, evidence that the alpha adjusted portfolio generates positive alpha with respect to the Fama-French-Carhart model would not only demonstrate that our technique is economically relevant. It would also vindicate the claim in Dybvig and Ross (1985a). At the same time, it would demonstrate that markets do not move to

CAPM, or that markets move towards CAPM sufficiently slow for there to be exploitable mean-variance inefficiencies. This is exactly what we find.

To ensure that our strategy would work in practice, we do not use an academic index as benchmark (e.g., the CRSP index), but instead focus on investable indices, namely, two of Vanguard's ETF (Exchange Traded Fund) indices. In addition, we use a number of ETFs as candidate extensions of those indices. As such, our results are not only aimed at an academic audience, but should be of interest to practitioners as well.

Concurrent with our analysis, Levy and Roll (2015) have investigated alpha-based strategies for portfolio improvement. There are a number of key differences between their and our investigations. First, Levy and Roll (2015) determine whether weights on component stocks of an index can be changed in order to improve performance, while we focus on *additions* of various types of ETFs to a given index. There are two differences, as a result: (i) we look at extending the index, while Levy and Roll (2015) investigate changing weights; (ii) we consider diversified ETFs rather than individual stock. The latter is important because alphas of individual stock cannot be estimated precisely, while those of ETFs, because of their lower volatility, are far more precise. Second, Levy and Roll (2015) aim at improving in-sample performance: alphas are estimated over a ten-year period, new weights are computed based on those alphas, and Sharpe ratio improvements, *over the same ten-year period*, are recorded. Instead, the analysis in this study is entirely out-of-sample: we use alphas that are estimated over the prior sixty-month period in order to determine weights to be applied over the subsequent month; we then move our sixty-month estimation window and determine weights for the next month. Third, Levy and Roll (2015) study to what extent alpha-based adjustment can provide a globally optimal portfolio, while we are only interested in marginal improvement. Mathematically, alpha-based adjustment is meant only for marginal improvements, and then only when alphas are relatively stable over time. Levy and Roll (2015) find that, for the purpose of finding globally optimal portfolios, alpha-based adjustment does not work.[1]

If our procedure works, then the following academic exercise makes sense. Assume that investors are interested in improving the mean-variance efficiency of their portfolio. In that case, observed asset flows should correlate with alpha. If an asset has a positive alpha, then investors increase exposure, while if an asset has a negative alpha, then investors decrease

[1]In the spirit of Newtonian hill climbing, one should reestimate alphas and redetermine weights after each marginal adjustment, to eventually end up with the optimal portfolio. Instead, Levy and Roll (2015) merely scale the adjustments, conjecturing that alphas do not need to be reestimated.

exposure. We don't know which portfolio investors use as benchmark, however. Is it some market proxy? Or the Fama-French factor portfolios? One can infer the benchmark from the asset flows: the benchmark should be such that it generates positive alphas for assets toward which investors move, while it ought to generate negative alphas for assets from which investors retreat. Implications of such an exercise are discussed in Berk and van Binsbergen (2016) and Barber et al. (2014). The approach makes sense only if investors believe that alpha improves mean-variance efficiency. Our results suggest that such beliefs are warranted.

The remainder of the paper is organized as follows. Section 1.2 describes empirical methodology. We present main results in section 1.3, and discuss the results in section 1.4. Section 1.5 concludes.

1.2 Methods

We assume the investor starts from a benchmark index fund. Each period, she is considering several additions. So, each period, our investor is deciding how much to allocate to her benchmark index fund, and to alternative assets. Whether to invest in these alternatives will depend on their alphas, as estimated over a finite past history, with the index fund as benchmark. If alpha is estimated to be positive, the corresponding asset is *added* to the index; if the estimated alpha is negative, the corresponding asset is *shorted* (if the asset is part of the index, this effectively means that its weight is reduced). As mentioned before, the resulting portfolio will be referred to as *alpha adjusted index*.

As benchmarks, we use various equity index funds, such as the Vanguard S&P 500. We consider Exchange Traded Funds (ETFs) as potential additional investments. Our choices ensure tradability. Indeed, funds such as the Vanguard S&P 500 are probably among the most widely used index vehicles in the marketplace, as they are available for a low management fee, and because of their liquidity, involve less trading costs. We here follow a recent trend in the academic literature (e.g., Berk and van Binsbergen (2016)) to substitute tradeable funds for the previously more popular, but academic, factor portfolios such as the Fama-French factors. Nevertheless, we will evaluate performance of our alpha adjusted index with respect to these academic portfolios.

There is another, no less crucial reason why we use ETFs. In contrast to individual stock, their volatility is usually much lower, and hence, alphas are estimated with more precision.

As benchmark indices, we used the Vanguard S&P500 Index Fund (VFINX) and Vanguard Growth and Small Index Fund (VISGX). ETFs data are from the Center for Research in Security Prices (CRSP) Monthly Stock File. They carry Share Code 73. We applied filters to ensure ETFs to be tradable and to be liquid. We requrie the ETFs to have average daily dollar volume exceeds 1 million. ETF must have at least 72 monthly observations to be included. We start our sampling in January 2000 and stops at December 2014.[2]

To determine the alpha adjusted index for a particular month t, we ran a time series regression over the prior sixty months, with the excess return on a candidate investment (ETF) as dependent variable, and the excess return of the benchmark index as independent variable. We require the ETF to have at least 24 months return observations over the estimation period. Excess returns are computed relative to the one-month Treasury Bill Rate. The intercept of this regressions for ETF i, denoted alpha $\alpha_{i,t}$, is used subsequently to determine the ETF's weight $x_{i,t}$ in the alpha adjusted portfolio, as follows:

$$x_{i,t} = \begin{cases} \frac{\alpha_{i,t}}{\sum_{\{j:\alpha_{j,t}>0\}} \alpha_{j,t}} & \text{if } \alpha_{i,t} > 0, \\ \frac{\alpha_{i,t}}{\sum_{\{j:\alpha_{j,t}<0\}} \alpha_{j,t}} & \text{otherwise.} \end{cases} \tag{1.1}$$

As a result, the month-t return on the alpha adjusted index equals:

$$I_t + \sum_{\{i:\alpha_{i,t}>0\}} x_{i,t} E_{i,t} + \sum_{\{i:\alpha_{i,t}<0\}} x_{i,t} E_{i,t}, \tag{1.2}$$

where I_t denotes the month-t return on the index, and $E_{i,t}$ is the month-t return on ETF i.

In principle, our alpha-adjustment would need plenty of rebalancing each month. In fact, as we will demonstrate, estimated alphas were quite persistent, so that monthly weight adjustments were minimal, and hence, trading costs should be reasonable.

We used the following performance measures. First, we looked at the cumulative wealth over the investment period from January 2005 to December 2014 and compared it to that of buying and holding the benchmark index. This does not correct for risk, and hence, the results are relevant only for a risk-neutral investor. Second, we computed Sharpe ratios, which are relevant for someone with quadratic (or mean-variance) preferences. Third, we estimated alphas of our alpha adjusted indices with respect to the Fama-French-Carhart four-factor benchmark. This is relevant for the academic community, which traditionally uses the four-factor model to determine abnormal performance of an investment strategy.

Significance of improvements in Sharpe ratio relative to buying and holding the benchmark indices is determined using bootstrap estimation of the empirical distribution of

[2]ETFs only started to get popular around 2000, at which point the CRSP dataset reported on 31 funds. Given that we need 60 months to estimate alpha, this implies that the first return observation for our alpha adjusted index is for January of 2005.

Sharpe ratios. There, we randomly (with replacement) drew weight vectors $[x_{i,t}, i = 1, ..., N]$ from our histories of estimated weights, randomly permuting vector elements in order to avoid hindsight bias.[3] Significance of alphas relative to the Fama-French four-factor benchmark is determined by standard time series z-statistics.

1.3 Results

Figure 1.1 plots the evolution of wealth from the beginning of our exercise (January 2005) to the end (December 2014). For both benchmark indices, wealth (blue line) increases at a much faster pace than when merely buying and holding the benchmark index (red line). This increase does come at the cost of additional volatility, but the average return more than compensates: the Sharpe ratios (at 0.23 and 0.22, respectively) are substantially higher than those for the benchmark indices (0.12 and 0.14).

Figure 1.2 displays the empirical distribution of the bootstrapped (10,000 times) Sharpe ratios based on random drawing and scrambling of weight vectors. In both cases, the Sharpe ratios of the alpha adjusted benchmarks are comfortably above the 99th percentile of the empirical distribution, suggesting that they are significant at the 1% level. Alpha adjusted VFINX monthly Sharpe ratio is 0.226; Bootstrapped monthly Sharpe ratio at top 1% level is 0.194. Alpha adjusted VISGX monthly Sharpe ratio is 0.245; Bootstrapped Sharpe ratio at top 1% level is 0.176.

Table 1.1 presents time series regressions of excess returns on the VFINX index and the alpha adjusted VFINX index onto the Fama-French-Carhart four factors (market factor, size factor, value factor, and momentum factor). The intercept, i.e., the four-factor alpha, is significantly negative for the index, and is 84 basis points per month, significantly positive ($p < 0.01$) for our alpha adjusted index. Alpha adjustment therefore increases alpha by a sigificant 87 basis points as shown in column 3 of Table 1.1.

Table 1.2 replicates the previous table for the VISGX index. The four-factor alpha is insignificant for the index (2 basis points per month), and is significantly positive for alpha adjusted strategy ($p < 0.05$). Alpha adjustment increases alpha by 79 basis points.

1.4 Discussion

Alpha adjustment using a selection of ETFs appears to have significant effects on the performance of the VFINX and VISGX indices. Final wealth increases dramatically,

[3] When the tth weight vector is drawn and applied to adjust the benchmark index for period $t - \tau$, where $\tau = 1, ..., 60$, spurious increases in the Sharpe ratio emerge because the tth weight vector is based on estimates of alphas over the sixty months prior to t.

Sharpe ratios rise significantly and Fama-French-Carhart four-factor alphas are significantly positive. The economic magnitudes of the improvements are substantial: Sharpe ratios double or increase by one third, respectively; alphas increase on a monthly basis by 87 basis points and 66 basis points, respectively.

Behind our "alpha adjustment" is the idea that an investment's alpha relative to one's base holdings provides an indication of whether the investment is worth adding to one's portfolio (positive alpha) or worth shorting (negative alpha). Alphas for candidate investments are generally not computed for an individual's own base holdings, but for standard benchmarks. When the standard benchmarks are closely related to the individual's own base holdings, the latter alphas may still provide a good indication on how to invest. To determine whether this is the case for our benchmarks, the VFINX and VISGX, we replicated our alpha adjustment procedure, but used Fama-French-Carhart four-factor alphas instead of alphas relative to VFINX and VISGX. As expected, the improvements were not as good, but nevertheless quite satisfactory see Figure 1.1).

In our exercise, we decided each month whether to invest in, or short, an ETF based on that ETF's alpha with respect to the benchmark index (VFINX or VISGX), as estimated over the past 60 months. It is important to note that we did not decide based on an ETF's alpha with respect to the alpha adjusted index from the prior month. This could have been a plausible alternative, whereby one adjusts each month the alpha adjusted index, but the alternative approach estimates alphas for a portfolio whose weights in the ETFs are noisy because these weights are based on estimated alphas. As a result, errors in estimating alphas are compounded. Not surprisingly, when we implemented the alternative approach, outperformance of the alpha adjusted index disappeared entirely.

It is worth investigating to what extent the weights on the ETF investments in our alpha adjusted index change over time. If these weights change too much, then the outperformance may be lost in transaction costs. Closer inspection of the evolution of weights suggests, however, that they change only little from one month to another, and hence, that adjustment to the alpha adjusted portfolio are minimal. Figure 1.3 plots the evolution of weights for our two indices. This figure demonstrates that the weights are persistent over time.

Altogether, our findings confirm the practical validity of the alpha-based performance improvement technique advocated in Blume (1984) and Dybvig and Ross (1985a). Specifically, alphas are sufficiently stable over time for extensions of one's portfolio based on these alphas to lead to better out-of-sample performance (Sharpe ratios; Fama-French Four-Factor alphas).

At the same time, if the benchmarks we used can be considered proxies of the market portfolio, our findings discredit the CAPM or, at a minimum, prices do not adjust fast enough to eliminate alpha within our investment horizon, which was one month. If CAPM had consistently obtained within a month, we should not have been able to use alphas estimated from prior months and generate outperformance.

Of course, it could be that CAPM does hold but our benchmarks are bad proxies for the market. It would be interesting to investigate more closely the weights on individual investments of our alpha adjusted portfolio. Since performance did improve, since only the market portfolio (together with a risk free security) is optimal under CAPM, and since the market portfolio weighs all individual investments positively (Green (1986)), the signs of the weights in our alpha adjusted portfolio should be positive. We leave such an exercise for future investigation.

1.5 Conclusion

Because of our findings, we advocate the use of alpha to obtain marginal out-of-sample improvements to one's investments. Importantly, alpha is to be measured with respect to one's own benchmark, and not to someone else's investments, or to a set of portfolios of interest to academics (e.g., the Fama-French-Carhart factor portfolios).

