Strategy Distinctiveness of U.S. Equity Mutual Funds

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Abstract

According to basic economic principle, as more people are chasing a given return pattern, the profit from that pattern will eventually be mitigated. Using a simple model to compare a particular fund's return series with those of its peers, this study investigates whether managers standing out from the crowd can be said to possess more managerial skill, leading to subsequent superior performance. We turn to a measure of strategy distinctiveness previously applied in the world of hedge funds, called the Strategy Distinctiveness Index (SDI), which specifically investigates the co-movement in fund returns. The higher the measure assigned to a certain fund, the more distinct the strategy of that fund. Overall, our findings show that few mutual fund managers are pursuing unique investment strategies. However, the measure does significantly predict managerial skill and future fund performance. More specifically, looking at Carhart four-factor adjusted returns, funds in the highest SDI decile outperform funds in the lowest by 1.05% on average per annum.

Keywords: Mutual Funds, Strategy Distinctiveness, Active Management

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Contents

2 Introduction

Wealth-maximizing investors have lately been facing increasing management fees charged by financial intermediaries, who, in turn, are increasingly rewarded in spite of the hardening competition in the mutual fund industry. Nevertheless, there is uncertainty about whether active management actually does contribute to investor utility. Since Jensen (1968), little research has been able to provide evidence of mutual fund managers outperforming benchmarks.

Turning to basic economic principle, bearing in mind the increasingly fierce competition in the industry, there should be decreasing returns to scale in mutual funds. The more actors there are in a market, the more efficient that certain market will become. Thus, in the mutual fund industry specifically, it will be harder for the individual manager to generate positive alpha. However, managers might be attempting to overcome this crowding effect through applying innovative investment strategies in trying to avoid the situation described by Stein (2009): "Enough money chasing a given pattern in returns will necessarily eliminate that pattern." If investors wish to evaluate active managers given these conditions, they would be seeking a way of measuring how successful a manager is in differentiating his investment strategy from peer funds.

The rapid industry growth has resulted in an immense range of investment strategies and an even larger number of funds, featuring managers with diverse backgrounds and qualifications. In this study we try to estimate the distinctiveness of a fund's investment strategy, and thus measure the talent and innovation ability of the fund manager. Further, we examine whether a greater level of distinctiveness implies superior future performance. Hereby, we try to provide an indicator of managerial talent and a measure to distinguish the better performing funds in the mutual fund industry. More specifically, we use data on over 8,000 U.S. equity mutual funds, retrieved from the CRSP mutual fund database for a period from 2000 through 2011. We compute the *Strategy Distinctiveness Index* (further referred to as the SDI measure), following Sun, Wang and Zheng

(2012), as one minus the correlation between a fund's return with the returns of its peers. Hence, we interpret the ability of generating returns that differ from the peer group as managers applying more distinct strategies. The lower the correlation in historical returns, the higher the SDI of the particular fund. To control for the accuracy of the measure introduced, we set the SDI in relation to mutual fund performance and other fund characteristics, such as size, age, volatility in returns and actual management fees charged. We hypothesize that mutual fund managers with innovative ideas and managerial talent pursue more distinct investment strategies while funds with less skilled managers follow known strategies.

Previous research by Hendricks, Patel and Zeckhauser (1993) and Goetzmann and Ibbotson (1994) argue that past mutual fund returns predict future returns. In this study we examine a different aspect of historical returns, that is, to what extent a mutual fund correlates with its peers in terms of return series. The direct predecessors to this study are papers considering the distinctiveness of hedge fund strategies by Wang and Zheng (2008) and Sun, Wang and Zheng (2012), the latter introducing the most updated version of a strategy distinctiveness measure. Furthermore, Amihud and Goyenko (2011) attempt to use R-square, obtained from regressing mutual fund returns on multi-factor benchmarks, as a predictor of superior returns and find that the measure significantly predicts subsequent performance. Using R-square is comparable to the procedure of Wang and Zheng (2008), who are looking at the R-square from the regression of hedge fund returns against the average returns of peer funds. As they further develop their technique, using the correlation, we find this a suitable next approach in evaluating mutual funds as well.

First, the findings of this study show that funds with more distinct strategies can charge higher fees, while larger and older funds are less capable of introducing and pursuing innovative investment strategies. The negative relation between the measure and return volatility implies that the SDI is not associated with managers taking excessive risk in maximizing performance. More likely, the SDI measures talented managers adapting and implementing distinct strategies. Based on

these results, we conclude that the SDI can be used as a proxy of managerial skill.

Second, we show that the SDI has predictive power for future mutual fund performance. This implies the measure can be used by investors in approaching the vast supply of mutual funds in the industry today. We further examine this relation, forming equally weighted portfolios of funds based on their SDI level, and measure the subsequent performance. Considering a one year holding and rebalancing period, funds in the highest decile outperform those in the lowest by 1.05%, in terms of Carhart four-factor adjusted returns.

Finally, we examine the robustness of our findings. We ensure that the SDI is a measure of managerial skill rather than risk taking and gambling behavior through computing the measure based on absolute correlation. The Heckman correction further confirms that our results are not driven by survivorship bias. Overall, our findings suggest that the SDI is a valuable proxy for managerial skill and a way for investors to evaluate and select the better performing mutual funds.

Henceforth, the paper is organized as follows. Section 3 discusses previous literature. Section 4 introduces the data, measure and methods used. Section 5 presents the empirical findings on the relation between the SDI and future fund performance, followed by robustness tests in Section 6. Section 7 concludes.

3 Previous Literature

After the original study by Jensen (1968), extensive research has been made on what impact active management has on the performance of mutual funds. While the majority of recent studies support Jensen's conclusions, showing that active management does not provide excess returns on average, the increased flows into actively managed mutual funds suggest investors believe in active management. The question asked lately is whether managers do have superior stock picking abilities, and in that case, how to distinguish between skilled managers, providing persistence

in returns, and lucky ones. As stated by Wermers (2003), an immense number of performance measures have been proposed, attempting to capture managerial skill. These have further been criticized in subsequent studies finding the explanations are undermining the sources of abnormal performance due to luck, misspecification of models or statistical insignificance. Following this section, we bring up the most relevant findings, concluding that there is no clear consensus whether existing performance measures capture skill or not.

3.1 Alphas in Active Management

Fama and French (2009) present evidence of negative alphas provided by U.S. actively managed equity mutual funds during 1984-2006. In more depth, they argue that active investment is a zero sum game, before management fees and other costs. This would imply an average negative alpha in actively managed equity mutual funds, net of fees. The average alpha for the whole period of the Fama and French study, measured with their three-factor model, is -0.81% per annum. These returns are compared to, and needless to say, found to be below, the returns of an equivalent passive portfolio including the three benchmarks of the Fama French three-factor model. Furthermore, Malkiel (1995) shows that the persistence in mutual fund returns seen in the 1970s did not exist during the 1980s. Consistent with these results, a study by Harlow and Brown (2006) show that, from 1979 to 2003, the average mutual fund failed to generate superior returns. On the other hand, Hendricks, Patel and Zeckhauser (1993) and Goetzmann and Ibbotson (1994), argue that past mutual fund returns predict future returns.

Malkiel (1995) concludes that mutual funds tend to underperform the market, even gross of expenses. However, since these results represent the mutual fund world in aggregate, there might be positive-alpha funds, balanced by negative-alpha funds. For instance, Busse, Goyal and Wahal (2006) find nearly insignificant evidence of abnormal returns but state that some active managers might be able to deliver alpha over longer periods. Harlow and Brown (2006) provide evidence

that there are superior active managers, and further suggest that these managers can possibly be found by investors.

3.2 Managerial Skill

Daniel, Grinblatt, Titman and Wermers (1997) argue active managers are wasting resources when failing to beat passive mechanical strategies. Their study shows, as opposed to Fama and French's study (2009) that the average mutual fund manager does succeed in beating a simple mechanical portfolio strategy. Notwithstanding, the small amount of positive alpha generated is offset by the management fees imposed on investors. In addition, Daniel, Grinblatt, Titman and Wermers (1997) reinforce the findings of Grossman and Stiglitz (1980), showing that funds with the best performance (typically growth and aggressive growth funds) charge the highest fees, indicating funds that are able to outperform the market do so just enough to earn back the fees. Malkiel (1995) emphasizes that most investors would be maximizing utility by investing in low expense index funds, rather than seeking skilful active fund managers, in concluding markets are efficient.

Chevalier and Ellison (1999), suggest that stock picking ability does exist for a subgroup of managers, in particular those who attended more selective undergraduate institutions have higher performance than those who attended less selective ones. Berk and Green (2004) argue that with the existence of managerial skill, the lack of abnormal returns in the mutual fund universe can be explained by diminishing returns to scale. Establishing the level of manager skillfulness, Kacperczyk and Seru (2006) look at how mutual fund managers adjust portfolio allocation responding to changes in public information. Using an estimate of the sensitivity of a fund manager's portfolio allocation to changes in information they see that managers reacting less to changes in public information perform better.

3.3 Mutual Fund Characteristics and Their Impact on Performance

Instead of trying to establish manager skillfulness, other studies have looked at fund characteris-

tics in relation to performance. Harlow and Brown (2006) document various relationships between easily observable characteristics and fund excess returns as well as performance persistence. Pollet and Wilson (2008) particularly point out that funds with greater diversification perform better, especially when it comes to small cap funds. Furthermore, they find that, as funds grow, they tend not to increase diversification but rather their ownership in already existing investments, a finding that is even more evident for funds in large fund families.

