THE EXISTENCE OF SKILLED FUND MANAGERS

A STUDY ON ACTIVELY MANAGED MUTUAL FUNDS IN THE US MARKET

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The existence of skilled fund managers: A study on actively managed mutual funds in the US market

Abstract:

This paper uses a dataset of 19 689 domestic actively managed mutual funds in the US market during 1980-2020 to find the proportions of skilled- and unskilled funds. The method is based on the false discovery approach applied in a financial setting. We conclude that 58% of our sample are zero-alpha funds, 42% unskilled, and 0% skilled. We also show that, during 1980-2020, the number of skilled funds has decreased to zero, whereas unskilled funds have increased. Our results can be explained by the characteristics of actively managed funds such as high costs and the attempt to pick stocks. Additionally, our results show that the decrease in skilled funds coincides with an increase in the number of funds, suggesting a higher level of market efficiency.

Keywords: Mutual Fund Performance, Skill, Active Management, Alpha

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Introduction

Mutual funds are tradeable products within the financial industry where individuals can grow their wealth. A mutual fund pools investors' money and invests in financial securities. When entering the market, investors seek mutual funds that can give the highest returns. There are two sides regarding what type of investment strategy provides the best returns, passive versus active. The main difference is that actively managed mutual funds have the objective to outperform the market. In contrast, passive funds only strive to reflect its benchmark index. This discrepancy explains the difference in the fee structure. Since active mutual funds aim to outperform the market, they charge a higher fee than passive mutual funds (Miller 2007).

In 2019, the estimated number of mutual funds worldwide were 123 000, with a total of $54,9 trillion assets under management (Statista 2019 & Investment Company Institute 2020). Researchers have investigated this market in different geographical locations to identify if there exist fund managers that possess the skills to pick stocks that outperform the market net of fees. Most of the research has concluded that a small proportion of mutual fund managers outperform (Wermers 2000, Barras et al. 2010, Kosowski et al. 2006 and Cuthbertson et al. 2012), while other papers have concluded that there is no evidence of persistent stock-picking skills (Fama & French 2010). The research in this area has mainly focused on the performance of funds. However, only a few have investigated and brought up the discussion of whether the overperformance is due to luck or skill (Barras et al. 2010). The absence of distinguishing between luck or skill has resulted in the following research question:

Are actively managed mutual funds that present significant alphas skilled or lucky?

Our research question is answered by first replicating and then extending the research of Barras et al. (2010). The authors use a new approach within financial research to control for false discoveries in a multiple fund setting. They separate funds into unskilled, skilled, and zero-alpha funds by only estimating the proportion of zero-alpha funds through p-values of each fund's estimated alpha. This method enables the estimation of the proportions of the three skill groups and their location in the left- and right tail of the cross-sectional t-distribution. The methodology is simple and has proven to be robust and accurate (Andrikogiannopoulou & Papakonstantinou 2020).

We follow the methodology in Barras et al. (2010) and limit our data to the US market, including all actively managed mutual funds investing in domestic equity. We have chosen to pursue our research on the US market since it is the largest fund industry in shares of assets held (Statista 2019). Therefore, our research covers a broad spectrum of the total fund universe.

Further, we include all domestic actively managed mutual funds in our primary sample from 1980 to 2020 to determine the proportions of zero-alpha, skilled, unskilled, lucky, and unlucky funds. This sample is also used to identify the development of zero-alpha, skilled and unskilled funds over time by dividing the period into non-overlapping five-year periods. Another sample that we also use in our research is Growth and Growth & Income funds during 2010-2020, which are the same fund styles that are used in the paper of Barras et al. (2010). We believe our research is valuable for US investors as it examines if actively managed mutual funds could be a preferable investment strategy. We also consider that our research should be beneficial for investors and researchers worldwide since the findings will be of general interest.

Our empirical findings are the following: In our main sample of 19 689 funds, our results reveal that 42% are unskilled, 0% are skilled, and 58% are zero-alpha. Of the significant proportion of funds, our results show that most funds in the left tail are unskilled given the different significance levels. There are no skilled funds in the right tail at any significance level, and the significant proportion of funds observed in the sample does not exceed the estimated proportion of lucky funds. Hence, in a group setting, all significant funds in the right tail are lucky. The study of the development of our primary sample over time shows a significant increase of unskilled funds and a decrease in skilled funds. Regarding the proportion of zero-alpha funds, it is relatively consistent over time. The study of Growth and Growth & Income funds is similar to our main sample regarding the significant proportions of funds. Most of the funds in the left tail are unskilled at all given significance levels. In the right tail, there is no proportion of skilled funds; all significant funds are lucky in this group setting. The proportion of zero-alpha funds in this study is 38%, unskilled 62% and skilled 0%.