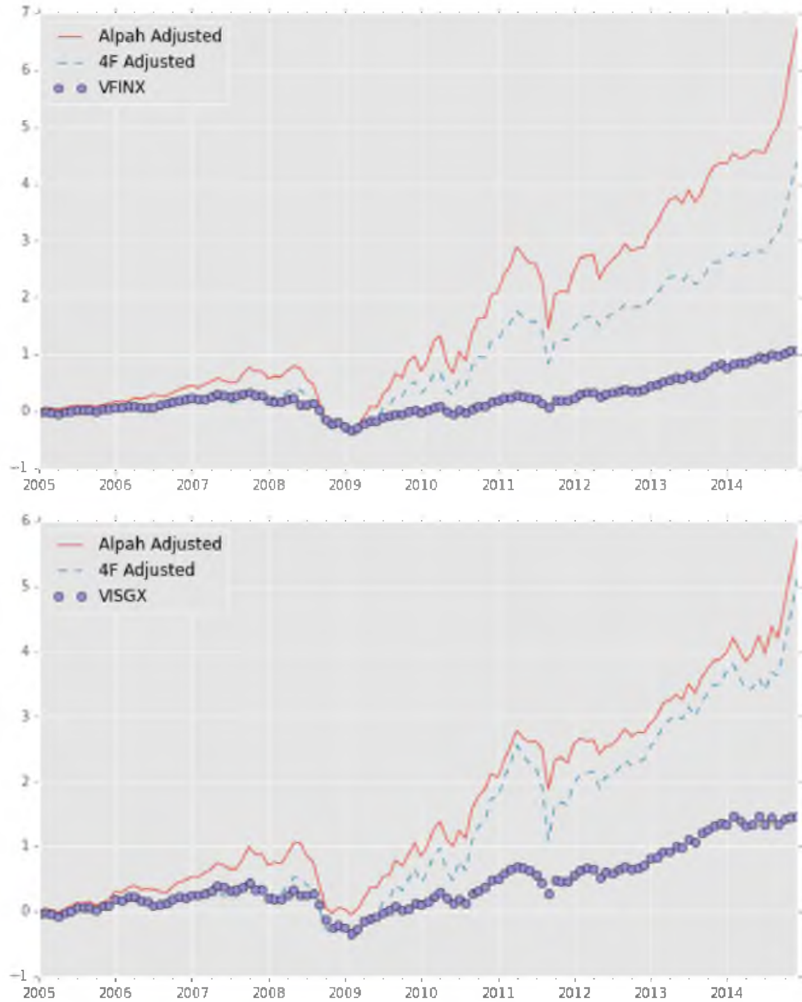

Figure 1.1: Wealth growth of alpha-adjusted strategy

Red solid lines: evolution of wealth invested in the alpha adjusted index (top: VFINX; bottom: VISGX), starting from one dollar; alpha adjustment is based on alphas estimated against VFINX (top) or VISGX (bottom). Blue dashed lines: evolution of wealth invested in the alpha adjusted index (top: VFINX; bottom: VISGX), starting from one dollar; alpha adjustment is based on Fama-French Four-Factor alphas, and not alpha relative to the indices. Purple dotted line: evolution of wealth invested in the index (top: VFINX; bottom: VISGX), starting from one dollar.

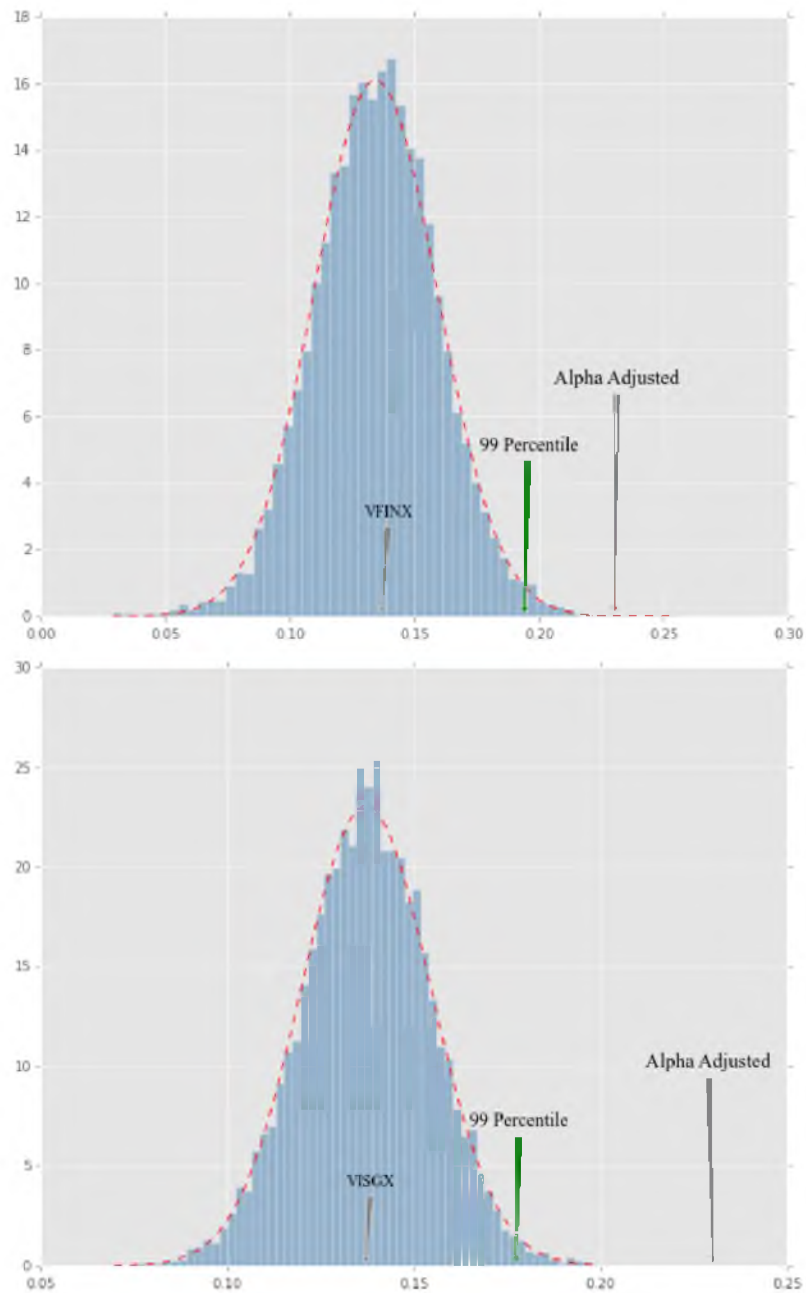

Figure 1.2: Histograms of bootstrapped Sharpe ratios

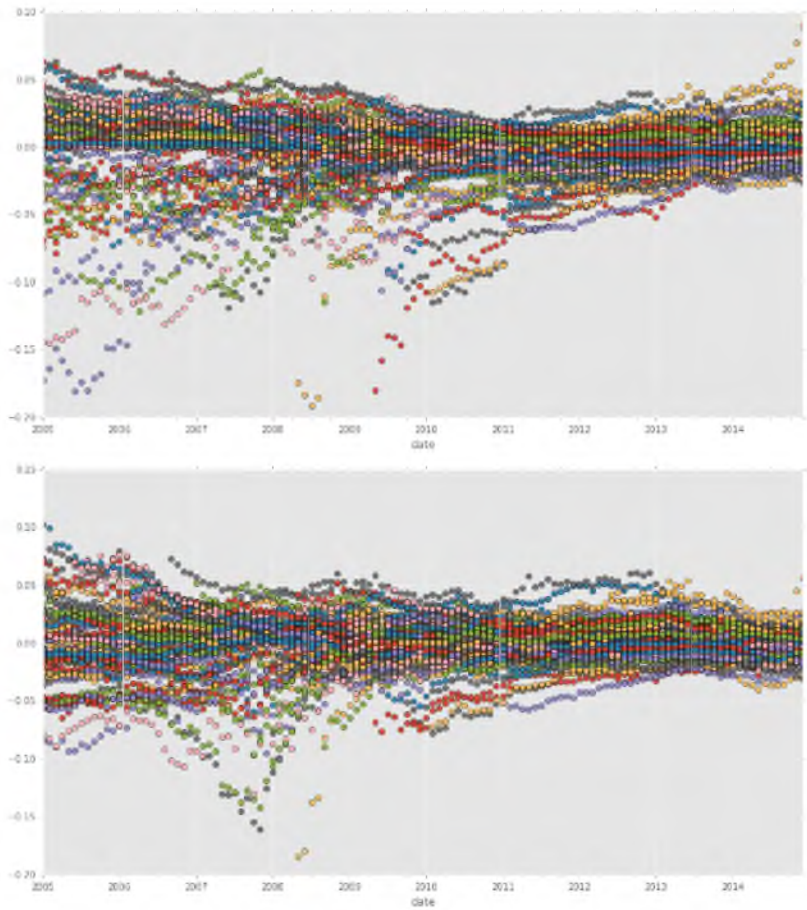

Figure 1.3: Evolution of portfolio weights for alpha-adjusted strategy

Table 1.1. Four-factor regression on alpha adjusted VISGX index

	VFINX (1)	Alpha Adjusted (2)	(2)-(1) (3)	4F Adjusted (4)	(4)-(1) (5)
intercept	−0.0003*	0.0084**	0.0087**	0.0057	0.0060*
	(0.0002)	(0.0040)	(0.0040)	(0.0036)	(0.0036)
mktrf	0.9987***	1.8950***	0.8962***	1.7280***	0.7292***
	(0.0047)	(0.1084)	(0.1085)	(0.0979)	(0.0976)
smb	−0.1469***	−0.3571*	−0.2101	−0.3269*	−0.1799
	(0.0083)	(0.1930)	(0.1931)	(0.1743)	(0.1737)
hml	0.0226***	−0.0705	−0.0931	−0.2363	−0.2589
	(0.0079)	(0.1829)	(0.1830)	(0.1651)	(0.1646)
umd	−0.0012	0.1245	0.1256	0.0952	0.0963
	(0.0039)	(0.0915)	(0.0915)	(0.0826)	(0.0823)
Observations	120	120	120	120	120
Adjusted R^2	0.9981	0.7609	0.3870	0.7601	0.3270

Table 1.2. Four-factor regression on alpha adjusted VISGX index

	VISGX (1)	Alpha Adjusted (2)	(2)-(1) (3)	4F Adjusted (4)	(4)-(1) (5)
intercept	0.0002	0.0082**	0.0079***	0.0062	0.0060*
	(0.0009)	(0.0032)	(0.0029)	(0.0038)	(0.0036)
mktrf	1.1084***	1.3915***	0.2831***	1.8377***	0.7292***
	(0.0233)	(0.0876)	(0.0789)	(0.1041)	(0.0976)
smb	0.7894***	0.5036***	−0.2858**	0.6095***	−0.1799
	(0.0414)	(0.1559)	(0.1404)	(0.1853)	(0.1737)
hml	−0.1440***	−0.4303***	−0.2863**	−0.4030**	−0.2589
	(0.0392)	(0.1477)	(0.1330)	(0.1756)	(0.1646)
umd	−0.0069	0.1428*	0.1497**	0.0895	0.0963
	(0.0196)	(0.0739)	(0.0665)	(0.0879)	(0.0823)
Observations	120	120	120	120	120
Adjusted R^2	0.9749	0.7607	0.1200	0.8013	0.3270

CHAPTER 2

INVESTMENT DIRECTION AND ACTIVE MANAGEMENT

2.1 Introduction

Despite the increasing popularity of index funds, the majority of delegated money is still actively managed.[1] With the rapid growth and increased competition in the mutual fund industry, it is getting more difficult for active mutual funds to identify profitable trading opportunities (Pástor and Stambaugh (2012)). In order to generate superior performance relative to passive benchmarks, mutual funds have to be active. Although being active might be necessary for superior performance, it is not sufficient. To obtain abnormal performance, funds need to be both active and trading in a direction that allows them to outperform relevant benchmarks. In this study, we show that the interaction effect between activeness and direction (as we define below) is critical for fund performance. This conjecture might seem obvious, but as we will show, previous literature has focused solely on the activeness-performance relation. We demonstrate empirically (i) that funds trading in the right direction are able to outperform those who do not, (ii) that active management is more effective in generating superior performance when the trading direction is correct, and (iii) that money flows into mutual funds that trade in the correct direction.

In contrast to the traditional wisdom (e.g., Jensen (1968) and Fama and French (2010)), a growing literature shows that active management is good for performance. Cremers and Petajisto (2009) propose a holdings-based measure of activeness for mutual funds: *active share*. Active share captures how much a fund's holdings deviate from the fund's benchmark's portfolio weights.[2] The authors show that high active share implies better performance as measured by four-factor alphas of the fund's benchmark-adjusted return. Amihud and Goyenko (2013) propose a return-based (as opposed to holdings-based) measure

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[1]The 2015 report from Investment Company Institute shows that the share of the index equity mutual funds is about 20% of equity funds in terms of total net assets.

[2]Formally, active share is defined as half of the Manhattan Distance between a mutual funds holdings weights vector and its benchmarks holdings weights vector.

of active management: *selectivity*. The idea is to measure how close a funds return are tracking the returns of common factors from a four-factor model (Fama and French (1993), Carhart (1997)).[3] The results support the claim that funds with high selectivity outperform those with low selectivity, in terms of four-factor alpha. Analogous to Cremers and Petajisto (2009), the dissimilarity of a fund with a common benchmark determines fund performance. Another more conventional measure of active management is turnover ratio. Existing evidence on the relation between turnover ratio and fund performance is conflicting. Elton et al. (1993) and Carhart (1997) find turnover is negatively correlated with fund performance. Chen et al. (2000) and Dahlquist et al. (2000) find a positive relation. However, all these studies focus on cross-sectional variation. In a recent new paper, Pástor et al. (2015a) document a clear positive relation between turnover ratio and fund performance. Their results are derived from a careful examination of time-series variation within fund.

However, controversy remains. *A priori*, it is not clear why active management such as more intense trading or trading away from a benchmark may generate superior performance. For example, if the level of activeness is orthogonal to a trading direction that generates higher returns[4], then more active management could potentially harm fund performance.[5] We argue that the direction towards which funds are trading needs to be considered as well. Then the natural question is: *what is the correct direction?*

Measuring direction empirically is more difficult as no readily available proxies exist. To start thinking about the correct investment direction, we need specify the first best portfolio that fund managers would hold in an ideal situation that maximizes their wealth or utility from wealth. We argue such first best portfolio should be mean-variance optimal for two main reasons.