The increasingly common incentive fees charged by actively managed funds have become another debated topic of recent studies. The reason behind funds using incentive fees is said to be that these attract more skilful or harder working managers. Elton, Gruber and Blake (2001) claim incentive-fee funds do have positive stock picking ability, but at the same time they take on more risk than funds without incentive fees, specifically increasing risk after experiencing poor performance. Interestingly, Elton, Gruber and Blake (2001) show that expense ratios are lower for incentive-fee funds than for funds without fees. In brief, the study advises investors are better off putting their money in incentive-fee funds due to higher risk-adjusted performance, better management and lower expenses. On the contrary, Gil-Bazo and Ruiz-Verdú (2008) show a negative relationship between gross returns and the fees charged to investors.

Carhart (1997) propose a strategy based on the persistence in performance among mutual funds and show that longing the top decile and shorting the bottom, based on last year's performance, will generate a return of 8% per annum. The spread is explained primarily by differences in market value and momentum of the assets held, but also expense ratios and transaction costs. Bollen and Busse (2004) also find short term persistence in abnormal returns, but argue the alphas disappear when funds are evaluated over longer periods. Studies by Grinblatt, Titman and Wermers (1995) and Carhart (1997), show superior performance is due to the momentum effect of Jegadeesh and Titman (1993). When including momentum, Carhart (1997) finds that performance persistence largely disappears, suggesting little stock picking ability among managers.

Bollen and Busse (2004) conclude that, despite short-term performance persistence, taking transaction costs and taxes into account, investors could just as well follow a buy-and-hold approach, rather than a strategy chasing performance, in order to generate superior returns.

3.4 Mutual Fund Strategies

Some mutual fund strategies are better than others, as shown by Lynch and Musto (2003). Their model predicts that mutual funds change strategy most often after poor performance, which is also enhanced by Chan, Chen and Lakonishok (2002). Furthermore, Lynch and Musto (2003) show that the funds that do change strategy receive dollar flow and future performance less sensitive to the current performance than funds not changing their strategy. In their study of mutual fund investment styles, Chan, Chen and Lakonishok (2002) specifically find that growth managers tend to do better than value managers on a style-adjusted basis. Most funds adopt styles close to a market index, with few funds taking extreme positions differing from the index, and when they occasionally do, they tend to favor growth over value and high past return over low past return.

Cumby and Glen (1990) find no evidence that funds provide investors with performance that exceeds that of a broad international equity index. On the other hand, they do find some evidence that funds outperform U.S. indices, most likely due to the benefits of international diversification. Kacperczyk, Sialm and Zheng (2004) investigate whether performance can be derived from the concentration of funds asset allocation. Their theory is that active managers might derate a diversified strategy on behalf of investments in industries where they have informational advantages. Berk and Green (2004) show theoretically that informational advantages among managers will be short-lived when certain investors direct their capital to "winners".

According to Brown and Goetzmann (1997), some mutual fund style categories, such as "growth" and "growth and income" might well be interpreted by managers as an invite into gamesmanship. Once a fund is included in a specified style category, managers have little incen-

tive to carry out an investment strategy ensuring future fund performance closely related to the style average. Turning to evidence from Sirri and Tufano (1992) and Goetzmann and Peles (1997), investors tend to flock to alpha-generating funds within each style category. Hence, maintaining a strategy in line with the style classification will not be rewarded.

4 Data and Methodology

4.1 Data Sample

4.1.1 Mutual Fund Sample

Using the CRSP Survivor-Bias-Free U.S. Mutual Fund Database, we have retrieved an extensive sample of U.S. equity mutual funds, including over 3 million monthly observations. The sample of return data ranges from January 2000 to December 2011. We have chosen 2000 as the first year of observations since the Lipper Style Classifications, forming our classification structure, were modified as per 1999[1]. The observations from previous years experience a lot of misleading style switching why we find it necessary to exclude them. Monthly returns are computed based on change in net asset values, including reinvested dividends but net of all management fees.[2] The return data is merged with data including explanatory variables, such as total net assets, management fees and investment objectives, on an annual basis, also retrieved from the CRSP database.

Wanting to look at active mutual funds with U.S. holdings only, we follow Wermers (2000) and further narrow down the sample, choosing general domestic equity mutual funds, denoted in U.S. dollars. Funds excluded from the sample includes fixed income funds, international funds, sector funds, metal funds, and such not investing significantly in U.S. domestic equity. A key assumption in this study is that the Lipper prospectus-based classifications are accurate enough to define

[1] As explained in the announcement "New Classification Structure for USDE Funds" (1998)
[2] CRSP Survivor-Bias-Free U.S. Mutual Fund Database Guide

peer funds. All of the funds in the sample are considered diversified, thus are also assigned a portfolio-based classification. These are derived from a holding-based classification methodology performed in two steps. First, a market-capitalization classification is assigned, followed by a style classification. The final sample consists of eleven classes of actively managed funds, namely Capital Appreciation, Dedicated Short Bias, Equity Income, Equity Leverage, Equity Market Neutral, Growth, Growth and Income, Long/Short Equity, Micro-Cap, Mid-Cap and Small-Cap. Table 1 provides descriptions of each class. There is an evident majority of funds in the Growth and Growth and Income categories and an obvious minority in the Equity Leverage and Equity Market Neutral categories. The total number of domestic equity mutual funds in our sample grows from 3,002 in 2000 to 6,370 in 2011.

As opposed to the Morningstar database, CRSP is said to be survivorship bias free, why this database is preferred. However, as pointed out by Elton, Gruber and Blake (2001), the CRSP database is subject to a similar bias, namely omission bias, causing inflation of performance measures. As described by Elton, Gruber and Blake (2001), omission bias arises due to differences in return observations, with some funds reporting only annually, some reporting monthly and some not reporting at all, generally overstating monthly returns. Monthly return data will tend to understate the number of mergers and liquidations, why the average return of the mutual fund universe tend to be overstated. However, referring to the CRSP quarterly update from March 2008[3], we will hereby assume that such misleading returns have been widely corrected from 1998 and forth. Furthermore, Elton, Gruber and Blake (2001) present evidence that the discrepancies between the CRSP database and Morningstar is much more observable in the beginning of their sample period, from 1979 and forth, than in later years, and is recently found to be more of a problem for small funds. In our original dataset, we find missing values in monthly returns corresponding to 1.66% of the total number of observations. Seemingly, months with missing observations are

[3] CRSP Survivor-Bias-Free U.S. Mutual Fund Database, March 2008 Quarterly Update

in the beginning or the end of a funds life, indicating it has been founded or liquidated in the middle of a calendar year. However, one cannot conclude that our data sample is completely survivorship bias free why there is a need of controlling for this bias, as conducted in section 6 Robustness.

Another advantage of the CRSP database is that the dataset indicates style classifications on a yearly basis, allowing us to observe whether the funds have been involved in style switching. In our study, we are assuming the Lipper style classifications are accurate. These style classifications are, to investors, the information the most readily available, why we chose to use them rather than introducing a best fit index as an alternate method.

4.1.2 Performance Measures

We use several different measures to capture the performance of mutual funds. According to Grinblatt, Titman and Wermers (1995), mutual funds tend to follow momentum investing or trend following strategies. Thus, our starting-point is the Carhart (1997) four-factor model:

$$r_{i,t} = \alpha_i + b_i * r_{m,t} + s_i * r_{smb,t} + h_i * r_{hml,t} + m_i * r_{mom,t} + \varepsilon_{i,t} \quad (1)$$

In the model, $r_{i,t}$ is the monthly excess return for fund *i*, (using the monthly 30-day T-bill yield as a proxy for the risk free rate), $r_{m,t}$ is the market excess return (calculated through a value weighted portfolio using CRSP data on the NYSE, Amex and NASDAQ) and $r_{smb,t}$, $r_{hml,t}$ and $r_{mom,t}$ are returns on factor portfolios (size, book-to-market and momentum). As shown by Griffin (2002), the factors are country specific, which is accounted for by only looking at U.S. domestic funds, using North American factor returns. We find the monthly Fama-French North American market factors and returns, including momentum, on the Kenneth French website.[4]

The predecessor model is the Fama-French three-factor model, which we use as a second predic-

[4] Kenneth R. French Homepage, Data Library

tor of performance:

$$r_{i,t} = \alpha_i + b_i * r_{m,t} + s_i * r_{smb,t} + h_i * r_{hml,t} + \varepsilon_{i,t} \quad (2)$$

For each of the two above models, we extract the alphas from the regressions, further explained in section 4.2.2 Data Treatment, to evaluate fund performance.

Cumby and Glen (1990) argue that the Jensen measure provides an accurate indication of fund performance when a manager has selectivity information but no timing information; meanwhile, Jensen (1972), Admati and Ross (1985) and Dybvig and Ross (1985a) show that superior timing information can cause the Jensen alpha to be negative. Therefore, we look at the performance considering the Jensen alpha, as per Jensen (1969):

$$\alpha_i = r_{i,t} - b_i * r_{m,t} + \varepsilon_{i,t} \quad (3)$$

We compute a couple of other performance measures in order to internally compare the different decile portfolios (constructed as described in section 4.2.2 Data Treatment). Hence, we examine each funds appraisal ratio and, to ensure that the portfolio based approach is not specific to our factor models, each funds Sharpe ratio. Sharpe (1966) concluded that the measure invented, considering risk and return of each mutual fund, allows for discovery of differences in performance exclusionary derived from objective differences, interpreted as differences in the persistence in risk taken on by funds. These measures are to be interpreted within the boundaries of this thesis, not to be used in a wider context, as the critique regarding estimation errors presented by Lo (2002) is applicable in this coherence.

The appraisal ratio for each fund is calculated by dividing the mean of its Carhart four-factor adjusted returns over the holding period by their standard deviation. We then take the average across funds within each decile portfolio to derive the corresponding portfolio appraisal ratio. Brown, Goetzmann and Ross (1995) show that survivorship bias is positively related to fund re-

turn variance. Therefore, including the appraisal ratio, alpha scaled by idiosyncratic risk, when evaluating portfolios mitigates this bias. We include the Sharpe ratio to capture the risk-return trade-off among mutual funds. It is calculated for each fund by dividing the mean of its monthly net fee returns in excess of the risk free rate over the holding period by the corresponding standard deviation of monthly excess returns. The portfolio Sharpe ratio is calculated using the same procedure as for the appraisal ratio.