Several factors contribute to our results. The first factor is market efficiency. The results show the increase in the number of mutual funds during 1980-2020, suggesting that the competition for finding positive alphas has increased. This phenomenon of a growing fund industry could also be a sign of market efficiency (G'arleanu and H. Pedersen 2018). Also, the technology development could be a factor making it more challenging for a manager to seek positive alphas since information is processed more rapidly (Hendershott 2010). Furthermore, the second factor driving the results is costs. Actively managed mutual funds have high expense ratios, making it more difficult for the fund manager to pick stocks well enough to cover their costs. In addition, these funds also have non-reported costs that could be nearly six times higher than the published expense ratios (M. Miller 2007). The third factor explaining our results could be market timing. When being in and out of the market, the risks of missing out on the best days increase, driving down the funds' returns significantly (J.P Morgan 2021).

The remainder of the paper is as follows: The first section will present related literature to our area of research. The second section will discuss our empirical background, including the methodology and data. Section three contain the empirical analysis, where we present and discuss the results of our study, while section four concludes.

Related literature

Methodology and results in the literature

The performance of mutual funds is well tested and documented using different methods, however, reaching similar results. The most common method was to use alpha as the performance measure, obtained from the risk-adjusted returns based on either the three- or the four-factor model (Fama & French 1993 and Carhart 1997), and then count the number of funds with significant alphas in different portfolio constructions (Carhart 1997). The results indicated that significant outperformance does not persist over an extended period of time due to transaction costs and expense ratios. Further, research regarding the long-term underperformance of actively managed funds concludes that only 1% of actively managed funds overperform (Wermers 2000 and Fama & French 2010). Wermer's paper studies the expected return and decomposes it into different explaining variables such as costs and stock-picking talent. Fama and French uses expected alpha through bootstrap simulations as the performance measure. Their paper also shows that overperformance exists in the extreme tails before costs. The underperformance of actively managed mutual funds has been concluded even earlier (Malkiel 1995). The author showed that the underperformance holds gross of fees during the period of 1982-1991.

On the contrary, there is evidence in the US market that managers exhibit skills and can pick stocks well enough to cover, or even exceed, their costs (Kosowski et al. 2006). The authors use a bootstrap procedure to uncover the distribution of the cross-sectional fund alphas, similar to the procedure proposed by Fama and French (2010); however, distinguishing between luck and skill. By doing so, they were able to uncover the true significant funds and concluded that specifically Growth funds showed superior performance, which was not solely due to luck. Moreover, another study has further tried to distinguish between skilled and lucky funds and found evidence that the proportion of skilled funds is 0.6% of actively managed funds and that 75.4% are zero-alpha funds (Barras et al. 2010). Their method is to test the performance in a multiple fund setting, contrary to the study by Kosowski et al. (2006), which tested the funds separately. Controlling for false discoveries, a method originally proposed to minimize statistical errors (Storey 2002), proved to be a robust method and was confirmed in a reply (Andrikogiannopoulou & Papakonstantinou 2020). In addition, a UK study used the same method reaching similar results (Cuthbertson et al. 2012).

Similar research has been conducted but during periods of crisis and uncommon events. There is evidence that funds tend to perform better during a crisis (Kosowski 2011). The study shows that the funds performed three to five percent better during the recessions and crises in 1962-2005. On the other hand, recent evidence during the Corona pandemic shows that actively managed mutual funds instead tend to underperform during crises (Pástor and Vorsatz 2020).

Moreover, research has shown that instead of using a fund's alpha, one can use the dollar-value added amount (Berk and Binsbergen 2015). The authors find that an average mutual fund adds value in monetary terms, which also is persistent over time. In addition to their value-added method, they test the funds with tradable assets as risk adjustment. Their results indicated that skilled mutual fund managers exist and, more importantly, indicates that they add monetary value. Lastly, the model of Berk and Green (2004) implies that all active managers exhibit a zero-alpha net of costs. This finding contradicts some of the results mentioned previously, as previous studies support that the majority of funds have true negative alphas net of costs.

Actively managed funds' characteristics

A difficult aspect to consider in the research area of the performance of mutual funds is the potential for survivorship bias. In general, it overestimates a mutual fund portfolio's performance since the predominant reason for closing a fund is underperformance (Rohleder et al. 2011). They also presented a survivorship bias amounting to 0.14% in a fund sample during 1993-2006. Additionally, the authors found evidence that value-weighted portfolios of mutual funds lead to a more negligible bias, both statistically and economically significant. However, since several databases are free of survivorship bias today, the use of a value-weighted portfolio is not necessary.