First, a mean-variance optimal portfolio guarantees positive evaluation alphas estimated using any benchmark, provided that the benchmarks are mean-variance inefficient. Mutual

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[3]Selectivity is defined as one minus the R-squared estimated from the four-factor model. Thus, a low R-squared for a fund means high selectivity.

[4]Indeed, we find our measure of correctness of direction has correlations close to 0 with measures of activeness.

[5]In a white paper Frazzini et al. (2015) present an analogous critique on active share. They argue there is no obvious theoretical foundation why active share can predict fund performance. They suggest that better performance of high active share funds is instead driven by benchmark performance. Both authors of Cremers and Petajisto (2009) have written responses. Here, our focus is not on the veracity of prior evidence. Instead, we try to offer perspective.

fund performance is often captured by some form of "alpha" (abnormal performance), which is usually estimated by certain benchmarks. We shall refer all types of abnormal returns used in fund performance evaluation as evaluation alpha, to highlight that the purpose of such alphas is performance evaluation. However, with the development of asset pricing theory, there is now a rich set of benchmark alternatives can be used to estimate evaluation alphas.[6] Thus, managers face ambiguity about the benchmark against which she will be evaluated. The mean-variance optimal portfolio becomes the ideal holding because it guarantees positive evaluation alpha against any (mean-variance suboptimal) benchmark. It has long been understood that the benchmarks used to estimate evaluation alphas must not be mean-variance efficient ex post because otherwise no evaluation alphas would be nonzero: Roll (1977) proved that evaluation alphas should be exactly zero if an ex post mean-variance efficient portfolio is used as benchmark.[7] Dybvig and Ross (1985), however, prove that a manager can guarantee a positive evaluation alpha by choosing a mean-variance efficient portfolio.

Second, fund managers' incentives are aligned with evaluation alphas. Fund managers prefer to manage large funds because their compensation is a fixed percentage of total assets under management. Thus, fund managers want to attract as much capital inflow as possible. So far, the mutual fund literature shows that the most important driving factor for fund flow is past performance, captured by some form of evaluation alpha.[8] Holding a mean-variance optimal portfolio yields positive evaluation alpha of any form, and thus attracts capital inflows. One may argue that the fund manager's compensation does not entirely depend on fees they charge. Some managers are compensated by bonus for beating a specified benchmark. However, this argument does not invalidate our claim that the first best portfolio choice for fund managers is mean-variance optimal portfolio because a mean-variance optimal portfolio will beat any (inefficient) benchmark.

Given that the surest portfolio for a fund manager is a mean-variance optimal portfolio, what a fund manager ought to do is to trade towards mean-variance efficiency; this way,

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[6]For example, Jensen's alpha uses a proxy of market portfolio as benchmark, the Fama-French three-factor alpha is based on a market factor, a size factor, and a value factor, the Fama-French-Carhart alpha uses a momentum factor in addition to the three factors, and Morningstar ratings are based on an index fund that differs across fund categories (as defined by Morningstar itself). In a recent paper, Berk and van Binsbergen (2016) listed fifteen alternative benchmarks with which to determine fund abnormal performance.

[7]In this sense, the evaluation alpha actually reveals more about the mean-variance efficiency of the benchmark, rather than the portfolio being evaluated.

[8]see Berk and van Binsbergen (2016), Lynch and Musto (2003), and Chevalier and Ellison (1997).

she will at least ensure positive outperformance (i.e., positive evaluation alpha) no matter what benchmark she will be evaluated against. As such, the correct trading direction of a mutual fund is towards mean-variance optimality.

But it is difficult to find mean-variance optimal portfolios directly. Instead of trying to find mean-variance efficient portfolio directly, managers could take a step-wise approach, improving their portfolio's mean-variance trade-off incrementally. If so, the portfolio theory of Dybvig and Ross (1985a) and Blume (1984)(henceforth Dybvig-Ross-Blume) becomes relevant. The theory suggests that, when a manager is considering to buy or sell a stock, she should estimate the "alpha" of that stock using her current holdings as benchmark, and not some external benchmark such as the S&P500 index. The manager should then buy more of (or sell some of) stock with positive (negative) "alpha" relative to her current holdings. This will put her in the direction towards mean-variance optimality. We shall refer to the alpha estimated against one's own portfolio as benchmark as the "investment alpha," to highlight its purpose as investment guide, and to distinguish from the evaluation alpha.

There are two important differences between investment alpha and evaluation alpha. First, unlike evaluation alpha, investment alpha is estimated using a manager's own portfolio as benchmark instead of some external benchmark(s). Among others, investment alpha, therefore, does not presuppose some equilibrium asset pricing model. Evaluation alpha requires one to specify an equilibrium asset pricing model in order for it to properly adjust for risk (therefore, the alpha is often referred as "risk adjusted abnormal return"). Second, investment alpha provides clear investment guidance on whether to buy or sell a given asset (or portfolio) marginally, while evaluation alpha cannot offer such guidance unless the manager's own holdings coincide with the benchmark portfolio used to estimate evaluation alpha.[9] It is tempting to think that if the benchmark used to estimate the evaluation alpha is highly correlated with the investor's holdings, then the evaluation alpha would be helpful for investors to make investment decisions. This is the typical counter argument for Roll's Critique. However, as Roll (1978) points out, even if the common benchmarks used to estimate evaluation alpha and the investor's holdings are highly correlated, alphas estimated using them may differ a lot from each other. Thus, evaluation alpha can't replace investment alpha even if it is generated from a benchmark that is highly correlated with investor own

[9]In their footnote 1, Fama and French (2010) cite Dybvig and Ross (1985) to justify why four-factor alpha can be used to judge good or bad performance. However, investors generally do not hold a combination of their four-factor portfolios, let alone the optimal combination. Here, we apply the theory from Dybvig and Ross (1985a) in a broader way, without assuming that managers hold a particular portfolio.

portfolio. Recently Bossaerts and Yang (2015) demonstrate that an ex-ante trading strategy based on investment alpha can significantly improve the performance of a passive index fund and produce significantly positive evaluation alpha (Fama-French-Carhart four-factor alpha, in this case). Additionally, they show that when using the four-factor alpha to make adjustments, the improvements are less significant than when investment alpha is used.

Applying the concept of investment alpha to the mutual fund context, we can empirically measure if managers trade towards mean-variance optimality. We use mutual fund holdings changes to infer managers' investment decisions. Specifically, we focus on the incremental portfolio, the portfolio consisting of all changes in positions over a given period. We then estimate the investment alpha of the incremental portfolio using the fund's prior holdings as benchmark, and use this alpha as our measure of direction. Funds that have higher investment alphas for their incremental portfolio are the ones that invested in the correct direction. Since investment alphas are estimated with error, we use its t-statistic, t_α, as error-adjusted measure of the direction in which managers moved their portfolios. We do not claim that managers who trade in the right direction are deliberately applying the Dybvig-Ross-Blume theory. It suffices that they invest "as if." This is analogous to utility theory: an agent whose choices are rational (e.g., satisfy the Von Neumann-Morgenstern axioms) need not literally maximize expected utility; she could merely act "as if" maximizing expected utility.

To test our conjecture, we use a sample of actively managed open-ended equity mutual funds for which the holdings data are most complete. In all empirical tests, we use t_α, which is the investment alpha of incremental portfolio scaled by its standard error, as the proxy for investment direction. The overall results support our hypotheses. We find that direction is positively correlated with fund performance. For example, the four-factor alpha spread between the highest and the lowest quintile sorted by t_α (our measure of correctness of investment direction) is 1.61% (t-stat=4.02) per year using gross return. We find quantitatively similar spread using fund net return. Based on double sorting, active and high t_α funds outperform active but low t_α funds significantly. For example, funds with the highest turnover ratio and the highest t_α produce 3.04% (2.96%) higher before- (after-) fee four-factor alpha than the funds with highest turnover but low t_α. The spread between high-active-share and high-t_α funds and high-active-share and low-t_α funds averages 1.99% per year. The same spread is 2.78% when double sorting is performed based on t_α and selectivity. These results remain robust when we split the sample based on fund size. Using regressions, we show that activeness becomes more effective when t_α is higher. By interacting turnover ratio, active share, and selectivity with dummy variables for the t_α's cross-sectional quintiles, we find that coefficients generally increase, except when selectivity is used as measure of activeness. The coefficients of the activeness measures in the first quintile are generally negative, suggesting that the activeness may even hurt the performance when the investing direction is not correct. Finally, investors appear to react to the direction of funds' portfolio changes. Indeed, we find that t_α positively predicts subsequent quarter's fund flow.

Our results are robust to different samples and different specifications. We test our hypotheses in a new sample constructed as in Pástor et al. (2015b). Using the regression framework developed in Pástor et al. (2015a), we are able to identify a significant interaction effect between t_α and turnover ratio. Double sorting results are also supportive when we use $grossR$, the Morningstar Category Index adjusted gross return, as performance metric.

This paper makes three main contributions. First, we derive an empirical measure that captures investment direction chosen by mutual fund managers, and we show that this metric sheds additional light on the fund performance. Second, we help address the controversy about the relation between active management and fund performance: we show that active management can improve performance but only when the fund is trading towards the mean-variance efficiency. Third, and more broadly, we propose a new concept of alpha, namely, investment alpha. This type of alpha can be used to help investors improve the mean-variance trade-off of their current holdings. Unlike evaluation alpha, investment alpha is "model-free." That is, one does not need an equilibrium asset pricing model for it to work, and thus is immune to the "bad model" problem.

The remainder of the paper is organized as follows. In section 2.2, we construct our main investment direction metric,. Section 2.3 describes the data sources and sample construction process. We present our main results in section 2.4, and robustness tests in section 2.5. Section 2.6 concludes.

2.2 Measuring Direction

2.2.1 Theoretical Motivation of Investment Alpha

Alpha is a concept of abnormal return, where the "normal return" is defined by some asset pricing model. Therefore, alpha must be paired with an asset pricing model. For example, Jensen's Alpha refers to the alpha estimated based on the Capital Asset Pricing Model developed by Sharpe (1964) and Lintner (1969). The most common use of alpha is to evaluate the performance of an investment (Jensen (1968)). The idea is that alpha represents the part of the return that is not explained by the risk-return trade off as specified by the asset pricing model. Thus, alpha can capture the superior skill of a portfolio manager, i.e., the ability to generate higher returns without bearing additional risks. However, this interpretation requires the models used to estimate alpha to fully characterize the risk-return trade off. If there is a specification error, then the interpretation of the alpha is ambiguous. Positive alphas can be attributed either to the portfolio manager's skill or to some type of risk that is missing from the asset pricing model. Roll (1978) highlights this problem and shows that the estimate of alpha[10] is very sensitive to the imperfect proxy of market portfolio. In this paper, we call this type of alphas "evaluation alpha."

Here, we propose a different way of interpreting alpha. We call this type of alpha "investment alpha." To illustrate the idea, let's consider following formulation of alpha:

$$\alpha_{i,b} = \mathbb{E}[R_i - R_f] - \beta_{i,b}(\mathbb{E}[R_b - R_f]) \tag{2.1}$$

where R_i is the return of some portfolio and R_b is the return of some benchmark. $\beta_{i,b}$ is the beta coefficient of portfolio i with respect to portfolio b, i.e., $\beta_{i,b} = cov(R_i, R_b)/var(R_b)$. Notice when R_b is the market portfolio, then $\alpha_{i,b}$ is the Jensen's Alpha. But the definition of alpha in (2.1) is more general. The benchmark here can be any portfolio. It is particularly meaningful if we consider b as the investor's current holdings in this paper. Assuming that we find $\alpha_{i,b} > 0$ the following two statements hold: (a) the benchmark portfolio on the right hand side is mean-variance suboptimal; (b) by combining R_i and R_b, one can improve the mean-variance efficiency of R_b. The statement (a) is a direct result of Rolls Critique (Roll (1977)). In his famous critique on empirical tests of CAPM, Richard Roll shows that if R_b in equation (2.1) is the return of an *ex post* mean-variance efficient portfolio in a given sample, then $\alpha_{i,b} = 0$ for any stock i in that sample. The statement (b) was proven by Dybvig and Ross (1985) in their Theorem 5. A similar result is obtained in Blume (1984). Additionally, Michael R. Gibbons (1989) also prove the statement (b) in their paper and construct the well known Gibbons-Ross-Shanken (GRS) test statistic based on it.

Here, we call $\alpha_{i,b}$ in equation (2.1) as the investment alpha of portfolio i for the investor who is holding b. For this investor, the investment alpha provides a clear indication on whether the investor should buy or sell portfolio i. Notice, to estimate investment alpha, the key input is the investor's current holdings. Those are not typically available. Since mutual funds are required to report their holdings, they become suitable for this exercise.

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[10] Jensen's Alpha in this context

2.2.2 Investment Direction

We wish to infer whether managers choose the right direction from the available data by applying the idea of investment alpha. The data we have are snapshots of mutual fund quarterly holdings from the Thomson Reuters Mutual Fund Holdings Database.[11] From quarter $q-1$ to q, the holdings of a mutual fund f change from H^f_{q-1} to H^f_q. For brevity we shall omit the superscript f in all following notations. H_q is a vector where element i is the number of shares of stock i, $s_{i,q}$, held by the fund at q. We focus on the number of shares rather than the weights because share changes capture the real active part of fund management, while weight changes could be purely driven by market price fluctuation without managers actively changing the number of shares.