4.2 Method

4.2.1 Defining the SDI Measure and Hypotheses

The goal of this study is to examine whether a distinct investment strategy is an indicator of managerial skill and has predictive power of superior future performance. As concluded by Busse and Irvin (2004), recognizing the dynamic nature of the holdings of mutual funds would improve performance predictability. Hence, drawing conclusions about strategy distinctiveness, we are using a measure previously applied in analyzing hedge fund strategies, known for their dynamic holdings. The SDI measure seeks to examine to which extent funds returns differ from the returns of its peers.

We make the assumption that an individual fund's return that co-moves less with those of its peer group indicates a more distinct and unique investment strategy. The measure proposed to determine strategy distinctiveness, the SDI, is therefore based on past fund returns. The SDI will range between 0 and 2 and can be viewed as a distance measure: the higher the SDI, the further away from its peers, hence the more distinct a funds strategy. Thereby, the measure attempts to mirror the uniqueness of each funds strategy. The specific formula shows how the returns of an individual fund are correlated with the average returns of funds in the same style category ($\mu_{It} = \frac{\Sigma_{i \in I}(r_{it})}{count(i \in I)}$):

$$SDI = 1 - \text{corr}(r_i, \mu_I) = 1 - \frac{\sum_{t=1}^{24}(r_{it} - \bar{r}_i)(\mu_{It} - \bar{\mu}_I)}{\sqrt{\sum_{t=1}^{24}(r_{it} - \bar{r}_i)^2 \sum_{t=1}^{24}(\mu_{It} - \bar{\mu}_I)^2}} \quad (4)$$

The interpretation of this measure is based on basic economic principle, suggesting that the more well known a trading strategy is, thus the more people applying it, the lower the profits generated from that particular strategy will be. Based on previous literature and the discussion held up until this point, we state our null and alternative hypotheses:

$\mathbf{H_N}$: *Skilled managers are more capable of generating, and likely to pursue, unique investment strategies that should result in superior performance.*

$\mathbf{H_A}$: *Skilled managers are* ***not*** *more capable of generating, nor likely to pursue, unique investment strategies that should result in superior performance.*

From the null hypothesis follows that less skilled managers are more likely to practice well known strategies, thus competing with a large number of other managers for the same returns. If this hypothesis is accurate, there ought to be a positive relation between strategy distinctiveness and performance.

To convert the hypothesis into a testable forecast, we first measure strategy distinctiveness through the correlation between the returns of fund *i* and the returns of its peers. We continue by ranking managers based on the SDI measure, assuming that more skilled managers should be those with lower correlation. To validate the relationship between the SDI measure and managerial skill and subsequent performance, we make two predictions, following below.

Prediction 1: Strategy distinctiveness is a measure of managerial skill.

Our first prediction examines the relation between our measure and managerial skill. We interpret the correlation between the SDI measure and known fund characteristics. In line with previous research, we expect the SDI to increase with management fees, while it is forecasted to decrease

with the volatility of returns, fund age and fund size. Relating SDI to volatility of returns is consistent with testing for managers pursuing gaming strategies and taking on excess risk, which should not be confused with managerial talent. On the other hand, we predict managers of younger and smaller funds to more likely pursue innovative and agile investment strategies. Incentive fees were initially introduced as a motivating factor to managers in designing more innovative strategies yielding better performance. As shown by Elton, Gruber and Blake (2001), there is superior stock picking ability among incentive-fee funds, why we forecast a positive relation between the SDI and management fees. If these predictions are rejected, instead the alternative hypothesis is supported.

Prediction 2: Strategy distinctiveness is positively related to subsequent portfolio performance.

In the case of managerial skill, these managers should be able to generate superior performance in using unique investment strategies, standing out from less skilled managers. Thus, we predict a positive relationship between past SDI and future performance. The prediction would be rejected if the SDI is found to have no explanatory power of future performance**.**

When interpreting the SDI measure, funds in broadly defined classes might appear relatively more distinct than funds in narrowly defined classes. The reason is quite intuitive, as funds in broader classes will be spread to a larger extent than those in narrowly defined classes. Therefore, we have investigated the distribution of the SDI measure within each style class to take into consideration this possible confusing style effect, see Figure 1C. As shown by Sun, Wang and Zheng (2012), the spread of the SDI will be much larger within groups based on the pre-defined style classifications than when clustering historical returns in order to group funds with their closest cohorts (however, in their study, the TASS styles used are only reported in the end of each funds life, while the CRSP provide continuous updates regarding fund style classifications). Furthermore, the SDI measure can be reversed due to counteracting mechanisms. Managers taking on

excess idiosyncratic risk, pursuing so called gaming strategies, may appear to have distinct strategies without delivering superior performance. Hence, in this case strategy distinctiveness is not synonymous with managerial skill.

4.2.2 Data Treatment

In our main analysis, we define fund styles according to pre-specified Lipper prospectus-based classifications, as described above in section 4.1.1 Mutual Fund Sample. The importance of correctly defined styles is heavily emphasized in the study by Sun, Wang and Zheng (2012). Even though we recognize the method described by Brown and Goetzmann (1997, 2003), defining investment styles by clustering historical returns, we will be using the pre-defined style classifications in determining which one of the eleven style classes each fund belongs to. This information is the most readily available to investors, who are the most interested in a measure such as the SDI. In treating style switching, we have assumed funds can only switch style in the beginning of the year as the summary statistics can only be retrieved on a yearly basis from the CRSP database. Following Aragon (2007) we filter out funds missing a Lipper style classification, as they cannot be analyzed.

For funds switching style, we create new fund identification numbers, ultimately interpreting the fund as two different funds, before and after the switch. There is a possibility that these funds are of great interest to us, as the managers taking the initiative to switch style might be the more skilled ones. In order to control for this theory we calculate the switching rate of each decile portfolio, further explained in this section.

Furthermore, we follow Sun, Wang and Zheng (2012), limiting the sample by only including funds with a minimum of 24 months of returns in order to reduce the noise in the measure, and prepare for analysis using a 24 month rolling window. Following Elton, Gruber and Blake (1996) we drop funds with less than $15 million in total net assets. Our final sample contains 9,560

funds (8,660 without taking switching into consideration) and 656,573 observations of monthly returns.

Using monthly return observations, we compute the correlations within each class with a step-by-step method. This is done with a 24-month rolling window (as per the Equation 4) for each term in the SDI-formula. Further, with similar 24-month estimations, we find both the three- and four-factor alphas for each fund on a monthly basis. The same procedure is used to retrieve the Jensen alpha for each fund.

We proceed with testing our first prediction, that strategy distinctiveness is a measure of managerial skill. We look for determinants of the SDI using a multivariate panel regression, controlling for fund-clustering and time fixed effects. Daniel and Titman (1997) find that stock characteristics do better than factor loadings in explaining the cross-sectional behavior of average returns. We look at a couple of specific fund characteristics in addition to our performance measures. Wermers (2000) show that the average mutual fund held stocks that beat the CRSP index by 130 basis points per annum, while net return averaged 100 basis points below the index. For this reason we see the need of controlling for management fees. Specifically, the variables examined are fund age, monthly return volatility, fund size measured by total net assets, management fees and performance of each fund. We estimate the following multivariate panel regression for each of the three alphas from the Carhart, Fama-French and Jensen models:

$$SDI_{i,t} = c_{0i} + c_{1i} * FundCharacteristics_{i,t-1} + e_{i,t} \quad (5)$$

The control variables are lagged by one year in line with Brown and Goetzmann (1995) and Gruber (1996).

In order to test our second prediction, looking at the relationship between the SDI and performance, we apply a second regression defining our three different alphas as dependent variables,

and the SDI and fund characteristics as independent variables. First, we use a similar multivariate panel regression approach, adjusting for fund-clustering and time fixed effects. Second, we perform the same analysis, using Fama-MacBeth (1973) cross-sectional regression with style fixed effects and Newey-West heteroscedasticity and autocorrelation adjustment. The Fama-MacBeth regression is a two-step approach. First, cross sectional regressions are used in each time period to estimate the parameters which, in the second step are used in time series regressions to obtain the final estimates for parameters and standard errors and thus t-statistics. As shown by Petersen (2009) the fund effect is best accounted for by clustering standard errors. To take the time effect into consideration, as returns might be correlated across funds at a given point in time, the most appropriate approach is using Fama-MacBeth regression. Hence, we need to apply both of these techniques. In order to do so, we estimate the following regression equation:

$$\alpha_{i,t} = c_{0i} + c_{1i} * SDI_{i,t-1} + c_{2i} * FundCharacteristics_{i,t-1} + e_{i,t} \quad (6)$$

If our null hypothesis holds, we wish to investigate whether we can exploit the relationship found between the SDI and future fund performance by constructing equally weighted portfolios of the deciles based on the SDI level of each fund. We look at three different holding periods: quarterly, semiannual and annual. Rebalancing the portfolios accordingly, we compound the performance measures, averaged across funds within each portfolio. These are, as earlier explained, the different alphas, and appraisal and Sharpe ratios.

5 Results

As seen in Figure 1A, a majority of funds (>95%) have an SDI below 0.20. Considering the histogram bins, of 0.02 each, one can see that most funds are found in the 0.00 to 0.10 bins, while funds scoring an SDI higher than 0.20 account for less than 5% of the sample. Those with an SDI greater than 1 have returns that are in fact negatively correlated with the average returns of

their style class peers. These funds account for less than 1% of the sample.[5] As expected, our findings show that few mutual fund managers are pursuing unique investment strategies, partially explained by restrictions and extensive disclosure in the mutual fund industry.