Moreover, costs are another critical aspect to consider when examining mutual funds' performance in general and active funds in particular. Due to the nature of actively managed mutual funds, they charge higher management fees and generate higher transaction costs and other costs associated with the nature of stock-picking (Miller 2007). When determining the active share of a fund and decomposing the costs into one passive- and one active share, evidence shows that the true mean active expense ratio is 7% instead of the published expense ratio of 1,5% (Miller 2007). In addition, the high turnover ratio has also shown to contribute to costs and subsequently contribute to underperformance (Champagne et al. 2018). Another characteristic of actively managed mutual funds is that they, on average, demand immediacy and not provide immediacy (Rinne & Suominen 2014). Demanding immediacy is a phenomenon where funds have to trade an asset due to e.g., a specific market event. Providing immediacy on the other hand, is when funds do not have to trade an asset and can instead provide the asset to those who demand it. Demanding immediacy is associated with costs and is a factor that explains the underperformance of actively managed mutual funds. The costs explanatory power can be illustrated with an arithmetic argument (Sharpe 1991). If the gross return of both passive and active funds is the same, then it must be the case that the return of active management is less due to higher costs.

Further, the fund industry consists of actively- and passively managed mutual funds, but the industry has seen a shift towards passive investing among investors (Anadu et al. 2020). The proportion of these two types of funds is central in the research area of market efficiency. A recent study concludes that the market efficiency is approximated by the search costs for investors and the information costs for the managers (G'arleanu and H. Pedersen 2018). Another prediction from the model they use is that the high fees associated with active management are due to the high search cost for the managers. Also, the development of technology has changed the way how securities are traded and have resulted in more efficient pricing of securities (Hendershott 2010).

Contribution

Most of the research use well-known models such as the Capital Asset Pricing Model and the three- and four-factor model. However, recent studies have extended the literature with different methods to distinguish between luck and skill. Our contribution to the previous literature is to continue testing the recent models, in this case the false discovery approach. We will test the performance of the whole domestic active mutual fund universe in the US market, extending the period up to the end of 2020. This will include the recent crisis caused by Covid-19. We will also study the development of domestic mutual funds in the US market between 1980-2020. As such, this thesis is closely related to the literature mentioned above and seeks to extend and develop the existing research further.

Hypotheses

The proportion of skilled fund managers

Most prior research concludes that skilled fund managers exist in a small proportion. Hence, we expect to find a small proportion of skilled fund managers exhibiting stock-picking skills to cover their costs during 1980-2020.

This paper investigates the hypothesis by testing two samples with the use of the false discovery approach. The first sample includes all US domestic actively managed mutual funds, and the second includes US Growth and Growth & Income funds, investing in domestic equity. Thus, our first hypothesis is the following:

Hypothesis 1: There exists a small proportion of skilled fund managers during 1980-2020.

The proportion of skilled fund managers over time

More recent papers identifies that the proportion of skilled fund managers has decreased over time, whereas the proportion of unskilled fund managers has increased. Therefore, we expect to find a similar trend during 1980-2020.

We test the hypothesis by testing the sample of all US domestic actively managed mutual funds in non-overlapping five-year periods with the false discovery approach. Thus, our second hypothesis is the following:

Hypothesis 2: During the time period of 1980-2020 the proportion of skilled fund managers decrease, and the proportion of unskilled fund managers increase.

Methodology

We will replicate the method by Barras et al. (2010), and the complete methodology is in his paper. The method is new in finance theory and has recently been confirmed as robust by Andrikogiannopoulou & Papakonstantinou (2020). This section will describe the method and present the regression framework.

Briefly, the basis of this method is a standard procedure of testing each fund's performance independently. However, the false discovery approach will be added to measure the proportion of zero-alpha-, unskilled- and skilled funds. The definitions of the three skill-groups are as defined by Barras et al. (2010):

- *Zero-alpha funds*: Funds with managers with stock-picking skills sufficient to recover its costs and expenses, $(\alpha = 0)$
- *Unskilled funds*: Funds with managers with stock-picking skills insufficient to recover its costs and expenses, $(\alpha < 0)$
- *Skilled funds*: Funds with managers with stock-picking skills sufficient to exceed its costs and expenses, $(\alpha > 0)$

To calculate the frequency of each different skill group, the t-statistic of each fund's alpha is used to observe significant funds in the left- and right tails of the t-distribution. The t-statistic replaces alpha as the performance measure since it has greater statistical properties (Kosowski et. al 2006). The t-statistic is extracted through a multiple hypothesis test from fund *i* to fund M, where M is the sample size. The null hypothesis is that all funds are zero-alpha funds compared to the alternative hypothesis that funds have either positive or negative alpha values.