We could take two approaches to measure the correctness of the investment direction of a manager. We can estimate investment alpha for each stock within the held portfolio, and then examine whether the fund increased (decreased) the weights for stocks that had positive (negative) investment alphas. This approach, although intuitive, is subject to serious estimation error. It has been well known that the variance-covariance structures of individual stocks are estimated with error (Jensen et al. (1972), Fama and MacBeth (1973)), and this leads to errors in estimating individual alphas. The most common and simple practice to deal with such estimation error is to use a portfolio. Thus, instead of estimating investment alpha at the individual stock level, we estimate investment alpha for one single portfolio, the *incremental portfolio*. This portfolio consists of all the stocks (held by the fund) whose number of shares have been changed from quarter $q-1$ to q, with weights proportional to the changes in shares. If a fund manager follows the portfolio theory from Dybvig and Ross (1985a) and Blume (1984) to marginally improve the mean-variance efficiency of her portfolio, she will increase (decrease) positions on securities with positive (negative) investment alpha. The incremental portfolio is the result of this individual adjustment process, and will have long (short) positions in securities with positive (negative) investment alpha. Thus, the incremental portfolio itself will have positive investment alpha.

Specifically, we construct the incremental portfolio as following. The holdings change from $q-1$ to q is denoted $H^{\Delta}_q = H_q - H_{q-1}$. If stock i was not included in the portfolio at $q-1$ but was at q, then we augment H_{q-1} with i, setting $s_{i,q-1} = 0$, and *vice versa*. We define the incremental portfolio to be the portfolio based on the holdings vector H^{Δ}_q as follows:

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[11] Mutual funds disclose their holdings quarterly. Before 2005, mutual funds were required to report their holdings only semi-annually, but more than half of the funds still reported their holdings quarterly. Since 2005, mutual funds have to report their holdings every quarter.

$$W_q^{\Delta} = \frac{H_q^{\Delta} \circ P_{q-1}}{H_q^{\Delta} \cdot P_{q-1}} = \begin{pmatrix} w_{1,q}^{\Delta} & w_{2,q}^{\Delta} & \cdots & w_{N,q}^{\Delta} \end{pmatrix}, \tag{2.2}$$

where $\cdot$ stands for dot(scalar) product and $\circ$ denotes the element-wise product, P_{q-1} is the vector of prices with elements being the price of stock i in (at the end of) quarter $q-1$. The incremental portfolio captures the portfolio that the fund invested in on top of H_{q-1} in order to arrive H_q. The investment alpha of portfolio W_q^{Δ} reveals the correctness of the investment direction. The benchmark portfolio used to estimate the incremental portfolio's investment alpha is the portfolio based on holdings H_{q-1}, i.e. $W_{q-1} = (H_{q-1} \circ P_{q-1})/(H_{q-1} \cdot P_{q-1})$.

Using the portfolio weights vector W_q^{Δ}, we can recover the historical returns (past 36 monthly returns) of the incremental portfolio from individual stock returns:

$$\begin{aligned} r^{\Delta}_{\tau_{q-1}-1} &= \textstyle\sum_{i=1}^{N} w^{\Delta}_{i,q} r_{i,\tau_{q-1}-1} \\ \vdots &= \vdots \\ r^{\Delta}_{\tau_{q-1}-s} &= \textstyle\sum_{i=1}^{N} w^{\Delta}_{i,q} r_{i,\tau_{q-1}-s} \\ \vdots &= \vdots \\ r^{\Delta}_{\tau_{q-1}-36} &= \textstyle\sum_{i=1}^{N} w^{\Delta}_{i,q} r_{i,\tau_{q-1}-36} \end{aligned} \tag{2.3}$$

In (2.3), $r_{i,\tau_{q-1}-s}$ is the return for stock i over *month* $\tau_{q-1} - s$, and τ_{q-1} indicates the last month of quarter $q-1$. Similarly, we can recover the historical return of the portfolio at the end of quarter $q-1$ based on W_{q-1}, following the same logic:

$$\begin{aligned} r_{\tau_{q-1}-1} &= \textstyle\sum_{i=1}^{N} w_{i,q-1} r_{i,\tau_{q-1}-1} \\ \vdots &= \vdots \\ r_{\tau_{q-1}-s} &= \textstyle\sum_{i=1}^{N} w_{i,q-1} r_{i,\tau_{q-1}-s} \\ \vdots &= \vdots \\ r_{\tau_{q-1}-36} &= \textstyle\sum_{i=1}^{N} w_{i,q-1} r_{i,\tau_{q-1}-36} \end{aligned} \tag{2.4}$$

Notice in both Equation 2.3 and Equation 2.4, we use the weights from W_q^{Δ} and W_{q-1} to construct historical returns. We do this intentionally because we want to estimate the investment alpha of the particular incremental portfolio defined by W_q^{Δ} w.r.t. the particular "currently held" portfolio defined by W_{q-1}.

With the historical returns of incremental portfolios and previously held portfolios thus computed, we can the estimate the investment alpha of the incremental portfolio by running a time-series regression for each fund (with fund subscript omitted; rf denotes the risk free rate):

$$r_t^{\Delta} - rf_t = \alpha + \gamma(r_t - rf_t) + \varepsilon_t \tag{2.5}$$

The main estimate of interest is the intercept in Equation 2.5. This is the investment alpha of the incremental portfolio. To further control for the estimation error, we use the t-statistic of the intercept rather than the estimate of the intercept as our main variable of interest. We label it t_{α}.

2.2.3 Discussion about the Empirical Design

The estimation period consists of the 36 months till the last month of quarter $q-1$. We then study fund performance from (the end of) quarter $q-1$ to (the end of) quarter q. As such, our study is not strictly predictive. The purpose of our study was to determine what happened to returns of funds that invested in the correct direction over the period $(q-1, q)$, while disentangling the impact of activeness and direction. The goal was not to propose another predictor for future fund performance. It is important to note that our study does not suffer from hindsight bias. We strictly exclude any return information over the period $(q-1, q)$ in estimating t_α; likewise, we do not use any stock price information at time q (the end of quarter q). We do need holdings changes from time $q-1$ to q, in order to determine what funds did (in order to determine the incremental portfolio composition), but performance cannot be derived from mere knowledge of their holdings changes.

2.3 Data and Sample Construction

The data was drawn from two major mutual fund databases. We obtained fund historical returns, total net asset (TNA), fees, turnover ratios, and other fund characteristics from the Center for Research in Security Prices Survivor-Bias-Free Mutual Fund Database. Mutual fund holdings data were extracted from the Thomson Reuters Mutual Fund Holdings Database. Antti Petajisto's website[12] provided active share data. The details for construction of this measure is documented in Petajisto (2013).

We focus on domestic equity funds. The holdings data is most complete for this sample. We started by identifying in the CRSP dataset a sample of domestic equity mutual funds based on fund styles. Following Bessler et al. (2010), we used a combination of Lipper, Wiesenberger, and Strategic Insight style codes. We first selected funds based on a set of Lipper style codes. If Lipper code was missing, we filtered on a set of Wiesenberger style codes. If both Lipper and Wiesenberger codes were missing, we filtered on a set of Strategic Insight codes.[13] To further account for any incompleteness or inaccuracy, we applied style filters from the Thomson Reuters Mutual Fund Holdings database. Specifically, we excluded International, Municipal Bonds, Bond and Preferred and Balanced funds. We also excluded

[12] http://www.petajisto.net/data.html

[13] Lipper style codes were CA, EI, EIEI, G, GI, I, LCCE, LCGE, LCVE, MC, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, FS, H, NR, S, SESE, TK, TL, and UT; Wiesenberger codes were AGG, G, G-I, G-I-S, G-S, G-S-I, GCI, GRI, GRO, IG, I-G-S, I-S, I-S-G, IEQ, ING, LTG, MCG, S-G, S-GI, S-I-G, S-I, SCG, ENR, FIN, HLT, TCH, and UTL; Strategic Insight codes were AGG, GMC, GRI, GRO, ING, SCG, ENV, FIN, HLT, NTR, SEC, TEC, and UTI.

index funds [14]. Because CRSP reports data on fund share class level while Thomson Reuters reports holdings at fund level, we aggregated share classes using MFLINKs. We required funds to have Total Net Assets (in 2013 dollars) of at least 5 million. However, once a fund passed the \$5 million threshold first time after inception, we no longer excluded this fund even if its TNA dropped below \$5 million afterwards. Since both Cremers and Petajisto (2009) and Amihud and Goyenko (2013) started their sample around 1990, we started our sample from 1990 and stopped in 2013. Then we matched the sample with holdings data. Our final sample includes about 2,965 unique mutual funds from 1990 to 2013.

In Table 2.1, we report the summary of statistics. On average, the fund size is \$1,517 million (in 2013 dollars). Consistent with established stylized fact that active mutual fund fail to generate superior performance, we find the t-statistic of the past 36 months four-factor alpha is -0.23. Fund average annual expense ratio is about 1.2%, and average turnover ratio is round 95%. The average active share is 80% and selectivity is 14%. In Table 2.2, we sort funds into quintile-based t_α and then report average values of fund characteristics for each quintile. The lowest quintile has an average t_α of about -1.74 and the highest one is 1.44. From lowest to highest, the fund size, turnover ratio, and expense ratio remain almost constant. Factor loadings on the four-factor model are the same, except that the loadings on the momentum factor increase slightly. Past performance, measured by four-factor alpha from prior 36 months, does not exhibit any particular pattern. Average monthly fund flow increases across quintiles. These univariate results show that t_α does not correlate with most fund characteristics, reducing the concern that t_α is confounded with other factors.

It is also interesting to look how the investment alpha is distributed empirically across all the funds. In Figure 2.1, we show the histogram of t_α based all the observations. In general, t_α is centered around 0 and seems normally distributed (with slight negative skewness). The empirical distribution of t_α implies that actively managed mutual funds in our sample do not invest towards the correct direction on average. This coincides with the stylized fact that actively managed mutual funds do not outperform the passive funds in aggregate.

Another important property to investigate is the persistence of investment alpha. There is a large literature on cross-sectional persistence of evaluation alphas. As shown in Carhart (1997) and Brown and Goetzmann (1995), the fund performance usually persists on the losing side but not on the winning side. To provide a simple and intuitive description on the persistence of investment alpha, we do the following. In each quarter, we sort fund

[14] Index funds are identified by either the CRSP index fund flag or by the fund name containing "index."

into quintiles based on their investment alphas. The we look backwards and forwards up to 5 quarters to calculate the average t_α for each quintile. In Figure 2.2, we plot the average t_α for each quintile in each relative quarter. Clearly, investment alpha exhibits little persistence. The top quintile remain top in 2 quarters around the sorting period. However, the difference between top quintile and other quintiles become very small. The bottom quintile is somewhat persistent up to 3 quarters around the sorting period. All the quintiles almost converge at -5 and +5 quarters. There are two possible explanations for the lack of persistence. Firstly, mutual fund managers are not acting as prescribed by Dybvig-Ross-Blume. They use different methods to make portfolio choices. And when they act *as if* they are making marginal improvements, their funds outperform. But since they are not consciously following investment alpha's direction, investment alphas do not persist. Secondly, fund managers might be aware of the marginal improvement. But when they make correct decisions and thus outperform, they attract a capital inflow to the fund. When the fund grows, it becomes difficult for them to find space to make marginal improvements. This is the diseconomy of scale story offered by Berk and Green (2004) when they try to explain why mutual fund investors chase fund performance even the performance does not persist.

2.4 Empirical Results

2.4.1 Investment Direction and Performance

We start our analysis by examining the relation between t_α and fund performance. Our hypothesis is that funds with high t_α should perform at least as well as those with low t_α. The intuition is straightforward. High (low) t_α funds are trading towards to right (wrong) direction. When a fund invests in the right direction, the worst case scenario is to have performance similar to funds that move in the wrong direction. This happens when high t_α funds are inactive. Thus, we predict that t_α correlates positively with fund performance.

In Table 2.3, we sort funds into quintiles based on t_α in each quarter. For each quintile, we run four-factor time-series regressions using the portfolio's monthly return and report the four-factor alpha. We report results for all funds, small funds, and large funds in Panels A, B, and C. In general, four-factor alphas increase with t_α. For example, in Panel A, high t_α funds outperform low t_α by 1.63% (t-stat=4.06) annually. This spread holds for both net return and gross return. The spreads are stronger for large funds and weaker for small funds, but remain robust in both cases.

In order to further explore the relation between t_α and performance, we run a regressions with multiple control variables. The results are reported in Table 2.4. We put either gross return or net return on the left hand side. We include regressors fund characteristics such as turnover ratio, expense ratio, size and flow. To control for fund risk exposure, we also include factor loadings from a four-factor regression over the past 36 months. We include time fixed effect in our specifications. As shown in Pástor et al. (2015a), the coefficients will only reflect cross-sectional variation when time fixed effects are included. The coefficients are essentially variance-weighted average coefficients from each pure cross-sectional regression. This approach is arguably more efficient than the pure cross-sectional methodology in Fama and MacBeth (1973), where the cross-sectional coefficients are equally weighted, because the cross-sectional variation is taken into account. We also report regression results for large funds and small funds separately. In all 6 specifications, t_{α} has a positive and significant coefficient. The results confirms our hypothesis, as well as the sorting results in Table 2.3.