Looking at the distribution differences among live and dead funds, we see that dead funds score a higher average SDI over the period from 2000 through 2011. Live funds have an average SDI of 0.06 while dead funds score 0.07 on average. The distribution of the SDI between live and dead funds (Figure 1B) remains fairly constant, indicating that the relationship between the SDI and performance is not dependent on levels of the SDI among live and dead funds.

Figure 1C presents the distribution of the SDI among different style classifications. However, despite fairly similar distributions overall, Equity Market Neutral and Long/Short Equity are strategies experiencing significantly higher standard deviation of the SDI. These findings could, on the other hand, be explained by the number of funds observed within these clusters, see Table 2. We still believe that the number of funds within each style class is sufficient enough to report unbiased results.

Table 2 and 3 further describes the dataset in terms of basic statistics, such as yearly switching and drop-out rates and emphasizes the return characteristics for each of the style classification clusters used in this study.

As shown in Table 4, we have not found average positive alphas, based on net fee returns, which is in line with recent studies discussed in previous sections. The mean monthly alphas for all funds are negative, ranging between -0.14 (average three-factor alpha) and -0.05 (average Jensen alpha). However, there are significant differences in the average alphas and their standard deviations of dead funds compared to live funds, with both the four-factor and three-factor average alphas being close to three times larger (negative) for dead funds.

[5] Looking at the findings in the hedge fund industry, Sun, Wang and Zheng (2012) show that, using TASS predefined style classifications, as much as 10% of funds have SDIs higher than 1.

Looking at fund characteristics, yearly average (and median) management fees for live funds have been lower than for dead funds during the sample period, found to be 0.69% and 0.73% respectively. However, the standard deviation of the management fee is higher among live funds. Furthermore, live funds are generally older than dead funds and have a larger average volatility in net monthly returns. Comparing the total net assets, we see much higher figures for live funds, when it comes to each of the descriptive measures. For instance, the median is twice as large for live funds as for dead funds ($138 M and $70 M respectively) and the maximum value of observed total net assets is almost six times as large ($102,105 M and $17,404 M respectively). Some researchers argue that size can kill while we believe the difference can be explained by the relationship between past performance and fund flows.[6]

We present the time-series average of the pair-wise correlations between the SDI and available fund characteristics. Referring to Panel B of Table 4, most notably we see a positive relationship between the SDI and both the three-factor and Jensen alphas. This supports our prediction of the SDI being a measure of managerial skill. However, the four-factor alpha is negatively correlated with the SDI, though insignificant at the 10% level, most probably because of the momentum factor creating an imminent amount of negative alphas. Furthermore, as expected, the correlation between the SDI and management fees is positive while it is negative looking at age, volatility of net fee returns and total net assets. Hence younger and smaller funds along with funds with higher management fees tend to have a higher SDI.

To gain a greater understanding of how the SDI measure varies with different fund characteristics we perform a multivariate panel regression. Table 5 emphasizes the findings described above, as they are all consistent with the results from the correlation matrix, apart from the fact that the panel regression generates a highly significant positive coefficient for the four-factor alpha as

[6] Bogle (1997) argues that "nothing fails like success" in describing the recent evolution and growth of the mutual fund industry, while Berk and Green (2002) concludes that there is a strong relationship between past performance and subsequent fund flows.

well. The SDI increases with past performance, which again corresponds with the skill effect. The negative coefficient of return volatility implies that the SDI measure is not associated with managers taking excessive risk in order to maximize performance. More likely, the SDI measures innovative managers adapting and implementing distinct strategies, in line with our null hypothesis. Further, even more intuitive, managers of younger funds are seemingly more innovative in designing investment strategies, managers of smaller funds are more agile in their portfolio allocations and higher management fees do provide fund managers with a larger incentive of keeping their strategies up to date (or the other way around; more talented managers have the possibility of charging higher fees thanks to higher demand).

At this point we have presented evidence of the SDI being a proxy for managerial skill. To move on, we test our second prediction, that the SDI is positively related to subsequent portfolio performance, in order to finally confirm or reject our hypothesis. In doing so, the approaches used are multivariate panel regression, Fama-MacBeth regression and an equally weighted portfolio approach.

We present the results of the multivariate panel regression in Table 6. The t-statistics are adjusted for fund-clustering and time fixed effects. The four-factor, three-factor and Jensen alphas act as dependent variables. The results are statistically significant, showing that the SDI is related to each of the three alpha measures, when controlling for fund characteristics in the regression. In addition, the management fee, return volatility and fund size are overall significantly and negatively related to the different alphas. This is in line with earlier research which argues that incentive fees, as an expense, mitigates future alpha (Elton, Gruber and Blake (2003) and Fama and French (2010)). As discussed by Berk and Green (2004), there are decreasing returns to scale in the mutual fund industry causing performance corrosion with increased fund flows. The regression results related to the total net assets are in line with their study, showing a negative relation between size and future alpha. Fund age, on the other hand, is vaguely but significantly positively

related to future alpha. Using standardized independent variables and a panel regression, the four-factor coefficient of the SDI is 0.20, implying a one standard deviation increase in the SDI would result in an increase in the subsequent annual four-factor alpha of 0.20 standard deviations. In the same way, the standardized coefficients for the three-factor alpha and the Jensen alpha on the SDI are 0.16 and 0.24 respectively. The corresponding results from the regression of Equation 6 using a Fama-MacBeth approach are presented in Table 7. For the four-factor alpha, the results are not as significant as using a panel regression. Nevertheless, the results for the three-factor alpha and the Jensen alpha are significant at the 10% and the 1% level respectively, showing a positive relation with the SDI.

Further examining this relation, we use an equally weighted portfolio approach, measuring the subsequent performance over three different holding periods. Considering each of our five performance measures, now including the appraisal and Sharpe ratios, the results show that funds in the highest decile outperform funds in the lowest. Specifically, looking at a one year holding and rebalancing period, funds in the highest decile outperform those in the lowest by 1.05% in terms of Carhart four-factor adjusted returns, as seen in Panel A of Table 9. While this performance measure is the most exhaustive in this study, the spread between the high and low portfolios are even greater turning to the three-factor and the Jensen alphas. All of the three different alphas increase (approaches a positive level, since net fee alphas are negative) almost monotonously with the SDI level for all three holding periods, and the Jensen alpha even turns out to be positive for the two top decile portfolios for all of the holding periods. Notable, however, is that neither the Carhart four-factor adjusted returns, nor the Fama-French three-factor adjusted returns are ever positive. Similar findings have recently been discussed by researchers (e.g. Fama and French (2010)) arguing that alphas in net fee returns are negative for the aggregate mutual fund universe. Thus, even though mutual funds on average generate negative alphas given net fee returns, we find that the SDI does predict subsequent superior performance. In further comparing the port-

folios, the appraisal and the Sharpe ratios are presented in Panel B of Table 9. Evaluating the portfolios, taking unsystematic risk into consideration, we find that the appraisal ratio show a tendency of increasing with the SDI level, as do the Sharpe ratio. Regardless of holding period and performance measure, funds in the top decile consistently outperform funds in the bottom decile.

In Table 8, the characteristics associated with the portfolios are presented. Specifically, the number of switching funds clearly increase with the portfolio number, thus with the SDI level. Furthermore, the management fee follows a similar pattern, with the low SDI funds charging an average management fee of 0.47% per annum while the highest decile SDI funds charge 0.86% on average. As expected, there is an evident decrease in size as the SDI level and portfolio number increases. Meanwhile, the average volatility in net returns and the age of the funds seem to be less distinctive for the funds in the different deciles.

6 Robustness Tests

6.1 SDI Based on Absolute Correlation

A mutual fund will, per definition, have a high SDI when the correlation of its returns with the returns of its peers is low. This implies the measure might be tracing a manager pursuing a unique investment strategies or one that is simply betting against its peers. To enhance the SDI being a measure of managerial skill rather than a measure of different risk taking and/or gambling behavior among managers, we construct an alternative distinctiveness index based on the absolute correlation. The SDI($|correlation|$) measure is defined using the same procedure as for the regular SDI, with the addition of absolute correlation. Thus, in contrast to those managers who basically bet against their peers, resulting in a negative correlation in returns, only managers with unique investment ideas will score a high SDI.

Running the same panel and Fama-MacBeth regressions as previously described in section 4.2.2 Data Treatment, Panel A and B of Table 10 show the SDI remains statistically significant and positive, implying predictive power of future fund performance[7]. Other control variables show similar results as well.

Further, we sort funds and construct decile portfolios based on their SDI(|*correlation*|) measure. Panel D and E of Table 10 show that for equally weighted portfolios with a holding period of one year, funds in the highest decile portfolio outperform funds in the lowest by 1.05%, 1.21% and 3.04% when considering the four-factor, three-factor and Jensen alphas, respectively. The spread in the appraisal ratio is 1.25 and 0.03 based on the Sharpe ratio.

Third, Panel C of Table 10 shows that the correlation between SDI and SDI(|*correlation*|) equals 0.77, suggesting a great level of overlapping funds between portfolios sorted on SDI and SDI(|*correlation*|). Overall, these results support our findings of the SDI being a measure of managerial skill.

6.2 Survivorship Bias

Survivorship bias is often an issue to consider when analyzing overall performance from historical data, widely known among researchers and financial economics. As explained in section 4 Data and Methodology, we have tried to mitigate this potential problem, e.g. by using the CRSP Survivor-Bias-Free U.S. Mutual Fund Database, excluding funds holding less than $15 million to reduce the risk of survivorship bias due to reporting conventions (Elton, Gruber and Blake (1996)) and using the appraisal ratio, when evaluating portfolio performance (Brown, Goetzmann and Ross (1995)). Still, this potential problem, which might be due to funds merging or dropping out, raises the question whether the SDI decile portfolio performance depends on survival rates. To asses this problem we use the Heckman correction.