$$H_0: \alpha_i = 0, H_A: \alpha_i \neq 0$$

$$\ldots$$

$$H_0: \alpha_M = 0, H_A: \alpha_M \neq 0$$

A multiple hypothesis test comes with difficulties, such as determining the significance level at which a fund is considered to have a significant p-value. For simplicity, at any given significance level, γ, the probability that zero-alpha funds exhibit bad- or good luck is defined as $\gamma/2$. Hence, given the proportion of zero-alpha funds, π_0, the proportion of lucky funds, which is significant funds that are truly zero-alpha, is calculated as the following (a full description of the notations is presented in Appendix table 6):

$$E(F_\gamma^+) = \pi_0 * \gamma/2 \tag{1}$$

If the entire proportion of significant positive-alpha funds is denoted as $E(S_\gamma^+)$, then using equation (1), we can derive the proportion of truly skilled funds as:

$$E(T_\gamma^+) = E(S_\gamma^+) - E(F_\gamma^+) = E(S_\gamma^+) - \pi_0 * \gamma/2 \tag{2}$$

Since the probability of the fund being either lucky or unlucky is the same, the expression for deriving the proportion of truly unskilled managers is the same as equation (2), except that we solve for $E(T_\gamma^-)$:

$$E(T_\gamma^-) = E(S_\gamma^-) - E(F_\gamma^-) = E(S_\gamma^-) - \pi_0 * \gamma/2$$

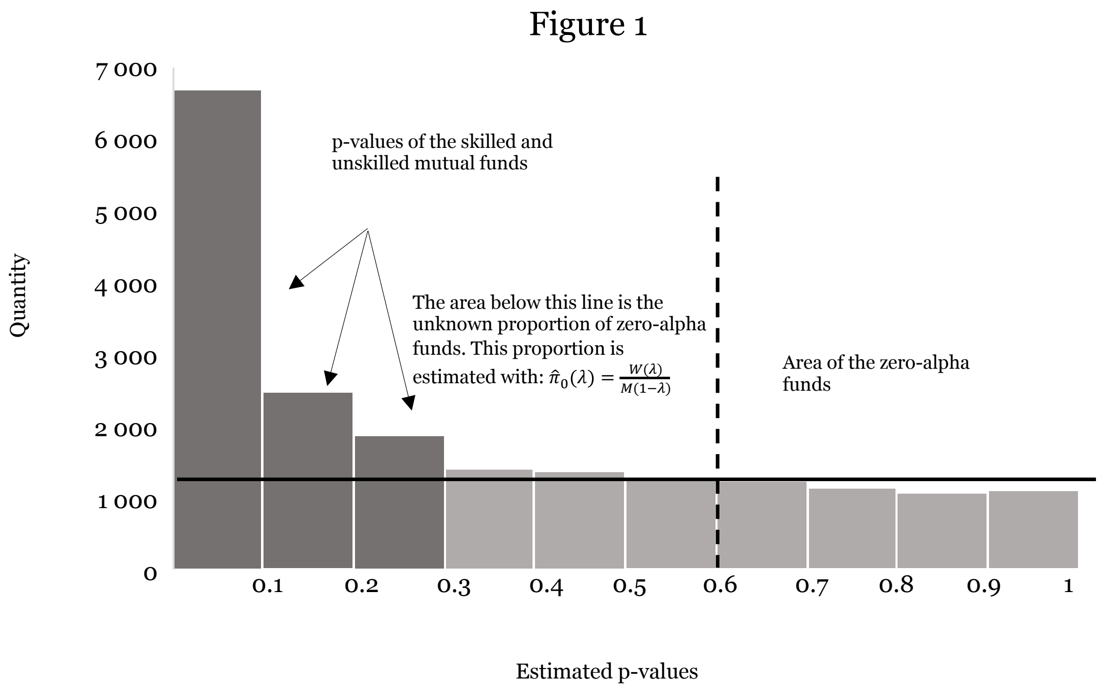
One of the additional objectives in the study by Barras et al. (2010) and ours is to locate the skilled- and unskilled funds in the tails. This is done by testing different values for the significance level, γ, and examining if the number of skilled- or unskilled funds rise or fall in γ. If they rise, they are dispersed in the tails; otherwise, the funds are most likely concentrated around a specific significance level.

The only requirement to calculate the above equations is an estimation of the true proportion of zero-alpha funds, π_0. Here, the false discovery approach, FDR (Storey 2002), is used, where its inputs are two-sided p-values associated with the alpha t-statistics of every individual fund. The FDR approach builds upon the information from the centre of the cross-sectional distribution between the three skill groups. It is dominated by the funds exhibiting a zero alpha, and it is possible to correct the tails for luck and unluck, respectively. Suppose we draw t-statistics from the same distribution, i.e. all funds are zero alpha funds. The resulting p-values associated with the t-statistics would be evenly distributed with equal proportions in the respective confidence interval. However, when the t-statistics are drawn from different distributions, the significant observations will overlap and show a greater proportion of small p-values (which corresponds to significant t-statistics). Hence, we can correct for luck and unluck in the tails, respectively, by estimating the proportion of zero-alpha funds with the histogram shown in figure 1. Then subsequently determine the proportion of skilled and unskilled funds.