2.4.2 Investment Direction and Turnover

Turnover ratio captures how heavy mutual funds trade relative to the assets under management. Ex ante, the prediction of turnover's impact on fund performance should be neutral. Mutual funds will trade more if they had identified profitable trading opportunities, and may therefore lead to better performance. On the other hand, too much trading incurs excessive transaction costs, which damages fund performance. Consistent with this intuition, previous evidence on cross-sectional relation between turnover and performance is mixed. Some studies have documented a positive relation between the turnover ratio and fund performance,[15] while others show a negative relation.[16]

We argued that investment direction, measured by t_{α}, should be taken into consideration when determining the relation between activeness and performance. Thus, the main focus here is the interaction effect between turnover ratio and t_{α}. We rely on double sorts to investigate the interaction effect. Our main performance metric is the popular Fama-French-Carhart four-factor alpha. We present results based on before and after fee return as each one of them answers different important questions. Our study is an application of a portfolio theory in the context of mutual fund. Gross return captures the direct effect of a fund manager's portfolio decision on performance. Thus we mainly rely on gross return to test our conjectures. However, even when fund managers make correct portfolio decisions, the

[15]See Chen et al. (2000) and Dahlquist et al. (2000)

[16]See Carhart (1997) and Elton et al. (1993).

benefit may be extracted by the management through higher-fund fees. Therefore, it is important to also determine whether investors can benefit from portfolio decisions using net return.

In Table 2.5, we sort funds into quintiles based on t_α first. Then within each t_α quintile, we further sort funds into quintiles based on turnover ratio. Thus the values of t_α are held constant across turnover ratio quintiles. The sorting produces 25 fund portfolios. The portfolios are rebalanced quarterly as t_α is updated quarterly. We report Fama-French-Carhart four-factor alphas estimated using fund monthly gross return. In the top panel, the results are based on all the funds in our sample. Consistent with one-way sorting results, fund performance increases with t_α in general. More careful examination yields the following observations. First, four-factor alphas increase from first row to fifth row (i.e., across t_α quintiles), and the magnitude of the increment becomes larger when turnover ratio is higher. The spread between highest and lowest t_α quintiles increases with turnover ratio from 0.7% to 3.04%. Second, when looking at the sorting results along the turnover ratio dimension, we find that for the first 4 rows, the spreads of four-factor alphas between highest and lowest turnover ratio quintiles are not statistically different from 0. However, for the highest t_α quintile, the four-factor alphas get more positive and significant across turnover ratio quintiles, from 0.75% to 2.88% per year, producing a 2.13%(t-stat= 2.68) spread in annual four-factor alpha. These results are consistent with our conjecture that direction plays an important role in fund performance. Moreover, when funds become less active (low turnover ratio), even if they trade in the correct direction (high t_α), they do not outperform. When funds trade in the wrong direction, being more active does not help either.

In the middle and bottom panel of Table 2.5, we perform the same sorting on large and small funds, defined by fund's Total Net Assets quintiles. The overall results remain similar. For large funds, the effect of turnover ratio becomes weaker for high t_α quintile, but the underperformance of funds with low t_α becomes stronger when turnover ratio is high. The results from small funds are much noisier. In Table 2.6, we report four-factor alphas based on net returns to see the wealth effects on investors. In general, we observe very similar pattern as in Table 2.5. But now the spread is mainly driven by negative four-factor alphas from low t_α funds, instead of positive four-factor alphas from high t_α funds.

Table 2.5 and Table 2.6 report four-factor alphas. These provides risk adjustment in ways that interest academic researchers. It is interesting though to also investigate the impact of direction and activeness when we control important fund characteristics such as fund size, flow, expense ratio, past performance, and risk exposure in a multivariate context. We interact turnover ratio with indicator variables for t_α quintiles, which allows the coefficient on turnover ratio to change across t_α quintiles. By comparing the coefficients across t_α quintiles, we can see whether active management will be more effective when the investment direction is correct. Specifically, we run the following regression model:

$$r_{i,t} = a_t + b_1 A_{i,t} + \sum_{k=2}^{5} b_k A_{i,t} \times \mathbb{1}_{Q(t_\alpha)=k} + \sum_{k=2}^{5} c_k \mathbb{1}_{Q(t_\alpha)=k} + \gamma X_{i,t} + \varepsilon_{i,t} \tag{2.6}$$

where a_t is the time-fixed effect, $A_{i,t}$ is level of activeness (turnover, active share and selectivity), $\mathbb{1}_Q(t_\alpha)$ is a indicator if the cross-sectional quintile of t_α is k, and $X_{i,t}$ includes controls such as fund size, past performance, past flow, risk exposure. By including the time fixed effect a_t, the regression coefficients are essentially weighted average of cross-sectional regression coefficients, where the weights are proportional to variance and number of observations in each cross-section.[17]

In Table 2.7, we report regression results from Equation 2.6 when turnover ratio is considered as proxy of activeness, for both gross return and net return, and for the full sample, and stratification by large and small funds[18]. Our main focus is on the change of the coefficients to turnover ratio. The coefficient of turnover ratio alone (first row) in this regression is actually the coefficient for the first t_α quintile. Across different specifications (columns), this coefficient is always negative and significant for the full sample and for large funds. Recall that the first t_α quintile contains funds trading in the wrong direction. More activeness can only hurt the performance in this case. Coefficients to $turnover * t_\alpha(i)$ capture the difference for quintile i relative to the first quintile. The coefficients generally increase from $i = 2$ to $i = 5$. The increments are more significant among large funds. For example, in the third column, the difference of turnover ratio coefficients between the fifth t_α quintile and the first t_α quintile is 24.7. The total effect of turnover ratio for the fifth t_α quintile is 11.6 ($= 24.7 + (-13.1)$). Overall, the results are very similar with gross return (first three columns) and net return (last three columns) as regressand.

In short, the regression results show that active management becomes more effective when the investment direction is correct. This interaction effect is strong for large funds but weak for smaller ones. When turnover ratio is used to proxy mutual fund activeness,

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[17] see Pástor et al. (2015a) for details.

[18] defined as top and bottom cross-sectional quintiles of lagged assets under management

the results are consistent with our conjecture. Investment direction is key in determining how effective active management is in generating superior fund performance.

2.4.3 Investment Direction and Active Share

Cremers and Petajisto (2009) and Petajisto (2013) introduce active share as a measure of mutual fund active management. Active share is computed as $\frac{1}{2}\sum_{i=1}^{N}|w_{fund,i} - w_{index,i}|$, where $w_{fund,i}$ is the weight of stock i in fund and $w_{index,i}$ is the weight of stock i in the index that is disclosed as benchmark in the fund prospectus.[19] This measure has a nice interpretation. If active share equals 1, then the fund has no overlap in holdings with its benchmark. If active share is 0, then the fund holds exactly the same assets as its benchmark. Active share has been shown to predict future fund performance and therefore attracted a lot attention in both academia and industry. We would argue that active share can viewed as a proxy for mutual fund activeness. To beat its benchmark, a fund must deviate from its benchmark. However, simply holding a deviating portfolio should not guarantee superior performance. An important missing dimension is direction: only funds that deviate in the correct way should generate better performance.

To test our hypothesis, we perform similar double sorting based on t_α and active share, and report results in Table 2.8 (gross return) and Table 2.9 (net return). We find some evidence to support our conjecture. In Table 2.8, high t_α funds are able to outperform low t_α funds when active share is high. For example, highest t_α funds minus lowest t_α funds yield an annualized spread of about 2% (t-stat = 2.61) for the full sample, 3.2% (t-stat = 2.07) for large funds, and 3.33% (t-stat = 1.56) for small funds. High active share funds outperform low active share funds by about 1.7% per year when t_α is high in the full sample. For net return results (Table 2.9), funds in highest t_α quintile outperform those in lowest t_α quintile only when active share is high.

However, we find only weak evidence that high active share funds outperform overall. For example, in the top panel of Table 2.8, high active share funds outperform low active share funds by 1.68% per year only when t_α is in the highest quintile. This spread is similar for small and large funds, but no longer significant. In Table 2.9, the spreads between high active share and low active share funds are not significant. The potential explanation for lack of significance is that Cremers and Petajisto (2009) use benchmark adjusted return to estimate four-factor alpha, while we use funds returns without subtracting their benchmark

[19] Alternatively, the authors use an index fund that best matches the fund's holdings.

returns.[20]

We present regression results based on Equation 2.6 in Table 2.10. The purpose is again to see if the coefficient of active share on fund performance changes across t_α quintiles. The coefficient of active share itself is in fact the coefficient of active share in the first t_α quintile, and active share*$t_\alpha(i)$ is the difference between the coefficient of active share in ith t_α quintile and the coefficient of active share in the first quintile. We find that the coefficients for quintiles 2 to 5 are indeed significantly (t-stat around 2) larger than that of the first quintile, suggesting that active share is more effective in generating better performance when t_α is higher. Still, the coefficients do not increase monotonically from the second to the fifth quintile.

In summary, we find evidence to support our hypothesis when considering active share as a measure of fund activeness. The results are weaker than when we use turnover ratio to proxy activeness. We offer a potential explanation here. Active share is the deviation of a fund's holdings from its benchmark. Active management is indeed required to deviate, but after the deviation it is not necessarily the case that a fund manager keeps being active – in fact, she has to do nothing to keep active share equal. For instance, if a fund shifts its style after inception, it will have high active share even if it remains completely passive. Confirming our speculation, Cremers and Petajisto (2009) show that there is very low correlation between active share and turnover ratio.

2.4.4 Investment Direction and Selectivity

In the spirit of Cremers and Petajisto (2009), and to measure for mutual fund active management, Amihud and Goyenko (2013) propose to use one minus R-squared, which is estimated from four-factor time-series regressions. They call this measure "selectivity" and argue it is a simpler, yet effective measure to capture fund activeness and selectivity. Selectivity has a few advantages over active share. First, it is easy to calculate, because it does not require any holdings data. Second, it is more general because it measures how different the fund is from common risk factors rather than fund-specific benchmarks. Active share is subject to the concern of style shifting over time (Sensoy (2009)).

Here, we consider selectivity to be another proxy for fund activeness, and test its interaction effect with t_α. We repeat previous double sorting exercise and report results in Table 2.11 (gross return) and Table 2.12 (net return). We find the results supportive in

[20] One of the points of critique made in Frazzini et al. (2015) is that the positive alpha of active funds is from the under-performance of a fund's benchmark rather than superior performance of the fund itself.

general. Funds with high selectivity outperform low selectivity funds when t_α is high. The spread between high t_α and low t_α increases with selectivity. The sorting results are strong for the full sample, robust for large funds, and more noisy for smaller funds. In Table 2.13, we report the regression results where we interact selectivity with indicators of t_α quintiles. However, we did not find that coefficients increase across t_α quintiles. The coefficients of interaction terms are mostly insignificant, suggesting that the effect of selectivity on performance does not vary much with t_α.

Overall, when selectivity is considered as measure of activeness, the sorting results are very supportive to our conjecture, but the multivariate regression results are not.

2.4.5 Investment Direction and Fund Flow

Are investors able to identify the funds that conduct active management in the right direction, and then invest in those funds? Since Berk and Green (2004), academics have started to realize that the mutual fund industry, unlike other industries, equilibrates through capital flows instead of prices (fund fees are fixed most of the time as percentage of assets under management). Thus, an investor's reaction to fund manager investment decisions should be evaluated using fund flows. The existing evidence shows that investors react to past fund performance (e.g., Lynch and Musto (2003) and Chevalier and Ellison (1997)), although little persistence is found on outperforming funds (Carhart (1997)). Berk and Green (2004) argue the investors are nevertheless making rational decisions, because the competition among investors drive away any net abnormal return and fund managers extract the rents through fees. In a recent study, Berk and van Binsbergen (2016) use fund flow to assess asset pricing models and find that the performance-flow relation does exist and that investors care about CAPM alpha (Jensen's Alpha) most, among a large set of evaluation alphas. However, the overall results show that there is not much difference between popular models used to estimate evaluation alpha. For example, CAPM Alpha and FFC Alpha (estimated using Fama-French-Carhart four-factor model) have almost the same probability (around 63%) that, conditional on a positive alpha, the sign of fund flows is positive.

Unlike past fund performance, the investment direction is not easily accessible to and understandable for mutual fund investors. Thus, one should not really expect much predictive power from t_α on fund flows. Nevertheless, to test whether investors react to t_α, we regressed future fund monthly flows on t_α as well as other fund characteristics that may have affected fund flows. The results are reported in Table 2.14. The dependent variable is the monthly fund flow calculated by:

$$flow_t = \frac{TNA_t - TNA_{t-1}(1 + r_t)}{TNA_t} \tag{2.7}$$

where TNA_t is the fund Total Net Assets at month t, and r_t is fund return for month t. All the independent variables are lagged by one quarter. All the three models presented in the table are based on the same specification except we use different measures of activeness. A quick preview shows that coefficients on loadings of value and momentum factors are positive and significant, suggesting some mutual fund investors are attracted by the "beta." On the other hand, mutual fund investors appear to understand the fund exposure to market and size factor, indicated by the indifferent coefficients. Consistently with previous evidence, the coefficient on past performance, measured by the t-statistic of past 36-month four-factor alpha, is the very strong. More importantly, across three columns, t_α has positive and significant coefficient after controlling for past performance and other fund characteristics. However, the coefficient of t_α is smaller than the coefficient of the t-statistic of the four-factor alpha estimated from fund returns over the past 36 months. These results together suggest that investors do react to the correct direction, but to a lesser extent than past performance.

2.5 Robustness

Almost all the mutual fund studies on holdings use the Thomson-Reuters and CRSP databases to construct samples. Recently a few studies have built new mutual fund samples by combining the Morningstar and CRSP mutual fund databases, though those do not involve holdings data. Berk and van Binsbergen (2015) build a comprehensive sample of mutual funds by uniting the Morningstar and CRSP mutual fund databases. Based on Berk and van Binsbergen (2015), Pástor et al. (2015b) constructed a finer sample, again by intersecting the Morningstar and CRSP mutual fund databases. Here, for the first time, we combine the Morningstar mutual fund database, the standard CRSP, and Thomson Reuters database, and create a new sample, which we use for robustness tests. Our robustness test sample is built on top of Pástor et al. (2015b). We first identify a sample of domestic equity mutual funds based on Morningstar and CRSP, following the data construction process documented in the data appendix of Pástor et al. (2015b).Then, based on the resulting sample, we match funds to the Thomson Reuters Mutual Fund Holdings database, through the CRSP fund identifier.