[7] Except from the Carhart four-factor adjusted alpha in the Fama-MacBeth regression, t-statistic(0.77)

The Heckman correction is a two-step procedure. First, we use a probit model to estimate the survival probability of mutual funds over the next twelve months. Here, the dependent variable takes the value of one if the fund survives the following twelve months and zero otherwise. Second, we add the inverse mills ratio (Heckman Lambda) from the first-step regression to our control variables in the panel and Fama-MacBeth regressions from Equation 6.

Panel A of Table 11 reports the results of the probit regression, showing that younger funds are associated with a lower probability of survival, while larger funds with better past performance and higher SDI have a higher probability. The second-step regression results from the Heckman correction, including the inverse mill ratio, are presented in Panel B of Table 11. The coefficient of interest, the SDI, remains statistically significant and positive, as before, in Table 6 and 7, suggesting that the previous positive relationship between strategy distinctiveness and mutual fund performance is not due to survivorship bias.

7 Conclusion

Wealth-maximizing investors are interested in the evaluation of mutual funds, attempting to find innovative managers pursuing unique investment strategies. With increasing flows into mutual funds, and a corresponding increase in the supply of different funds for investors to choose from, there is also a greater need for evaluating the contribution of active management to investor utility. Specifically, a measure easily assessing managerial ability in the fierce competition defining the mutual fund industry of today would be desirable for investors. In this study, following Sun, Wang and Zheng (2012), we examine to what extent a fund correlates with its peers in terms of return series. We hypothesize that skilled managers are more likely to generate and pursue unique investment strategies, thus deliver superior performance relative to that of less skilled managers. In order to access the hypothesis we formulate two predictions. First, we predict that strategy distinctiveness is a measure of managerial skill. Second, we predict that strategy distinc-

tiveness is related to superior performance.

To measure a mutual fund's strategy distinctiveness, we define and estimate the strategy distinctiveness index, SDI, as 1 minus the correlation of its returns with the returns of its peers, being clustered by pre-defined style classifications. Our findings suggest that the SDI is an indicator of managerial skill and innovative talent. We see that younger and smaller funds are able to pursue innovative and agile investment strategies. Furthermore, we find that management fees act as a motivating factor for managers in designing more innovative strategies. Looking at the volatility of returns, we conclude that the SDI is not affected by managers pursuing gaming strategies, taking on excessive risk.

The main results of this study prove that the SDI is related to significantly better mutual fund performance, in line with findings in the hedge fund industry[8]. Our analyses continuously show that funds with higher SDI consistently outperform funds with lower SDI. This evidence indicates that skilled active managers do exist. Thus, our overall findings provide investors with a measure that can be used in evaluating and selecting mutual funds, further facilitating finding managers with the capability of generating superior future performance. However, skillfulness is rare, only attributable to a minority of fund managers, with most mutual funds generating largely correlated returns. Thus, despite investors having the possibility of identifying superior mutual fund managers, the overall negative net of fee alphas suggest that investors are better of indexing their investments. However, an investor should bear in mind that this study has been executed during a time characterized by large shifts in the financial markets. To investigate the accuracy of the measure given different market conditions, extended evaluation should take into consideration potential differences caused by periods of market downturn and boom respectively.

[8] Referring to evidence of Sun, Wang and Zheng (2012).

This study is performed using an investor perspective, taking the CRSP pre-defined styles as given. The results show that certain strategies tend to perform better than others, in particular, these are found within the Equity Market Neutral and Long/Short Equity styles. An extension of this study should redefine style clusters based on a "best fit" approach, similar to that of Brown and Goetzmann (1997, 2003). Previous literature has shown that mutual funds are often subject to misclassification, sometimes even due to managers consciously deviating from the pre-defined styles. Thus, our measure would be more accurate comparing funds with their closest cohorts as found through clustering historical returns.

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9 Appendix

9.1 Figure 1: Histogram of the SDI

Figure 1A presents the histogram of the SDI for all funds in the sample during 2000-2011. Figure 1B presents the histogram of the SDI on Live and Dead (Graveyard) Funds. Figure 1C presents the histogram of the SDI for each style classification. Note: All figures show SDI levels up to (max) 0.5 for visual reasons.

Figure 1A: Histogram of the SDI on the Full Sample

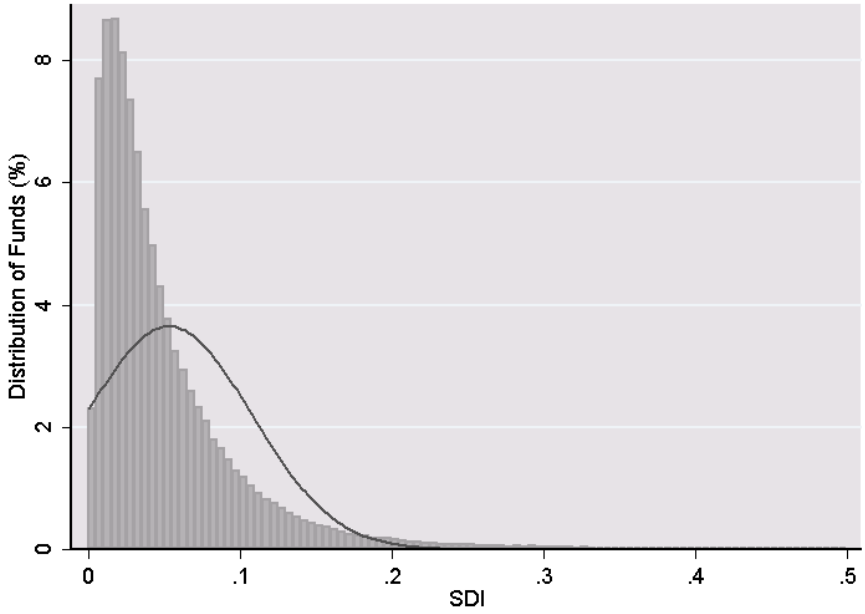


Figure 1B: Histogram of the SDI on Live and Dead Funds

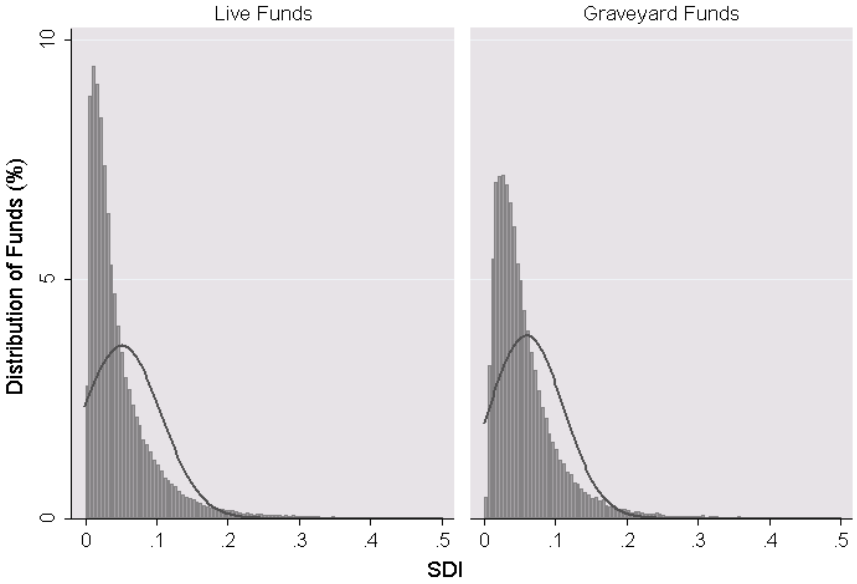
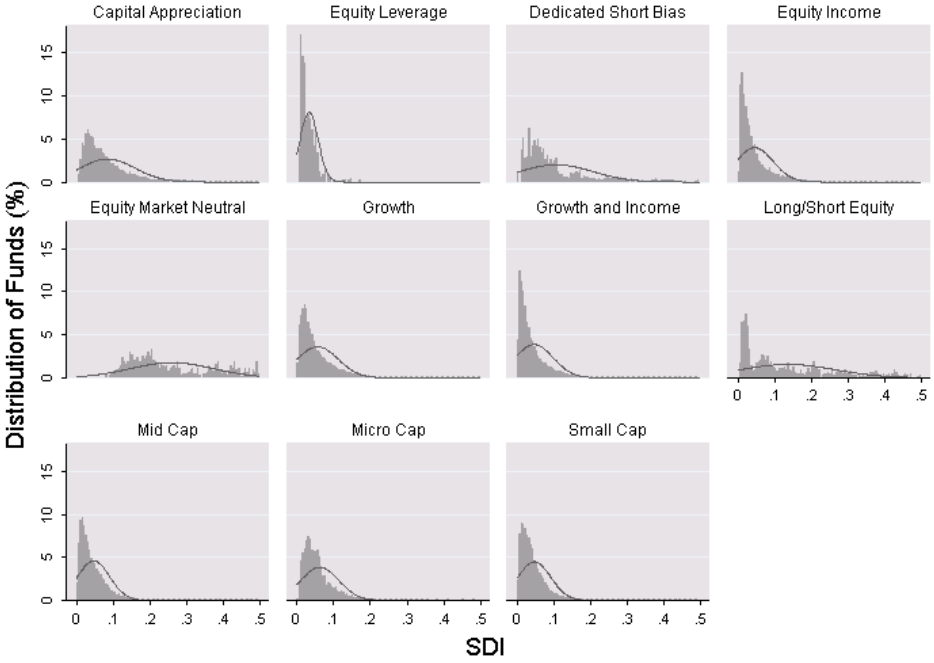


Figure 1 – continued

Figure 1C: Histogram of the SDI per Style Classification



9.2 Table 1: Classification Descriptions

Table 1 presents the Lipper Style Classifications with descriptions as found through "U.S. Open-End, Closed-End, and Variable Annuity Fund Classification Descriptions" on the Lipper web.