When estimating the p-values, the FDR approach allows us to calculate the proportion of zero-alpha funds without knowing the distribution of the skilled- and unskilled p-values. The procedure is based on the fact that zero-alpha funds satisfy the null-hypothesis and must therefore have p-values uniformly distributed over the interval (0,1). On the contrary, the p-values of skilled- and unskilled funds are small since their t-statistics are significantly far from zero. Our resulting histogram is presented in figure 1.

Figure 1 – Histogram of the funds' p-values

Figure 1 displays the histogram of the p-values obtained from the Carhart four-factor regression during the period of January 1980 to December 2020. The histogram represents a sample of 19,689 US actively managed mutual funds. The threshold for estimating the proportion of zero-alpha funds is set to 0.6 ($\lambda^* = 0.6$).



If a sufficiently high threshold, λ^*, is set, we know that a sizable majority of the funds exceeding that threshold is zero-alpha funds. In our calculations, we set λ^* to 0.6, supported by Barras et al. (2010), who tested its sensitivity with a bootstrap procedure. After setting the λ^* to 0.6 we can calculate the area consisting of merely zero-alpha funds and extend it over the entire region, the whole area below the line in figure 1. The calculation is based on the following formula:

$$\hat{\pi}_0(\lambda) = \frac{W(\lambda)}{M(1-\lambda)},$$

where $W(\lambda)$, is the number of funds having p-values greater than λ^* and M is the number of funds included in the sample. Notably, this methodology was used in the study by Barras et al. (2010) and was tested against a Monte Carlo analysis that confirmed this approach's robustness.

Using equation (1) and substituting π_0 with the estimated proportion of zero-alpha funds, $\hat{\pi}_0$, we can obtain the estimated proportion of lucky- and unlucky funds through the following formula:

$$\hat{F}_{\gamma}^{+} = \hat{F}_{\gamma}^{-} = \hat{\pi}_0 * \gamma/2$$

Also, we replace $E(S_{\gamma}^{+})$ and $E(S_{\gamma}^{-})$ with the observed proportion of significant funds in the right and left tail and substituting the result in equation (2) in combination with equation (1). We get the following two equations estimating the proportion of skilled and unskilled funds:

$$\hat{T}_{\gamma}^{+} = \hat{S}_{\gamma}^{+} - \hat{F}_{\gamma}^{+} = \hat{S}_{\gamma}^{+} - \hat{\pi}_0 * \gamma/2$$

$$\hat{T}_{\gamma}^{-} = \hat{S}_{\gamma}^{-} - \hat{F}_{\gamma}^{-} = \hat{S}_{\gamma}^{-} - \hat{\pi}_0 * \gamma/2$$

Lastly, the proportions of skilled and unskilled managers in the entire sample of funds are calculated using a sufficiently high threshold of significance level, γ^*. In Barras et al. (2010), this level is set by a bootstrap procedure, however the authors concluded that simply setting γ^* to values between 0.35-0.45 produces similar estimates. Moreover, the threshold must be high enough to capture all skilled and unskilled funds in cases where the funds are spread out in their respective tails. When we chose a threshold between 0.35-0.45 that captured all of the significant funds, we calculated the proportions using the following equations:

$$\hat{\pi}_A^{+} = \hat{T}_{\gamma^*}^{+}$$
$$\hat{\pi}_A^{-} = \hat{T}_{\gamma^*}^{-},$$

where $\hat{\pi}_A^{+}$ and $\hat{\pi}_A^{-}$ denote non-zero alpha funds that are skilled and unskilled, respectively.

The regression framework

We use the four-factor model presented by Carhart (1997), an extension to the Fama-French three-factor model (1993) as the momentum factor has been added. This will be the basis for the regression as well as for calculating the performance of the funds:

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

where $r_{i,t}$ is the month *t* excess return of fund *i* over the risk-free rate, which is a proxy of the one-month T-Bill rate; $r_{m,t}$ is the month *t* excess return on a value-weighted portfolio on all NYSE, AMEX and NASDAQ stocks; and $r_{smb,t}$, $r_{hml,t}$ and $r_{mom,t}$ are the month *t* excess returns for the factors size, book-to-market and momentum.

Each fund's alpha and t-statistics are calculated by running a multiple regression of all the funds individually. According to prior research by Kosowski et al. (2006), a fund's t-statistic has superior statistical properties compared to its alpha and is therefore the parameter used to determine the performance of funds. Further, the two-sided p-value is also obtained from the multiple regression.