We conduct two types of robustness tests. First, we check whether t_α still interacts with activeness, measured by turnover, but now in a time-series framework. Pástor et al. (2015a) recently provided new evidence on the turnover-performance relation. They found that turnover predicts fund returns positively over time. They also showed that this predictive power is much weaker in cross-section. Second, we repeat our cross-sectional double sorting exercise on the new sample. This sample allows a new performance measure, $grossR$. This measure is defined as the fund before-fee return minus the fund's Morningstar Category benchmark return. $grossR$ was first introduced in Pástor et al. (2015b) and has some advantages compared to Fama-French-Carhart risk adjustments because the factor portfolios in the four-factor model cannot be invested in easily. In addition, it provides more accurate control on fund styles by taking advantage of Morningstar categories. Our robustness tests mainly focus on using turnover ratio as proxy of activeness for two reasons. First, based on results in previous section, turnover ratio seems to be the best proxy for activeness among three measures covered in this study. Second, Pástor et al. (2015a) focused solely on turnover ratio. Our robustness sample and test framework are both based on the design in Pástor et al. (2015a).

2.5.1 Time-Series Relation

Pástor et al. (2015a) provides novel evidence on turnover-performance relation. They show that when considering the time-series relation between activeness and performance rather than the cross-sectional relation as we did in our previous analysis, turnover ratio can unambiguously predict future performance. This time-series relation is obtained through fund fixed effect regressions. Pástor et al. (2015a) show that coefficients from a panel regression with individual fixed effect is equivalent to the variance-weighted averaging of coefficients from pure time-series regressions on each individual fund. They argue that funds will trade more when they are facing more profitable trading opportunities. Thus turnover ratio in this context can be interpreted as activeness to exploit time-varying mispricing. We test whether our measure of direction, t_α, can contribute to this time-series relation by interacting t_α with turnover ratio using the fixed effects framework proposed by Pástor et al. (2015a).

We estimate four regression models in Table 2.15. We multiply the dependent variable, $grossR$, by 10,000 to convert its unit into basis points, for easier readability. In the first column, we regress $grossR$ on turnover ratio including fund fixed effect and time fixed effect. We include time fixed effects, to remove any market-wide effect. Our results are consistent with Pástor et al. (2015a). Turnover ratio is indeed positively associated with future performance when fund fixed effects are included. In the second column we run the same regression with t_α as explanatory variable. The coefficient is significantly positive. In column 3, we put turnover ratio and t_α together. The results are almost the same as in the univariate regression case, suggesting little correlation between turnover ratio and t_α. We are mostly interested in the interaction effect between t_α and turnover ratio. In column 4, we interact turnover ratio with dummy variables that indicate to which t_α quintile (formed cross-sectionally) the fund belongs. This allows us to get the turnover ratio for each quintile. Similar as in previous results, we find that the coefficients on the turnover ratio become stronger and more significant when we move from the first quintile (1.11, coefficient of variable *turnover*) to fifth quintile (6.81, coefficient of $t_\alpha(5) * turnover$ plus coefficient of *turnover*).

The results in Table 2.15 are consistent with our hypothesis that at times when a fund trades in the right direction, active management becomes more effective in generating outperformance; when they do not, they cannot generate outperformance.

2.5.2 Cross-Sectional Relation

With the new sample, we can repeat our previous double sorting exercise as well and check its robustness. One important advantage of the new sample is the availability of $grossR$. This measure provides an additional performance metric. We repeat our double sorting exercise using $grossR$. We sort on t_α first, then sort on measures of turnover ratio within each t_α quintile. In Table 2.16, we report the time-series average of $grossR$ for the resulting portfolios. There are three panels for the entire sample, and for the large and small funds subsamples separately. The results are generally consistent with our previous findings. In the full sample, funds that have high t_α and high turnover ratio tend to outperform others. In the large-fund sample, highest turnover funds underperform lowest-turnover funds when t_α is low, and highest-t_α funds outperform lowest-t_α funds when turnover ratio is high. The results are more noisy and weaker for small funds.

2.6 Conclusions

In this study, we started from the proposition in Dybvig and Ross (1985) and Blume (1984) that investment alpha provides the direction to investors to improve the mean-variance efficiency of their portfolio. We apply the intuition behind investment alpha to the mutual fund industry to address the seemingly puzzling relation between active management and performance, where activeness has been found to positively correlate with performance. Our hypothesis is that activeness and direction interact to generate outperformance: without good direction, active management is futile; without sufficient activeness, good direction may not help. We measure activeness using turnover, active share, and selectivity. We capture direction of a mutual fund's investments through the investment alpha of the fund's incremental portfolio. The incremental portfolio is the portfolio constructed from the changes in holdings from one quarter to the next. If a mutual fund's holdings are moving towards mean-variance optimality, then the incremental portfolio should have a positive investment alpha. We show empirically that funds which invest in the correct direction experience better performance in terms of Fama-French-Carhart four-factor alpha. Additionally, we find that the interaction between direction and acitveness affects the fund performance as we hypothesized: funds that are more active in a better direction outperform others. And active management becomes more effective in generating fund performance when direction is correct. Finally, we find that investors react to the correct investment direction direction, in addition to the well known effect of past performance on future fund flows.

The study abstracts away from the situations where asymmetric information is present. Anat R. Admati (1985) and Dybvig and Ross (1985b) show that when differential information among fund managers is considered, the traditional evaluation alphas have little power to detect abnormal performance. This applies to virtually all the performance measures based on linear asset pricing models. We, however, show that even when the information asymmetry is not incorporated, the investment alpha of the incremental portfolio is still an empirically powerful measure to differentiate the cross-section of the mutual funds on the direction they are trading to.

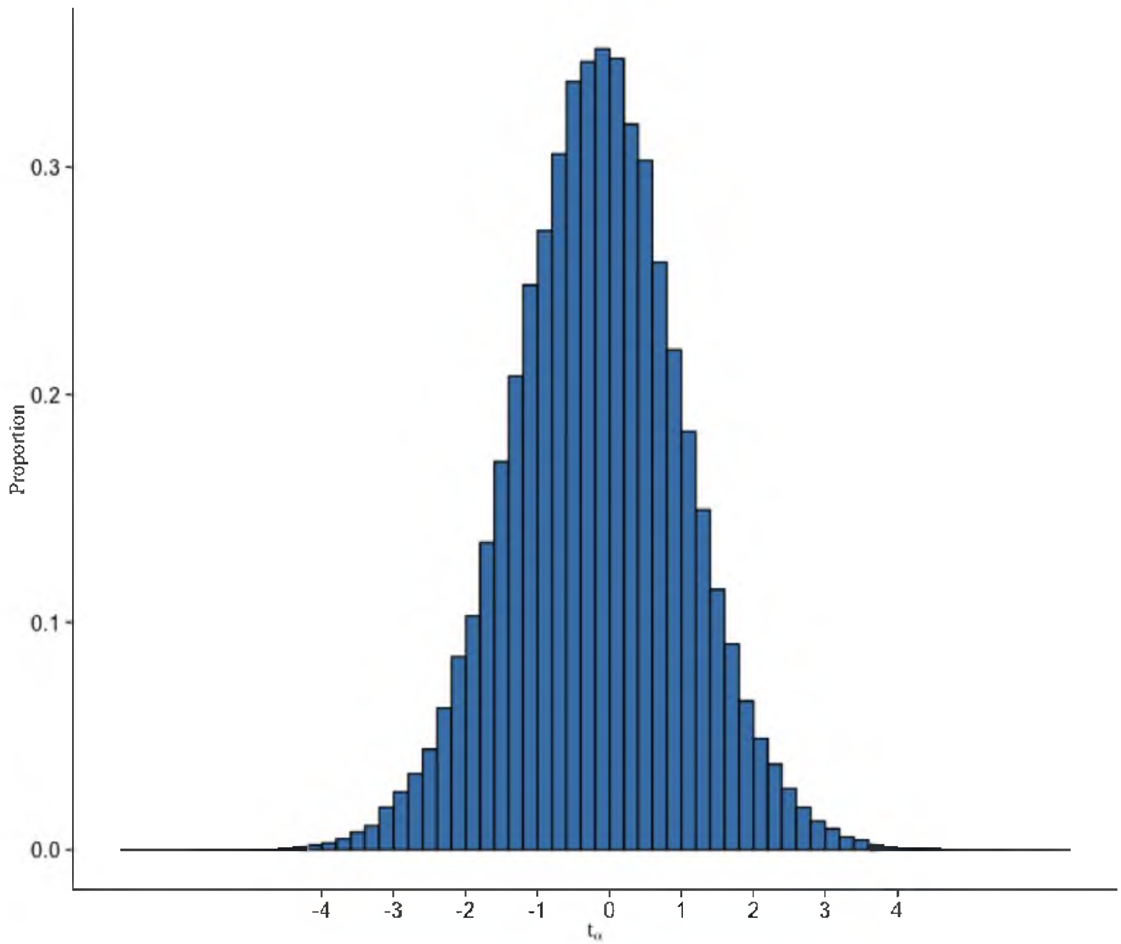

Figure 2.1: Empirical distribution of t_α

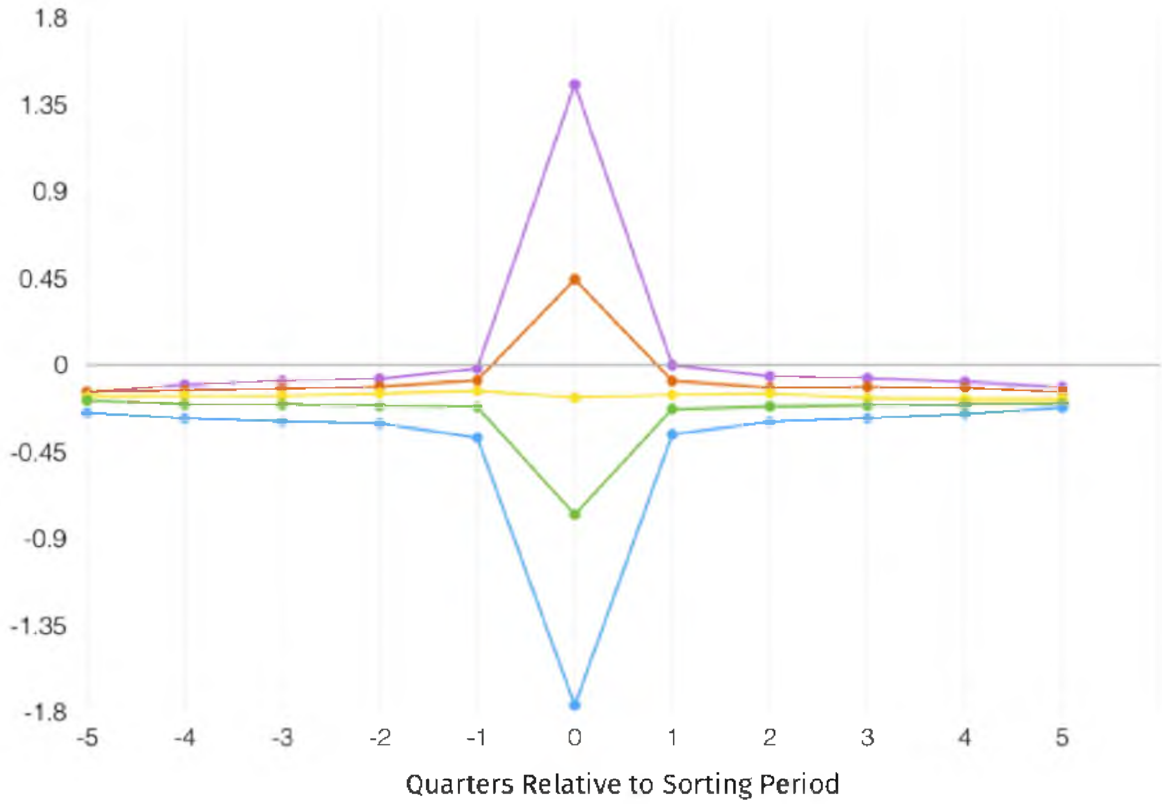

Figure 2.2: Persistence of investment direction

Table 2.1. Summary statistics of overall sample.