Classification	Description
Capital Appreciation Funds	Funds that aim at maximum capital appreciation, frequently by means of 100%-or more portfolio turnover, leveraging, purchasing unregistered securities, purchasing options, etc. The funds may take large cash positions.
Dedicated Short Bias Funds	Funds that employ portfolio strategies consistently creating a "net short" exposure to the market. This classification also includes short-only funds, i.e., funds that pursue short sales of stock or stock index options
Equity Income Funds	Funds that seek relatively high current income and growth of income through investing 65% or more of their portfolio in equities.
Equity Leverage Funds	Diversified and non-diversified equity funds that seek daily investment results of more than 100% of the daily performance of a stated benchmark through any combination of futures contracts, derivatives, and leverage.
Equity Market Neutral Funds	Fund that employ portfolio strategies generating consistent returns in both up and down markets by selecting positions with a total net market exposure of zero.
Growth Funds	Funds that normally invest in companies with long-term earnings expected to grow significantly faster than the earnings of the stocks represented in the major unmanaged stock indices.
Growth and Income Funds	Funds that combine a growth-of-earnings orientation and an income requirement for level and/or rising dividends.
Long/Short Equity Funds	Funds that employ portfolio strategies combining long holdings of equities with short sales of equity, equity options, or equity index options. The funds may be either net long or net short, depending on the portfolio manager's view of the market.
Micro-Cap Funds	Funds that, by prospectus or portfolio practice, invest primarily in companies with market capitalizations less than $300 million at the time of purchase.
Mid-Cap Funds	Funds that, by prospectus or portfolio practice, invest primarily in companies with market capitalizations less than $5 billion at the time of purchase.
Small-Cap Funds	Fund that, by prospectus or portfolio practice, invest primarily in companies with market capitalizations less than $1 billion at the time of purchase.

9.3 Table 2: Yearly Observations

Table 2 shows descriptive statistics containing switching and drop-out rates as well as data on each of the style classifications.

	Total	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	Mean	Median	Min	Max	Std
Nr of Funds (before switching)	8 660																	
Nr of Funds (after switching)	9 560	3 002	3 392	3 650	3 865	4 243	4 451	4 759	5 240	6 075	5 902	6 350	6 370	4 775	4 605	3 002	6 370	1 196
Yearly change in nr of funds (%)			12.99	7.61	5.89	9.78	4.90	6.92	10.11	15.94	-2.85	7.59	0.31	7.20	7.59	-2.85	15.94	5.30
Dead Funds	2 475	1 333	1 453	1 457	1 385	1 431	1 305	1 202	1 137	903	627	423	242	1 075	1 254	242	1 457	426
Yearly drop out rate (%)	25.89	44.40	42.84	39.92	35.83	33.73	29.32	25.26	21.70	14.86	10.62	6.66	3.80	25.75	27.29	3.80	44.40	14.23
Live Funds	7 085	1 669	1 939	2 193	2 480	2 812	3 146	3 557	4 103	5 172	5 275	5 927	6 128	3 700	3 352	1 669	6 128	1 589
Switching funds	2 185	165	205	230	259	286	293	314	343	340	322	328	265	279	290	165	343	56
Yearly switching rate (% of total #funds)	22.86	5.50	6.04	6.30	6.70	6.74	6.58	6.60	6.55	5.60	5.46	5.17	4.16	5.95	6.17	4.16	6.74	0.79
Yearly switching rate (% of #live funds)	30.84	9.89	10.57	10.49	10.44	10.17	9.31	8.83	8.36	6.57	6.10	5.53	4.32	8.38	9.07	4.32	10.57	2.20
Capital Appreciation Funds	533	228	236	259	276	305	313	272	269	288	274	290	286	275	275	228	313	25
Dedicated Short Bias Funds	153	1	1	1	1	1	1	36	69	105	87	110	92	42	19	1	110	47
Equity Income Funds	441	144	161	163	157	184	191	200	225	275	269	291	289	212	196	144	291	55
Equity Leverage Funds	43	0	0	0	0	0	0	0	0	31	32	37	34	11	0	0	37	17
Equity Market Neutral Funds	72	0	0	0	0	0	0	18	34	39	44	60	59	21	9	0	60	25
Growth Funds	3 263	974	1 154	1 229	1 317	1 427	1 529	1 622	1 786	2 062	2 046	2 160	2 152	1 622	1 576	974	2 160	416
Growth and Income Funds	2 058	690	754	817	842	906	920	971	1 052	1 233	1 220	1 397	1 446	1 021	946	690	1 446	250
Long/Short Equity Funds	95	0	0	0	0	0	0	18	41	53	58	71	71	26	9	0	71	30
Micro-Cap Funds	85	42	45	52	45	50	57	62	65	56	45	42	43	50	48	42	65	8
Mid-Cap Funds	1 229	336	381	424	470	534	570	633	717	843	821	841	846	618	602	336	846	193
Small-Cap Funds	1 588	587	660	705	757	836	870	927	982	1 090	1 006	1 051	1 052	877	899	587	1 090	169

9.4 Table 3: Style Class Statistics (mean values 2000-2011)

Table 3 describes the style classifications in terms of average sample period SDI, performance measures including four-factor, three-factor and Jensen alpha, and average yearly appraisal and Sharpe ratios.

	SDI	Carhart 4-factor alpha (%p.m.)	Fama-French 3-factor alpha (%p.m.)	Jensen's alpha (%p.m.)	Appraisal Ratio (p.a.)	Sharpe Ratio (p.a.)
Capital Appreciation Funds	0.174	-0.172	-0.179	-0.084	-1.117	0.116
Equity Leverage Funds	0.087	-0.366	-0.407	-0.099	-3.299	0.495
Dedicated Short Bias Funds	0.366	-0.968	-0.963	-0.981	-4.189	-0.491
Equity Income Funds	0.046	-0.055	-0.051	-0.016	-0.458	0.376
Equity Market Neutral Funds	0.523	-0.094	-0.089	-0.062	-1.609	-0.027
Growth Funds	0.057	-0.162	-0.159	-0.155	-1.026	0.031
Growth and Income Funds	0.048	-0.123	-0.110	-0.071	-1.244	0.160
Long/Short Equity Funds	0.177	-0.188	-0.163	-0.148	-1.692	0.166
Mid-Cap Funds	0.050	-0.047	-0.055	0.081	-1.553	-0.350
Micro-Cap Funds	0.062	-0.110	-0.117	0.185	-0.754	-0.143
Small-Cap Funds	0.047	-0.144	-0.160	0.093	-0.969	0.396

9.5 Table 4: Summary Statistics (2000-2011)

Table 4 presents the data used in greater detail. Panel A presents the time-series average of cross-sectional summary statistics for the main variables divided on the full sample and live and dead funds. Variables included are number of funds per year (during the period 2000-2011), the SDI measure, and fund characteristics such as monthly net returns, four-factor alphas and the corresponding appraisal ratio, the three-factor alphas, Jensen alphas, Sharpe ratio, management fees, fund age, volatility of monthly returns (net of fees) and total net assets. Further explaining these variables, Panel B summarizes the pair-wise correlation between these variables.

Panel A: Fund Performance and Characteristics

	Full Sample (9 560 unique funds)					Live Funds (7 085 unique funds)					Dead Funds (2 475 unique funds)				
	Mean	Median	Min	Max	Std	Mean	Median	Min	Max	Std	Mean	Median	Min	Max	Std
SDI	0.062	0.036	0.000	1.986	0.123	0.062	0.034	0.000	1.986	0.129	0.065	0.045	0.000	1.784	0.095
Net fee returns (%p.m.)	0.327	0.794	-94.202	64.038	5.730	0.415	0.878	-94.202	64.038	5.700	0.011	0.521	-38.600	59.616	5.824
Carhart 4-factor alpha (%p.m.)	-0.135	-0.119	-9.602	6.472	0.410	-0.102	-0.962	-9.602	4.280	0.394	-0.269	-0.230	-5.169	6.472	0.442
Fama-French 3-factor alpha (%p.m.)	-0.136	-0.120	-9.896	6.133	0.429	-0.101	-0.096	-9.896	4.017	0.413	-0.275	-0.234	-6.090	6.133	0.463
Jensen's alpha (%p.m.)	-0.048	-0.078	-10.246	6.687	0.505	-0.011	-0.048	-10.246	4.541	0.490	-0.200	-0.200	-5.600	6.700	0.500
Appraisal Ratio (p.a.)	-0.707	-0.612	-2.911	1.247	1.303	-0.601	-0.507	-2.911	1.247	1.274	-1.109	-1.108	-2.911	1.247	1.331
Sharpe Ratio (p.m.)	0.210	0.265	-1.424	1.572	0.931	0.269	0.314	-1.424	1.572	0.908	-0.007	0.104	-1.424	1.572	0.980
Management fee (%p.a.)	0.699	0.719	0.001	4.014	0.280	0.691	0.710	0.001	4.014	0.288	0.726	0.740	0.001	2.680	0.251
Age (years)	9.536	7.000	1.000	87.000	9.456	9.716	8.000	1.000	87.000	9.447	8.881	7.000	1.000	86.000	9.460
Vol of monthly returns (%p.m.)	4.644	4.668	0.002	21.244	1.942	4.761	4.914	0.002	21.244	1.923	4.162	3.619	0.003	15.262	1.943
TNA($M) (p.a.)	644	116	15	102 105	2 707	760	138	15	102 105	3 032	226	70	15	17 404	609
Nr of funds (p.a.)	4 775	4 605	3 002	6 370	1 196	3 700	3 352	1 669	6 128	1 589	1 075	1 254	242	1 457	426