Data

Our mutual funds sample and the factors in the four-factor model are retrieved from the Center for Research in Security Prices, CRSP, a Wharton Research Data Services product, WRDS. We use the CRSP objective codes for the funds and other sorting tools provided with the following criteria:

- The fund must be open to investors;
- it must be categorized as an actively managed mutual fund;
- and it must only invest in domestic equity.

While the sample is free from survivorship bias, only funds that have a minimum of 60 months of return have been included in an attempt to obtain as precise alpha estimations as possible. Also, funds with monthly returns labeled as zero are treated as a missing return since CRSP have no data on these months. The returns from CRSP are net of fees; hence, later calculations will be based on the net of fees returns.

Our final sample of funds consists of 19,689 funds with at least 60 months of return between 1980 – 2020. This sample is complemented with a sample of 7,410 Growth and Growth & Income funds from 2010 – 2020. Table 1 provides the estimated annual alpha and the factor loadings for our primary sample of 19,689 funds, where we constructed equally weighted portfolios. The portfolios are rebalanced every month to ensure that funds existing at the beginning of the month are included.

Table 1 – The performance of Equally-Weighted Portfolio of Funds

The descriptive statistics for the Carhart four-factor model regarding the equally weighted portfolio of all funds are shown in table 1. The regression is based on monthly data between January 1980 to December 2020 which includes all actively managed funds within in the US market, investing in domestic equity. The portfolio is rebalanced every month to include all funds that exists in the beginning of the month. Table 1 consists of the estimated annualized alpha, $\hat{\alpha}$, the estimated exposure to the market, $\hat{b}_m$, size, $\hat{b}_{SMB}$, book-to-market, $\hat{b}_{HML}$, and momentum factors, $\hat{b}_{MOM}$. Also, the adjusted R^2 of the equally weighted portfolio is shown, which includes all the funds at the beginning of each month. The second row of the table depicts the standard error for each factor.

TABLE 1						
	$\hat{\alpha}$	$\hat{b}_m$	$\hat{b}_{SMB}$	$\hat{b}_{HML}$	$\hat{b}_{MOM}$	R^2
All funds (19,689)	-1.13%	0.904	0.173	0.017	-0.003	0.98%
(Standard error)	0.000	0.007	0.010	0.010	0.006	

Similar to previous studies, we found a negative annualized alpha in our sample. The factor loadings are tilted towards the market, and the R squared explains 98% of the variation in the portfolio. The results presented later are based on the statistical characteristics in table 1.

Evaluation of method and data

Barras et al. (2010) provide the reader with several tests confirming the robustness of their method. They use a Monte Carlo simulation to confirm that the results are in line with the true values. The simulation also demonstrates that the method is not overly concerned with cross-sectional dependencies. This is also the case for our sample as the multiple hypothesis test was conducted without any issues regarding predictability in returns. Moreover, problems can arise when the sample is too small. Therefore, we use a large sample (Barras et al. 2010).

Further, a criticism of this type of method regarding linear regression is that it assumes that the returns follow a normal distribution. According to Kosowski et al. (2006), this could lead to errors and therefore bootstrapping is necessary. However, the method has proved to be successful, even when assuming normality in the distribution. The estimates have been proven to be statistically robust, both in the paper by Barras et al. (2010) and in the reply by Andrikogiannopoulou & Papakonstantinou (2020). Concerning the FDR procedure used in this study, the tests can be done without any knowledge about the distribution of p-values, which is the only input needed to calculate the proportions.

Moreover, it is relevant to mention the contribution this method has in the research of finance. It is revolutionary in the sense that it enables to control for luck in a multiple fund setting. Instead of simply setting a chosen threshold for a significant alpha and count the number of funds exceeding the threshold (Carhart 1997), the false discovery approach can identify type I errors and more accurately determine the proportion of the truly skilled and unskilled funds, respectively. It also builds upon the critical finding from Kosowski et al. (2006) that t-statistics, instead of alpha, as a performance measure has superior statistical properties and provides more accurate results.

Results

This section will present the results of our study. We will present the results from our main sample (1980-2020 all US domestic equity funds), followed up by an additional test of the main sample, where we test the performance in nine sequential non-overlapping periods of five years. Lastly, we present the results from the sample that is an extension of Barras et al. (2010), where we select the same type of funds during a more recent period (2010-2020).

1980-2020 US domestic mutual funds

First, we start by measuring the proportion of zero-alpha funds, skilled funds and unskilled funds during the period of 1980-2020 of all actively domestic equity funds available on the US market. With our entire sample of 19,689 funds, we estimate that 58% (11,458) are zero-alpha funds. The proportion of skilled and unskilled funds is yet to be presented (see table 2).