	Statistics				
Variables	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
t_α	−0.165	1.178	−0.934	−0.159	0.601
$Turnover$	0.947	1.594	0.320	0.630	1.110
$Activeshare$	0.795	0.162	0.695	0.828	0.928
$Selectivity$	0.143	0.153	0.051	0.095	0.171
TNA (in 2013 dollar)	1,517.909	5,755.440	78.505	279.778	988.361
$Flow$	0.007	0.074	−0.016	−0.003	0.014
$Expense$	0.012	0.006	0.009	0.012	0.015
b	1.000	0.255	0.889	0.995	1.098
s	0.213	0.382	−0.073	0.130	0.479
h	−0.006	0.418	−0.245	0.006	0.238
u	0.023	0.210	−0.078	0.004	0.103
$alpha_{36}(t)$	−0.225	1.270	−1.040	−0.186	0.615

Table 2.2. Summary of statistics for each quintile.

	t_α Quintiles				
Variables	1	2	3	4	5
t_α	-1.765	-0.776	-0.169	0.442	1.453
$Turnover$	0.935	0.927	0.971	0.945	0.957
$Activeshare$	0.775	0.789	0.802	0.808	0.801
$Selectivity$	0.133	0.142	0.147	0.148	0.144
TNA (in 2013 dollar)	1673.463	1526.592	1448.447	1449.013	1491.793
$Flow$	0.005	0.008	0.008	0.007	0.008
$Expense$	0.012	0.012	0.012	0.013	0.012
b	1.014	1.002	0.997	0.992	0.996
s	0.190	0.204	0.221	0.228	0.221
h	-0.013	-0.012	-0.003	0.007	-0.009
u	0.015	0.021	0.024	0.028	0.027
$alpha_{36}(t)$	-0.343	-0.216	-0.180	-0.192	-0.194

Table 2.3. Sorting based on investment direction

	t_α Quintiles						
variable	1	2	3	4	5	spread	t-val
Full sample based on all funds							
net return	-1.38***	-0.86*	-0.64	-0.51	0.25	1.63	4.06
gross return	-0.19	0.36	0.6	0.7	1.42**	1.61	4.02
Subsample based on large funds							
net return	-2.00***	-1.17**	-1.50***	-0.80	-0.49	1.51	2.39
gross return	-0.99	-0.16	-0.52	0.22	0.51	1.50	2.33
Subsample based on small funds							
net return	-0.51	-0.11	0.61	0.21	1.40**	1.92	3.41
gross return	1.11	1.37**	1.93***	1.97***	2.78**	1.68	3.02

Table 2.4. Investment direction and fund performance

	Gross Return			Net Return		
	All	Large	Small	All	Large	Small
t_α	2.73	2.75	2.93	2.74	2.63	2.97
	(2.41)	(1.74)	(2.54)	(2.41)	(1.66)	(2.56)
$Turnover$	−2.06	0.01	−2.10	−2.14	−0.09	−2.14
	(−2.06)	(0.002)	(−2.15)	(−2.15)	(−0.02)	(−2.22)
$Expense$	413.50	−878.63	237.16	−541.16	−1,722.93	−669.95
	(1.61)	(−2.06)	(0.71)	(−2.14)	(−4.07)	(−2.05)
$Flow$	461.79	646.52	384.75	468.53	653.19	388.93
	(9.48)	(3.70)	(11.38)	(9.43)	(3.70)	(11.37)
$alpha_{36}(t)$	2.44	0.57	5.87	2.42	0.51	5.81
	(1.17)	(0.21)	(2.87)	(1.15)	(0.19)	(2.82)
$log(tna)$	−1.63	−0.46	0.32	−1.85	−0.53	−0.18
	(−2.10)	(−0.29)	(0.15)	(−2.48)	(−0.33)	(−0.08)
b	7.44	0.15	9.20	7.11	0.28	9.04
	(0.26)	(0.004)	(0.33)	(0.25)	(0.01)	(0.32)
s	29.69	27.84	37.87	30.10	27.96	38.61
	(1.85)	(1.55)	(2.55)	(1.86)	(1.55)	(2.58)
h	19.01	14.31	11.75	18.81	14.23	11.83
	(1.03)	(0.56)	(0.77)	(1.01)	(0.55)	(0.77)
u	16.57	2.70	20.68	16.57	2.20	20.34
	(0.40)	(0.05)	(0.58)	(0.40)	(0.04)	(0.57)
Observations	342,850	69,906	64,219	342,850	69,906	64,219
Adjusted R^2	0.73	0.76	0.71	0.73	0.76	0.71

Table 2.5. Double sorting on investment direction and turnover ratio, gross return

	Turnover Quintiles						
t_α	1	2	3	4	5	spread	t-val
Full sample based on all funds							
1	0.05	0.52	-0.1	-0.23	-0.15	-0.2	-0.24
2	0.41	0.59	-0.23	-0.37	0.63	0.22	0.25
3	1.39**	0.67	0.35	0.67	0.75	-0.64	-0.78
4	1*	0.48	0.91	0.88	0.69	-0.31	-0.42
5	0.75	1.27**	1.38**	1.83***	2.88***	2.13	2.68
spread	0.7	0.76	1.47	2.06	3.04		
t-val	1.16	1.54	2.56	3.44	3.74		
Subsample based on large funds							
1	-0.69	0.06	-0.67	-1.18	-2.27**	-1.58	-1.35
2	1.1	0.53	-0.45	-0.78	-1.16	-2.26	-1.88
3	-0.23	-0.54	-0.94	-0.49	-1.1	-0.87	-0.75
4	0.27	0.32	-0.5	0.81	-0.47	-0.74	-0.78
5	0.28	1.15	0.33	0.9	1.06	0.78	0.66
spread	0.97	1.09	0.99	2.08	3.33		
t-val	1.1	1.11	1.11	1.69	2.79		
Subsample based on small funds							
1	0.56	1.09	1.69	1.93	2.1*	1.55	1.22
2	2.24***	-0.24	1.87*	2.4**	0.48	-1.77	-1.14
3	3.41***	0.85	2.21**	0.77	3.28**	-0.13	-0.09
4	2.26***	1.76**	2.22**	3.07***	2	-0.26	-0.18
5	0.8	0.7	3.32***	4.86***	5.17***	4.38	2.71
spread	0.24	-0.4	1.64	2.93	3.07		
t-val	0.16	-0.38	1.26	1.97	2.11		

Table 2.6. Double sort on investment direction and turnover ratio, net return.

	Turnover Quintiles						
t_α	1	2	3	4	5	spread	t-val
Full sample based on all funds							
1	-0.94*	-0.63	-1.28*	-1.56**	-1.55*	-0.61	-0.73
2	-0.53	-0.56	-1.47**	-1.64***	-0.82	-0.29	-0.34
3	0.42	-0.61	-0.83	-0.64	-0.74	-1.16	-1.42
4	0.1	-0.61	-0.33	-0.44	-0.75	-0.85	-1.14
5	-0.24	0.14	0.21	0.54	1.41*	1.65	2.07
spread	0.7	0.77	1.48	2.09	2.96		
t-val	1.17	1.57	2.56	3.46	3.66		
Subsample based on large funds							
1	-1.59**	-0.88	-1.82**	-2.27**	-3.41***	-1.82	-1.52
2	0.27	-0.43	-1.48*	-1.84**	-2.26*	-2.53	-2.09
3	-1.24*	-1.52**	-1.91**	-1.62*	-2.2**	-0.96	-0.84
4	-0.47	-0.64	-1.56**	-0.29	-1.58*	-1.11	-1.17
5	-0.72	0.15	-0.72	-0.12	-0.07	0.64	0.54
spread	0.87	1.03	1.1	2.15	3.34		
t-val	1.01	1.04	1.23	1.74	2.8		
Subsample based on small funds							
1	-0.73	-0.28	0.49	0.46	0.45	1.18	0.93
2	0.91	-1.59	0.4	0.81	-1.35	-2.27	-1.44
3	2.1***	-0.67	0.74	-0.83	1.42	-0.68	-0.47
4	0.94	0.5	0.95	1.47	0.17	-0.77	-0.54
5	-0.37	-0.62	1.82	3.28**	3.35**	3.72	2.3
spread	0.37	-0.34	1.33	2.82	2.91		
t-val	0.25	-0.33	1.02	1.87	1.99		

Table 2.7. Interaction effect of investment direction and turnover ratio on fund performance

	Gross Return			Net Return		
	All	Large	Small	All	Large	Small
$turnover$	−3.524	−13.063	−1.556	−4.191	−14.158	−1.974
	(−1.763)	(−2.101)	(−0.634)	(−2.117)	(−2.283)	(−0.815)
$turnover * t_\alpha(2)$	1.825	3.121	0.599	1.927	3.477	0.587
	(0.904)	(0.474)	(0.247)	(0.947)	(0.527)	(0.242)
$turnover * t_\alpha(3)$	1.233	5.069	−1.944	1.394	5.195	−1.869
	(0.571)	(0.621)	(−0.660)	(0.646)	(0.635)	(−0.637)
$turnover * t_\alpha(4)$	1.856	19.452	−0.022	2.047	19.439	0.053
	(1.017)	(2.433)	(−0.009)	(1.119)	(2.429)	(0.022)
$turnover * t_\alpha(5)$	3.520	24.718	1.081	3.593	25.035	1.002
	(1.556)	(3.322)	(0.383)	(1.596)	(3.367)	(0.358)
$t_\alpha(2)$	3.269	1.711	4.396	3.014	1.187	4.075
	(1.062)	(0.378)	(0.773)	(0.981)	(0.264)	(0.719)
$t_\alpha(3)$	5.796	−0.808	8.241	5.443	−1.110	7.454
	(1.606)	(−0.114)	(1.370)	(1.505)	(−0.157)	(1.248)
$t_\alpha(4)$	4.020	−5.604	2.116	3.672	−5.905	1.671
	(1.158)	(−0.981)	(0.418)	(1.055)	(−1.033)	(0.332)
$t_\alpha(5)$	8.453	−3.425	9.344	8.157	−4.162	9.051
	(2.424)	(−0.633)	(1.794)	(2.367)	(−0.775)	(1.762)
$flow$	460.764	579.467	402.607	470.757	586.748	413.329
	(9.428)	(4.236)	(11.004)	(9.452)	(4.295)	(10.981)
$alpha_{36}(t)$	2.321	1.297	4.405	2.523	1.333	5.060
	(1.128)	(0.485)	(2.139)	(1.218)	(0.499)	(2.435)
$log(tna)$	−2.012	−1.255	−1.586	−1.348	−0.776	1.207
	(−2.937)	(−1.120)	(−0.823)	(−2.014)	(−0.687)	(0.618)
b	7.245	13.084	5.692	7.859	13.606	6.825
	(0.258)	(0.386)	(0.201)	(0.280)	(0.401)	(0.240)
s	30.500	23.801	35.248	28.934	22.762	33.991
	(1.893)	(1.402)	(2.309)	(1.788)	(1.338)	(2.214)
h	18.545	23.904	9.671	19.484	25.119	10.656
	(0.999)	(0.989)	(0.600)	(1.040)	(1.034)	(0.650)
u	16.752	8.573	18.268	16.409	8.405	17.975
	(0.406)	(0.165)	(0.498)	(0.396)	(0.162)	(0.489)
Observations	342,850	68,472	68,673	342,850	68,472	68,673
Adjusted R^2	0.726	0.764	0.700	0.727	0.765	0.701

Table 2.8. Double sort on investment direction and active share based gross return

	Activeshare Quintiles						
t_α	1	2	3	4	5	spread	t-val
Full sample based on funds							
1	0.08	-0.07	0.07	0.35	0.32	0.24	0.24
2	0.2	0.01	0.56	0.16	0.82	0.62	0.55
3	0.14	0.43	0.14	0.35	0.83	0.69	0.71
4	0.51	0.98	1.67**	1.52	0.83	0.32	0.35
5	0.62	1.1*	-0.2	0.96	2.3**	1.68	1.64
spread	0.54	1.18	-0.27	0.61	1.99		
t-val	1.32	1.76	-0.36	0.72	2.61		
Subsample based on small funds							
1	0.55	-2**	0.51	-0.74	-1.66	-2.21	-1.53
2	0.05	-0.26	0.56	-1.72	1.73	1.68	1.38
3	0.26	0.81	-0.81	-0.66	-1.02	-1.28	-0.92
4	0.58	0.12	-0.03	0.93	1.46	0.88	0.61
5	-0.28	0.8	0.27	-0.03	1.5	1.78	1.42
spread	-0.83	2.8	-0.24	0.71	3.16		
t-val	-1.28	2.25	-0.21	0.49	2.07		
Subsample based on small funds							
1	0.39	1.62	1.22	2.74*	-0.42	-0.81	-0.38
2	1.04	0.18	3.01*	5.25***	1.8	0.75	0.37
3	1.32*	0.93	3.69**	-0.5	2.06	0.73	0.36
4	2.33**	2.58**	1.99	3.8**	4.74***	2.41	1.32
5	1.31	3.51***	2.66*	1.29	2.92	1.61	0.85
spread	0.92	1.88	1.44	-1.45	3.33		
t-val	0.81	1.27	0.8	-0.8	1.56		

Table 2.9. Double sort on investment direction and active share based net return

	Activeshare Quintiles						
t_α	1	2	3	4	5	spread	t-val
Full sample based on all funds							
1	-0.73*	-1.19*	-1.02	-0.98	-0.93	-0.19	-0.2
2	-0.68*	-1.02**	-0.57	-1.05	-0.58	0.1	0.09
3	-0.81**	-0.84	-1	-0.93	-0.59	0.21	0.22
4	-0.53	0.02	0.38	0.21	-0.36	0.17	0.19
5	-0.44	-0.02	-1.25	-0.25	0.88	1.32	1.25
spread	0.3	1.17	-0.24	0.73	1.81		
t-val	0.73	1.77	-0.31	0.91	2.38		
Subsample based on large funds							
1	-0.2	-2.88***	-0.57	-1.76*	-2.63*	-2.43	-1.68
2	-0.86*	-1.08	-0.51	-2.26*	-0.44	0.42	0.35
3	-0.52	-0.24	-1.85**	-1.69	-2.01	-1.49	-1.09
4	-0.39	-0.72	-1.06	-0.05	0.15	0.54	0.37
5	-1.08**	-0.18	-0.78	-0.99	0.04	1.12	0.91
spread	-0.88	2.7	-0.21	0.77	2.67		
t-val	-1.3	2.35	-0.18	0.54	1.76		
Subsample based on small funds							
1	-1.12	0.08	-0.83	1.52	-2.44	-1.31	-0.6
2	0.49	0.16	1.56	4.26**	-0.05	-0.54	-0.25
3	-0.51	-0.87	2.41	-1.82	-0.34	0.18	0.09
4	1.11	1.42	1.01	1.78	3.75**	2.64	1.34
5	0.44	1.08	2.03	-1.43	2.15	1.71	0.92
spread	1.56	1	2.86	-2.94	4.59		
t-val	1.45	0.67	1.62	-1.63	2.07		

Table 2.10. Interaction effect of investment direction and active share on fund performance