Table 4 - continued

Panel B: Parwise Correlations

	SDI	Net fee returns (%p.m.)	Carhart 4-factor alpha (%p.m.)	Fama-French 3-factor alpha (%p.m.)	Jensen's alpha (%p.m.)	Appraisal Ratio (p.a.)	Sharpe Ratio (p.m.)	Management fee (%p.a.)	Age (years)	Vol of monthly returns (%p.m.)	TNA($M) (p.a.)
SDI	1.000										
significance level											
Net fee returns (%p.m.)	-0.022***	1.000									
	0.000										
Carhart 4-factor alpha (%p.m.)	-0.002	0.032***	1.000								
	0.197	0.000									
Fama-French 3-factor alpha (%p.m.)	0.0045***	0.042***	0.964***	1.000							
	0.002	0.000	0.000								
Jensen's alpha (%p.m.)	0.045***	0.070***	0.648***	0.679***	1.000						
	0.000	0.000	0.000	0.000							
Appraisal Ratio (p.a.)	0.055***	0.028***	0.687***	0.660***	0.474***	1.000					
	0.000	0.000	0.000	0.000	0.000						
Sharpe Ratio (p.m.)	-0.122***	0.320***	0.0415***	0.057***	0.125***	0.060***	1.000				
	0.000	0.000	0.000	0.000	0.000	0.000					
Management fee (%p.a.)	0.196***	-0.002	-0.036***	-0.039***	0.037***	0.064***	-0.019***	1.000			
	0.000	0.202	0.000	0.000	0.000	0.000	0				
Age (years)	-0.023***	0.004***	0.004***	0.003**	-0.021***	0.025***	0.014***	-0.035***	1.000		
	0.000	0.002	0.006	0.021	0.000	0.000	0	0.000			
Vol of monthly returns (%p.m.)	-0.143***	-0.102***	-0.064***	-0.053***	0.053***	-0.024***	-0.207***	0.037***	0.014***	1.000	
	0.000	0.000	0.000	0.000	0.000	0.000	0	0.000	0.000		
TNA($M) (p.a.)	-0.018***	-0.004***	0.043***	0.043***	0.015***	0.048***	-0.015***	-0.130***	0.283***	-0.039***	1.00
	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	

* 10% significance; ** 5% significance; *** 1% significance

9.6 Table 5: Determinants of the SDI

Table 5 reports the multivariate panel regression of the SDI, as the dependent variable, on one year lagged control variables - alpha, management fees, fund age, size and volatility in monthly net fee returns:

$$SDI_{i,t} = c_{0i} + c_{1i} * FundCharacteristics_{i,t-1} + e_{i,t}$$

In column I, the regression results are presented with the alpha being represented by the Carhart four-factor adjusted returns. In column II the Fama-French three-factor adjusted returns are set as the independent alpha variable in the regression and in column III the Jensen alpha is used. Each alpha and the volatility of returns (net of fees) are measured over a window of 24 months and lagged by one year. The t-statistics are presented in parentheses and adjusted for fund-clustering and time fixed effects.

	I	II	III
Alpha	0.437***	0.041***	0.158
(t-stat)	(3.2)	(2.76)	(1.36)
Management fee	0.002	0.002	0.001
	(0.41)	(0.4)	(0.33)
Fund age	-0.002***	-0.002***	-0.002***
	(-14.22)	(-14.16)	(-12.97)
Return volatility	-0.836***	-0.838***	-0.845***
	(-44.28)	(-44.54)	(-40.65)
ln(Total net assets)	0.122***	-0.002***	-0.002***
	(27.56)	(-2.81)	(-2.71)
Total number of funds	6 485	6 485	6 485
Total number of observations	380 925	380 925	380 925
R^2 (%)	20.13	20.12	20.03

* 10% significance; ** 5% significance; *** 1% significance

9.7 Table 6: Multivariate Panel Regression of Mutual Fund Performance on the SDI (2000-2011)

Table 6 presents the results of the multivariate panel regression with the three different adjusted alphas, estimated using a rolling 24-month window, as dependent variables on the one year lagged SDI and other fund characteristics, as per the following regression:

$$\alpha_{i,t} = c_{0i} + c_{1i} * SDI_{i,t-1} + c_{2i} * FundCharacteristics_{i,t-1} + e_{i,t}$$

Fund characteristics include management fee, fund age, size and volatility of monthly net fee returns. The t-statistics presented in parentheses are adjusted for fund-clustering and time fixed effects.

	Carhart 4-factor alpha	Fama-French 3-factor alpha	Jensen's alpha
SDI	0.007***	0.006***	0.010***
(*t*-stat)	(9.68)	(8.30)	(10.15)
Management fee	-0.001***	-0.001***	-0.001***
	(-2.92)	(-2.92)	(-3.00)
Fund age	0.000***	0.000***	-0.000**
	(13.66)	(11.99)	(-2.19)
Return Volatility	-0.033***	-0.026***	0.028***
	(-24.17)	(-17.81)	(16.27)
ln(Total net assets)	-0.001***	-0.001***	-0.001***
	(17.00)	(-17.55)	(-24.59)
Total number of funds	6 264	6 264	6 264
Total number of observations	370 576	370 576	370 576
R^2 (%)	6.67	5.11	11.03

* 10% significance; ** 5% significance; *** 1% significance

9.8 Table 7: Fama-MacBeth Analysis of Mutual Fund Performance on the SDI (2000-2011)

Table 6 presents the results of the Fama-MacBeth regression with the three different adjusted alphas, estimated using a rolling 24-month window, as dependent variables on the one year lagged SDI and other fund characteristics, as per the following regression:

$$\alpha_{i,t} = c_{0i} + c_{1i} * SDI_{i,t-1} + c_{2i} * FundCharacteristics_{i,t-1} + e_{i,t}$$

Fund characteristics include management fee, fund age, size and volatility of monthly net fee returns. The coefficients are multiplied by 100. The t-statistics presented in parentheses are adjusted for heteroscedasticity and autocorrelation.

	Carhart 4-factor alpha	Fama-French 3-factor alpha	Jensen's alpha
SDI	0.020	0.062*	0.203***
(*t*-stat)	(0.46)	(1.67)	(3.55)
Management fee	-0.045***	-0.050***	0.062***
	(-4.38)	(-5.70)	(7.19)
Fund age	-0.001***	-0.001***	-0.001***
	(-5.54)	(-6.42)	(-4.63)
Return Volatility	-3.951***	-3.370***	-4.351***
	(-4.67)	(-3.72)	(-3.37)
ln(Total net assets)	0.011***	0.012***	0.007***
	(10.55)	(12.49)	(5.90)
Total number of observations	370 576	370 576	370 576
R^2 (%)	6.34	6.39	12.11

* 10% significance; ** 5% significance; *** 1% significance

9.9 Table 8: Portfolio Descriptive Statistics

Table 8 describes the characteristics of the decile portfolios, based on the level of SDI.

	Number of switching funds	SDI	Management fee (%p.a.)	Age (years)	Vol of monthly returns (%p.m.)	TNA($M) (p.a.)
(Low SDI) 1	98	0.010	0.473	9.808	0.046	1 139.073
2	126	0.017	0.602	10.540	0.045	836.808
3	166	0.023	0.657	11.046	0.046	731.393
4	192	0.029	0.687	10.986	0.047	711.120
5	198	0.036	0.702	11.029	0.047	673.290
6	232	0.044	0.721	10.879	0.047	652.238
7	260	0.054	0.733	10.823	0.047	592.217
8	263	0.068	0.747	10.647	0.047	555.335
9	253	0.090	0.761	10.486	0.047	531.558
(High SDI) 10	397	0.254	0.856	10.155	0.043	501.628

9.10 Table 9: Portfolio Performance Based on the SDI

Panel A of Table 9 reports the time-series mean of the post-formation performance measures for each of the decile portfolios based on the SDI. The portfolios are equally weighted and re-balanced as per the holding periods defined, namely quarterly, semiannually and annually. Further presented is the spread between the high and the low portfolios for each alpha and holding period. Panel B of Table 9 reports the appraisal and Sharpe ratios as alternative performance measures. Further, the table is constructed in the same way as Panel A.

Panel A: Alphas

	Carhart 4-factor alpha			Fama-French 3-factor alpha			Jensen's alpha		
	3m (%p.q.)	6m (%p.sa.)	1y (%p.a.)	3m (%p.q.)	6m (%p.sa.)	1y (%p.a.)	3m (%p.q.)	6m (%p.sa.)	1y (%p.a.)
(Low SDI) 1	-0.382	-0.766	-1.693	-0.396	-0.789	-1.729	-0.282	-0.578	-1.192
2	-0.395	-0.792	-1.711	-0.407	-0.817	-1.757	-0.317	-0.633	-1.236
3	-0.450	-0.909	-2.067	-0.458	-0.903	-2.133	-0.293	-0.579	-1.284
4	-0.484	-0.933	-1.973	-0.488	-0.922	-2.064	-0.296	-0.545	-1.193
5	-0.498	-1.012	-2.005	-0.509	-1.023	-2.032	-0.274	-0.574	-1.195
6	-0.574	-1.229	-1.906	-0.613	-1.413	-1.983	-0.335	-0.810	-1.046
7	-0.483	-0.947	-1.865	-0.492	-0.966	-1.922	-0.175	-0.343	-0.708
8	-0.443	-0.860	-1.620	-0.441	-0.854	-1.616	-0.013	-0.009	0.019
9	-0.317	-0.626	-1.211	-0.290	-0.578	-1.118	0.248	0.508	1.021
(High SDI) 10	-0.136	-0.043	-0.640	-0.111	0.013	-0.515	0.510	1.388	1.844
Spread(High-Low)	0.247	0.723	1.052	0.285	0.802	1.214	0.792	1.966	3.036