Table 2 – The proportion of the three skill-groups during 1980 – 2020

The performance is measured with the Carhart four-factor model during the period of 1980-2020. Table 2 shows the estimated proportions of zero-alpha, $\hat{\pi}_0$, unskilled, $\hat{\pi}_0^-$, and skilled funds, $\hat{\pi}_0^+$, of the whole fund sample of 19 689 funds. The estimated proportion is determined at a significance level of 0.35 ($\gamma^* = 0.35$) and the lambda threshold is 0.6 ($\lambda^* = 0.6$).

TABLE 2				
	Zero-alpha ($\hat{\pi}_0$)	Non-zero alpha	Unskilled ($\hat{\pi}_0^-$)	Skilled ($\hat{\pi}_0^+$)
Proportion	58%	42%	42%	0%
Quantity	11458	8231	8231	0

Furthermore, we also estimate that 42% (8,231) of our sample of funds are unskilled, and 0% are skilled (see table 2). There does not exist fund managers who can outperform the market net of costs; instead, the funds are zero-alpha- or unskilled funds. Hence, these results reject the first hypothesis that there exists a small proportion of skilled fund managers.

By looking at our sample in more detail, table 3 shows that adjusting for luck gives a deeper understanding of our results. Table 3 gives us the proportion of significant alpha funds in both the left- and right tails at four significant levels (γ = 0.05, 0.1, 0.15, 0.20). In more detail, in Panel A the significant group in the left tail is divided into unlucky and unskilled funds. Panel B shows the significant group in the right tail divided into lucky- and skilled funds.

Table 3 – The location of the skilled and unskilled funds in the right and left tail respectively during 1980-2020

Table 3 shows the location of the proportions during the period of January 1980 to December 2020. Panel A exhibits the proportions of the significant funds in the left tail of the cross-sectional t-statistic distribution. The significant proportion, $\hat{S}_\gamma^-$, displays the observable proportion of significant funds in the left tail and the unlucky, $\hat{F}_\gamma^-$, - and unskilled, $\hat{T}_\gamma^-$, proportions are estimated. The distributions are counted at the following significance levels: $\gamma = 0.05, 0.10, 0.15, 0.2$.

Table 3 Panel B exhibits the proportions of the significant funds in the right tail of the cross-sectional t-statistic distribution. The significant proportion, $\hat{S}_\gamma^+$, displays the observable proportion of significant funds in the right tail and the lucky, $\hat{F}_\gamma^+$, - and skilled, $\hat{T}_\gamma^+$, proportions are estimated. The distributions are counted at the following significance levels: $\gamma = 0.05, 0.10, 0.15, 0.2$.

TABLE 3 PANEL A				
	Left tail			
Significance level (γ)	0.05	0.1	0.15	0.2
Significant proportion ($\hat{S}_\gamma^-$)	24.45%	32.23%	38.30%	43.02%
Unlucky ($\hat{F}_\gamma^-$)	1.45%	2.91%	4.36%	5.82%
Unskilled ($\hat{T}_\gamma^-$)	23,00%	29,32%	33,93%	37,20%

TABLE 3 PANEL B				
	Right tail			
Significance level (γ)	0.05	0.1	0.15	0.2
Significant proportion ($\hat{S}_\gamma^+$)	1.29%	2.12%	2.89%	3.81%
Lucky ($\hat{F}_\gamma^+$)	1.45%	2.91%	4.36%	5.82%
Skilled ($\hat{T}_\gamma^+$)	0.00%	0.00%	0.00%	0.00%

Our results in table 3 Panel A show that the proportion of significant alpha funds is high in the left tail, with the highest level of 43,02% at $\gamma = 0{,}20$. Also, we see a high percentage of truly unskilled funds far out in the tail and that the number funds that are unlucky is only a small fraction of all the significant funds. Further, in table 3 Panel B, we see that the proportion of lucky funds exceeds the observable number of significant funds. This means that the observable significant funds are less than the model's prediction of lucky funds; all the significant funds in the right tail are lucky. In other words, the amount of type I errors is higher in the right tail than in the left tail.

1980-2020 Five-year periods
Our second test consists of the same method as earlier, only that we have split the period of 1980-2020 into non-overlapping 5-year periods with separate regressions for each period. The tests are done with funds with at least 30 months of returns during the examined period, and new funds are added when they have existed for 30 months during the particular period. The purpose of this is to identify the development of the proportions of zero-alpha, skilled and unskilled funds over time. Figure 2 shows the development and in Appendix table 8 the proportions for each period is shown. The results indicate that, over time, the proportion of skilled funds decrease to zero, whilst the proportion of unskilled funds increase. These results are in line with the second hypothesis that there is a decrease of skilled fund managers and an increase in unskilled fund managers over time.