	Gross Return			Net Return		
	All	Large	Small	All	Large	Small
$activeshare$	−0.632	−28.896	−5.798	−8.621	−34.529	−13.455
	(−0.028)	(−1.108)	(−0.166)	(−0.382)	(−1.323)	(−0.384)
$activeshare * t_\alpha(2)$	26.786	33.830	70.485	29.110	33.740	72.912
	(2.065)	(1.354)	(2.083)	(2.245)	(1.350)	(2.149)
$activeshare * t_\alpha(3)$	25.767	27.537	54.255	27.498	27.812	55.769
	(1.798)	(0.983)	(1.728)	(1.938)	(0.993)	(1.794)
$activeshare * t_\alpha(4)$	18.919	33.311	15.614	21.344	34.596	14.348
	(1.485)	(1.378)	(0.515)	(1.682)	(1.419)	(0.469)
$activeshare * t_\alpha(5)$	27.401	31.631	54.119	28.358	29.462	55.950
	(2.173)	(1.502)	(1.715)	(2.243)	(1.408)	(1.764)
$t_\alpha(2)$	−17.425	−22.726	−55.988	−19.405	−22.740	−57.563
	(−1.683)	(−1.289)	(−2.156)	(−1.877)	(−1.291)	(−2.201)
$t_\alpha(3)$	−17.206	−19.297	−46.498	−18.980	−19.606	−47.968
	(−1.384)	(−0.914)	(−1.914)	(−1.534)	(−0.928)	(−1.991)
$t_\alpha(4)$	−8.591	−17.605	−7.776	−10.699	−18.656	−6.326
	(−0.775)	(−1.019)	(−0.319)	(−0.967)	(−1.067)	(−0.257)
$t_\alpha(5)$	−14.456	−14.125	−42.855	−15.708	−12.939	−44.673
	(−1.402)	(−1.011)	(−1.701)	(−1.518)	(−0.927)	(−1.760)
$flow$	369.435	577.113	327.924	377.378	584.642	340.692
	(4.626)	(2.540)	(5.211)	(4.692)	(2.576)	(5.369)
$alpha_{36}(t)$	2.668	2.376	4.565	3.031	2.572	5.209
	(1.355)	(0.792)	(2.131)	(1.530)	(0.864)	(2.423)
$log(tna)$	−2.574	−0.752	−5.397	−2.156	−0.289	−5.095
	(−3.480)	(−0.607)	(−1.438)	(−2.984)	(−0.232)	(−1.371)
b	0.096	−2.541	−17.375	0.043	−3.154	−16.256
	(0.003)	(−0.073)	(−0.625)	(0.001)	(−0.091)	(−0.580)
s	25.521	30.457	34.780	24.764	30.432	34.239
	(1.153)	(1.380)	(1.505)	(1.115)	(1.379)	(1.469)
h	20.336	29.066	7.483	21.621	29.648	9.110
	(0.901)	(1.283)	(0.332)	(0.955)	(1.308)	(0.401)
u	6.663	8.399	26.199	6.171	5.718	27.101
	(0.151)	(0.153)	(0.677)	(0.139)	(0.104)	(0.695)
Observations	159,307	31,772	31,944	159,307	31,772	31,944
Adjusted R^2	0.761	0.798	0.736	0.763	0.799	0.737

Table 2.11. Double sort on investment direction and selectivity based gross return

	Selectivity Quintiles						
t_α	1	2	3	4	5	spread	t-val
Full sample based on all funds							
1	-0.8	-1.27*	-0.12	0.85	0.54	1.33	1.34
2	-0.36	-0.55	0.12	1.6**	0.86	1.22	1.13
3	-0.19	0.13	0.49	1.68**	0.96	1.16	1.1
4	-0.2	0.54	0.97	1.6**	0.71	0.92	0.9
5	0.15	0.17	1.11	2.23***	3.32***	3.16	3.39
spread	0.95	1.44	1.23	1.38	2.78		
t-val	2.12	2.32	1.85	2.45	3.34		
Subsample based on large funds							
1	-0.32	-1.27*	-1.8**	-1.25	-0.46	-0.13	-0.11
2	0.2	-0.1	-0.7	-0.31	0.28	0.08	0.06
3	-0.8	-0.26	-0.51	-0.17	-1.01	-0.21	-0.15
4	-0.56	-0.03	1.09	0.96	-0.25	0.31	0.22
5	-0.87	0.6	0.12	1.52*	1.36	2.23	1.63
spread	-0.55	1.87	1.91	2.77	1.82		
t-val	-0.95	1.89	2.03	2.41	1.17		
Subsample based on small funds							
1	-0.17	0.33	1.08	1.05	3.99***	4.16	2.55
2	-0.45	0.93	1.72*	2.75***	2.19	2.64	1.64
3	1.61**	1.4	1.61	2.54***	3.73**	2.12	1.22
4	0.96	2.75***	1.55	2.4**	2.33*	1.36	1.09
5	1.6*	2.57***	1.08	4.88***	3.24**	1.64	1.09
spread	1.77	2.24	0	3.83	-0.76		
t-val	1.83	2.11	0	3.19	-0.45		

Table 2.12. Double sort on investment direction and selectivity based net return

	Selectivity Quintiles						
t_α	1	2	3	4	5	spread	t-val
Full sample based on all funds							
1	-1.59***	-2.29***	-1.35**	-0.46	-0.92	0.67	0.67
2	-1.18***	-1.68***	-0.98*	0.38	-0.93	0.25	0.23
3	-1.25***	-1.12**	-0.8	0.43	-0.15	1.1	1.04
4	-1.24***	-0.51	-0.36	0.35	-0.49	0.75	0.75
5	-0.87*	-0.93	-0.03	0.87	1.93**	2.8	2.99
spread	0.72	1.36	1.32	1.33	2.85		
t-val	1.62	2.24	1.99	2.36	3.38		
Subsample based on large funds							
1	-1.01*	-2.36***	-2.74***	-2.37**	-1.71	-0.7	-0.55
2	-0.56	-1.08	-1.6**	-1.38	-0.83	-0.28	-0.21
3	-1.74***	-1.01	-1.78***	-1.43	-1.99	-0.25	-0.17
4	-1.46***	-1.33**	0.52	-0.68	-1.03	0.42	0.3
5	-1.74***	-0.2	-0.87	0.19	0.33	2.06	1.54
spread	-0.73	2.16	1.87	2.56	2.03		
t-val	-1.26	2.21	2.02	2.22	1.3		
Subsample based on small funds							
1	-0.87	-0.84	-0.18	-0.56	1.52	2.39	1.57
2	-1.57*	-0.6	0.36	1.37	0.88	2.45	1.47
3	0.41	-0.46	0.34	1.12	1.62	1.21	0.67
4	-0.85	1.7*	0.2	1.27	0.02	0.87	0.69
5	0.4	0.83	0.68	2.66**	1.62	1.22	0.81
spread	1.26	1.68	0.86	3.22	0.09		
t-val	1.26	1.54	0.9	2.72	0.06		

Table 2.13. Interaction effect of investment direction and active share on fund performance

	Gross Return			Net Return		
	All	Large	Small	All	Large	Small
selectivity	28.223	−25.387	61.865	21.420	−30.938	48.842
	(0.911)	(−0.617)	(1.738)	(0.688)	(−0.750)	(1.361)
$selectivity * t_\alpha(2)$	−14.666	3.813	−16.693	−14.750	6.110	−17.408
	(−0.675)	(0.076)	(−0.383)	(−0.680)	(0.122)	(−0.396)
$selectivity * t_\alpha(3)$	−22.113	−17.962	−40.051	−20.730	−14.296	−37.944
	(−0.883)	(−0.396)	(−1.127)	(−0.825)	(−0.314)	(−1.040)
$selectivity * t_\alpha(4)$	−40.179	−40.538	−56.033	−39.764	−37.032	−58.790
	(−1.645)	(−0.898)	(−1.386)	(−1.623)	(−0.817)	(−1.451)
$selectivity * t_\alpha(5)$	32.265	48.579	−8.486	32.838	50.048	−6.479
	(1.403)	(1.002)	(−0.217)	(1.423)	(1.032)	(−0.164)
$t_\alpha(2)$	6.522	2.968	7.259	6.394	2.387	7.010
	(1.647)	(0.483)	(1.188)	(1.614)	(0.390)	(1.137)
$t_\alpha(3)$	9.844	5.113	11.543	9.487	4.425	10.666
	(2.191)	(0.851)	(1.951)	(2.111)	(0.735)	(1.795)
$t_\alpha(4)$	11.603	12.344	10.733	11.364	11.614	10.912
	(2.492)	(1.997)	(1.551)	(2.440)	(1.884)	(1.578)
$t_\alpha(5)$	6.392	7.362	11.055	6.085	6.678	10.355
	(1.334)	(1.058)	(1.618)	(1.271)	(0.958)	(1.507)
flow	461.294	572.772	400.795	470.166	580.901	410.417
	(9.504)	(4.335)	(10.709)	(9.515)	(4.403)	(10.677)
$alpha_{36}(t)$	2.263	1.948	4.301	2.614	2.105	5.107
	(1.110)	(0.759)	(2.100)	(1.274)	(0.820)	(2.464)
$log(tna)$	−1.482	−1.587	0.548	−0.795	−1.097	3.560
	(−2.179)	(−1.439)	(0.266)	(−1.186)	(−0.981)	(1.698)
b	12.317	10.745	12.468	11.885	10.847	11.467
	(0.442)	(0.309)	(0.448)	(0.427)	(0.312)	(0.413)
s	29.816	22.453	34.189	28.199	21.118	33.173
	(1.868)	(1.322)	(2.269)	(1.759)	(1.241)	(2.190)
h	18.043	24.660	9.186	19.330	26.179	10.178
	(0.982)	(1.014)	(0.567)	(1.043)	(1.072)	(0.619)
u	13.902	6.742	17.852	13.615	6.099	17.917
	(0.343)	(0.131)	(0.494)	(0.335)	(0.119)	(0.493)
Observations	350,435	69,980	70,197	350,435	69,980	70,197
Adjusted R^2	0.725	0.764	0.699	0.727	0.765	0.700

Table 2.14. Flow regression

	Flow		
	(1)	(2)	(3)
t_α	0.0002	0.0003	0.0002
	(2.00)	(2.74)	(1.94)
$turnover$	0.001		
	(2.01)		
$activeshare$		−0.02	
		(−6.46)	
$selectivity$			0.004
			(1.10)
$alpha_{36}(t)$	0.01	0.01	0.01
	(39.20)	(38.45)	(39.89)
$expense$	−0.20	−0.004	−0.14
	(−3.08)	(−0.03)	(−2.71)
b	−0.002	−0.004	−0.002
	(−1.17)	(−1.68)	(−0.89)
s	−0.001	−0.001	−0.001
	(−1.02)	(−0.38)	(−0.56)
h	0.01	0.02	0.01
	(3.64)	(9.32)	(3.41)
u	0.01	0.02	0.01
	(5.04)	(9.66)	(5.31)
$logtna$	−0.01	−0.01	−0.01
	(−24.50)	(−24.05)	(−25.10)
Observations	344,468	144,493	352,232
Adjusted R^2	0.10	0.18	0.10

Table 2.15. Robustness test: investment direction and turnover ratio

	grossR			
	(1)	(2)	(3)	(4)
t_α		1.29	1.28	
		(2.88)	(2.88)	
$turnover$	4.47		4.46	1.11
	(3.12)		(3.11)	(0.52)
$t_\alpha(2) * turnover$				2.90
				(0.80)
$t_\alpha(3) * turnover$				1.06
				(0.30)
$t_\alpha(4) * turnover$				6.88
				(2.24)
$t_\alpha(5) * turnover$				5.70
				(1.67)
$t_\alpha(2)$				0.85
				(0.36)
$t_\alpha(3)$				2.49
				(1.08)
$t_\alpha(4)$				−1.80
				(−0.77)
$t_\alpha(5)$				0.59
				(0.27)
Observations	231,186	231,186	231,186	231,186
Adjusted R^2	0.01	0.01	0.01	0.01

Table 2.16. Robustness test: double sorting on investment direction and turnover ratio based on *grossR*

t_α	Turnover 1	2	3	4	5	spread	t-val
Full sample based on all funds							
1	0.62	0.75	0.97**	0.78**	1.28**	0.65	0.92
2	1.29***	1.2***	1.51***	1.23***	0.84*	-0.45	-0.61
3	1.35***	1.15***	0.63	1.54***	0.92*	-0.43	-0.63
4	0.75	0.75*	1.36***	1.44***	1.48***	0.73	0.97
5	0.81*	-0.09	0.94**	1.67***	2.31***	1.5	2.12
spread	0.19	-0.84	-0.03	0.9	1.04		
t-val	0.37	-1.73	-0.04	1.69	1.63		
Subsample based on large funds							
1	1.7***	0.55	1.39**	-0.15	-0.9	-2.59	-2.43
2	1.49*	2.01***	1.7***	0.81	0.12	-1.37	-1.08
3	0.58	1.62**	1.21**	2.6***	0.68	0.1	0.08
4	0.99	-0.08	1.74***	2.63***	0.77	-0.22	-0.22
5	1.72***	0.91	1.9**	2.46***	2.18***	0.46	0.44
spread	0.03	0.36	0.51	2.62	3.08		
t-val	0.04	0.4	0.59	2.58	2.75		
Subsample based on small funds							
1	1.31*	0.06	1.1	-0.31	1.04	-0.26	-0.19
2	1.17	1.87**	1.66*	0.36	5.13***	3.96	3.44
3	1.8**	1.25	0.67	1.83**	-0.19	-1.98	-1.38
4	1.6*	1.45	1.28	2.28***	-0.33	-1.93	-1.32
5	1.96**	0.31	2.4**	2.46***	1.44	-0.52	-0.37
spread	0.65	0.25	1.3	2.77	0.4		
t-val	0.62	0.22	1.08	1.97	0.28		

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