Panel B: Alternative Measures

	Appraisal Ratio			Sharpe Ratio		
	3m	6m	1y	3m	6m	1y
(Low SDI) 1	-0.944	-1.000	-1.332	0.099	0.158	0.234
2	-0.802	-0.834	-0.985	0.103	0.159	0.236
3	-0.808	-0.858	-1.065	0.096	0.172	0.231
4	-0.801	-0.850	-0.910	0.099	0.189	0.229
5	-0.768	-0.824	-0.951	0.101	0.163	0.226
6	-0.754	-0.832	-0.712	0.094	0.107	0.248
7	-0.652	-0.683	-0.845	0.110	0.183	0.249
8	-0.545	-0.588	-0.616	0.115	0.200	0.310
9	-0.388	-0.485	-0.476	0.115	0.195	0.298
(High SDI) 10	-0.187	-0.160	-0.091	0.114	0.165	0.264
Spread(High-Low)	0.758	0.840	1.241	0.014	0.008	0.030

9.11 Table 10: Robustness - Regression Analysis of Mutual Fund Performance on the SDI(|correlation|) (2000-2011)

Panel A shows the results of the panel regression of mutual fund performance on the SDI measure based on absolute correlation and other fund characteristics during the full sample period, 2000-2011, as per the following regression:

$$\alpha_{i,t} = c_{0i} + c_{1i} * SDI(|corr|)_{i,t-1} + c_{2i} * FundCharacteristics_{i,t-1} + e_{i,t}$$

The post-formation adjusted alphas are used as dependent variables and control variables are lagged one year, including SDI(|correlation|), management fees, fund age, size, and volatility of monthly net fee returns. The t-statistics are reported in parentheses, adjusted for fund-clustering and time fixed effects. Panel B reports the corresponding Fama-MacBeth regression. T-statistics, presented in parentheses, are adjusted for heteroscedasticity and autocorrelation in standard errors. In Panel B, the coefficients are multiplied by 100. Panel C reports the pair-wise correlations between SDI and SDI(|correlation|). Panel D reports the time-series mean of the post-formation performance measures for each of the decile portfolios constructed sorting the SDI(|correlation|). The portfolios are equally weighted and rebalanced as per the holding periods defined, namely quarterly, semiannually and annually. Further presented is the spread between the high and the low portfolios for each alpha and holding period. Panel E reports the appraisal and Sharpe ratios as alternative performance measures, further constructed in the same way as Panel D.

	Panel A: Panel Regression			Panel B: Fama-MacBeth		
	Carhart 4-factor alpha	Fama-French 3-factor alpha	Jensen's alpha	Carhart 4-factor alpha	Fama-French 3-factor alpha	Jensen's alpha
SDI(|corr|)	0.008***	0.006***	0.012***	0.051	0.099*	0.392***
(*t*-stat)	(11.34)	(9.27)	(12.58)	(0.77)	(1.75)	(3.98)
Management fee	-0.001***	-0.001***	-0.001***	-0.049***	-0.054***	0.050***
	(-2.97)	(-2.95)	(-3.10)	(-4.70)	(-6.07)	(6.66)
Fund age	0.000***	0.000***	-0.000*	-0.001***	-0.001***	-0.001***
	(14.05)	(12.21)	(-1.76)	(-5.95)	(-6.61)	(-4.68)
Return Volatility	-0.033***	-0.026***	0.028***	-3.888***	-3.315***	-4.040***
	(-23.90)	(-17.64)	(16.43)	(-4.60)	(-3.67)	(-3.06)
ln(Total net assets)	-0.001***	-0.001***	-0.001***	0.011	0.012***	0.007***
	(-16.95)	(-17.51)	(-24.51)	(10.36)	(12.30)	(5.75)
Total number of funds	6 257	6 257	6 257			
Total number of observations	370 347	370 347	370 347	370 347	370 347	370 347
R^2 (%)	6.86	5.22	11.37	6.63	6.61	12.81

* 10% significance; ** 5% significance; *** 1% significance

Table 10 – continued

Panel C: Pairwise Correlations between SDI(corr) and SDI(|corr|)

	SDI	SDI(|corr|)
SDI	1.000	
(*t*-stat)		
SDI(|corr|)	0.767***	1.000
	(0.000)	

* 10% significance; ** 5% significance; *** 1% significance

Panel D: Alphas

	Carhart 4-factor alpha			Fama-French 3-factor alpha			Jensen's alpha		
	3m (%p.q.)	6m (%p.sa.)	1y (%p.a.)	3m (%p.q.)	6m (%p.sa.)	1y (%p.a.)	3m (%p.q.)	6m (%p.sa.)	1y (%p.a.)
(Low SDI(|corr|)) 1	-0.382	-0.766	-1.693	-0.396	-0.789	-1.729	-0.282	-0.578	-1.192
2	-0.395	-0.792	-1.711	-0.407	-0.817	-1.757	-0.317	-0.633	-1.236
3	-0.450	-0.909	-2.067	-0.458	-0.903	-2.133	-0.293	-0.578	-1.284
4	-0.484	-0.934	-1.975	-0.488	-0.922	-2.065	-0.297	-0.545	-1.195
5	-0.497	-1.011	-2.005	-0.509	-1.022	-2.033	-0.274	-0.574	-1.195
6	-0.573	-1.228	-1.903	-0.613	-1.411	-1.980	-0.335	-0.810	-1.044
7	-0.482	-0.945	-1.857	-0.492	-0.965	-1.913	-0.175	-0.341	-0.701
8	-0.444	-0.862	-1.625	-0.443	-0.856	-1.623	-0.017	-0.018	-0.001
9	-0.319	-0.628	-1.210	-0.292	-0.579	-1.115	0.245	0.507	1.032
(High SDI(|corr|)) 10	-0.133	-0.041	-0.644	-0.108	0.015	-0.518	0.517	1.396	1.847
Spread(High-Low)	0.249	0.724	1.049	0.287	0.804	1.210	0.799	1.974	3.039

Panel E: Alternative Measures

	Appraisal Ratio			Sharpe Ratio		
	3m	6m	1y	3m	6m	1y
(Low SDI(|corr|)) 1	-0.944	-1.000	-1.332	0.099	0.158	0.234
2	-0.802	-0.834	-0.985	0.103	0.159	0.236
3	-0.808	-0.858	-1.065	0.096	0.172	0.231
4	-0.801	-0.850	-0.910	0.099	0.188	0.228
5	-0.768	-0.824	-0.951	0.101	0.160	0.225
6	-0.753	-0.832	-0.712	0.093	0.104	0.246
7	-0.655	-0.685	-0.845	0.109	0.182	0.249
8	-0.549	-0.593	-0.620	0.114	0.199	0.310
9	-0.391	-0.487	-0.476	0.114	0.194	0.297
(High SDI(|corr|)) 10	-0.177	-0.153	-0.086	0.118	0.173	0.267
Spread(High-Low)	0.767	0.847	1.246	0.019	0.015	0.033

9.12 Table 11: Robustness - Survivorship Bias with Heckman Correction

Panel A of Table 11 presents the probit regression results on mutual fund survival probability. The dependent variable takes the value of one at any given point in time if the fund survives in the subsequent twelve months, and zero otherwise. The probit model estimates the survival probabilities of mutual funds over the next twelve months. From this model, the inverse mills ratio is used as the Heckman lambda in Panel B. Panel B.1 presents the panel regression and Panel B.2 the Fama-MacBeth regression of the different adjusted alphas on the SDI and other fund characteristics, including the Heckman lambda as one of the independent variables. We estimate the following Heckman adjusted regression:

$$\alpha_{i,t} = c_{0i} + c_{1i} * SDI_{i,t-1} + c_{2i} * HeckmanLambda + c_{3i} * FundCharacteristics_{i,t-1} + e_{i,t}$$

The t-statistics are presented in parentheses and adjusted for fund-clustering and time fixed effect and heteroscedasticity and autocorrelation respectively. In Panel B.2 the coefficients are multiplied by 100.

Panel A: Heckman Correction - Probit Model, Mutual Fund Survivorship

Variable name	Coefficient
SDI	0.189***
(z-value)	(5.48)
Net fee return	6.495***
	(29.66)
Carhart 4-factor alpha	39.344***
	(41.71)
Management fee	0.073***
	(4.82)
Fund age	-0.013***
	(-30.19)
Return volatility	5.678***
	(25.85)
ln(Total net assets)	0.383***
	(96.49)
Number of observations	451 801
LR chi2 (7)	16 210
Prob>chi2	0.1272

* 10% significance; ** 5% significance; *** 1% significance

Table 11 - continued

Panel B: Regression Analysis with Heckman Adjustment

	B.1: Panel Regression			B.2: Fama-MacBeth Regression		
	Carhart 4-factor alpha	Fama-French 3-factor alpha	Jensen's alpha	Carhart 4-factor alpha	Fama-French 3-factor alpha	Jensen's alpha
SDI	0.005***	0.004***	0.009***	0.043	0.084***	0.229***
(*t*-stat)	(7.23)	(5.92)	(8.97)	(1.28)	(2.97)	(4.78)
Heckman lambda	-0.036***	-0.036***	-0.030***	-2.972***	-2.921***	-2.772***
	(-25.84)	(-24.48)	(-20.18)	(-19.29)	(-20.06)	(-16.66)
Management fee	-0.002***	-0.002***	-0.002***	-0.096***	-0.101***	0.013*
	(-5.90)	(-5.55)	(-4.99)	(-9.28)	(-10.95)	(1.74)
Fund age	0.000***	0.000***	-0.000	0.004***	0.004***	0.003***
	(17.73)	(15.79)	(-0.68)	(15.81)	(15.93)	(14.82)
Return volatility	-0.045***	-0.037***	0.018***	-4.176***	-3.573***	-4.462***
	(-31.15)	(-24.50)	(10.37)	(-5.20)	(-4.20)	(-3.66)
ln(Total net assets)	-0.002***	-0.002***	-0.002***	-0.090***	-0.088***	-0.087***
	(-27.41)	(-27.24)	(-29.56)	(-19.71)	(-19.93)	(-16.14)
Total number of funds	6239	6239	6239			
Total number of observations	369319	369319	369319	369 319	369 319	369 319
R^2 (%)	14.37	12.23	15.1	16.08	15.77	18.37

* 10% significance; ** 5% significance; *** 1% significance