Also, we see how the proportion of zero-alpha funds over time has slightly decreased with a significant decline after the financial crisis in 2008-2009. The decline in zero-alpha funds is shown in the figure to have caused a similar increase in the proportion of unskilled funds.

Figure 2 – Development of the proportions of the three skill-groups during 1980 - 2020

Figure 2 displays the development of the proportions of zero-alpha funds, unskilled-, and skilled funds during January 1980 to December 2020. The estimation of the development is based on nine non-overlapping 5-year periods using the Carhart four-factor model. Every period includes funds with returns at least half of the period and new funds are added when they have existed for 2.5 years.

Growth and Growth & Income

The third part of our results is an extension of Barras et al. (2010) sample. We extend their study by analyzing Growth and Growth & Income funds during a more recent period, 2010-2020. The sample consists of 7,410 funds and the histogram of the p-values is in figure 4 in Appendix and the descriptive statistics are shown in table 7 in Appendix. Table 4 summarizes our results, and the proportion of zero-alpha funds, skilled funds, and unskilled funds are 38%, 0% and 62%, respectively. Hence, this sample also rejects the first hypothesis that there exist skilled fund managers.

In addition, we also see, in table 5 Panel B, the only funds that are statistically significant are lucky at any given significance level. Also, in table 5 Panel A, most of the significant proportion of funds are truly unskilled. The highest proportion is at the significance level γ = 0,20, where the proportion of unskilled funds was 55,79%. Our results indicate that the majority of all fund managers underperform the market and that during the period of 2010-2020 there are only lucky fund managers that overperform the market.

Table 4 – The proportion of the three skill-groups during 2010 - 2020

The performance is measured with the Carhart four-factor model during the period of 2010-2020. Table 4 shows the estimated proportions of zero-alpha, $\hat{\pi}_0$, unskilled, $\hat{\pi}_0^-$, and skilled funds, $\hat{\pi}_0^+$, of the Growth and Growth & Income sample of 7,410 funds. The estimated proportion is determined at a significance level of 0.35 ($\gamma^* = 0.35$) and the lambda threshold is 0.6 ($\lambda^* = 0.6$).

TABLE 4				
	Zero-alpha ($\hat{\pi}_0$)	Non-zero alpha	Unskilled ($\hat{\pi}_0^-$)	Skilled ($\hat{\pi}_0^+$)
Proportion	38%	62%	62%	0%
Quantity	2808	4602	4602	0

Table 5 – The location of the skilled and unskilled funds in the right and left tail respectively during 2010-2020

Table 5 shows the location of the proportions during the period of January 2010 to December 2020 in regard to Growth and Growth & Income funds. Panel A exhibits the proportions of the significant funds in the left tail of the cross-sectional t-statistic distribution. The significant proportion, $\hat{S}_{\gamma}^{-}$, displays the observable proportion of significant funds in the left tail and the unlucky, $\hat{F}_{\gamma}^{-}$, - and unskilled, $\hat{T}_{\gamma}^{-}$, proportions are estimated. The distributions are counted at the following significance levels: $\gamma = 0.05, 0.10, 0.15, 0.2$.

Table 5 Panel B exhibits the proportions of the significant funds in the right tail of the cross-sectional t-statistic distribution. The significant proportion, $\hat{S}_{\gamma}^{+}$, displays the observable proportion of significant funds in the right tail and the lucky, $\hat{F}_{\gamma}^{+}$, - and skilled, $\hat{T}_{\gamma}^{+}$, proportions are estimated. The distributions are counted at the following significance levels: $\gamma = 0.05, 0.10, 0.15, 0.2$.

TABLE 5 PANEL A				
	Left tail			
Significance level (γ)	0.05	0.1	0.15	0.2
Significant proportion ($\hat{S}_{\gamma}^{-}$)	38.84%	48.25%	54.54%	59.58%
Unlucky ($\hat{F}_{\gamma}^{-}$)	0.95%	1.89%	2.84%	3.79%
Unskilled ($\hat{T}_{\gamma}^{-}$)	37.90%	46.36%	51.70%	55.79%

TABLE 5 PANEL B				
	Right tail			
Significance level (γ)	0.05	0.1	0.15	0.2
Significant proportion ($\hat{S}_{\gamma}^{+}$)	0.16%	0.30%	0.54%	0.76%
Lucky ($\hat{F}_{\gamma}^{+}$)	0.95%	1.89%	2.84%	3.79%
Skilled ($\hat{T}_{\gamma}^{+}$)	0.00%	0.00%	0.00%	0.00%

Discussion of results

The results from our main sample show that most funds perform like index funds, meaning that the majority of funds are zero-alpha funds. Since most of the other actively managed mutual funds that attempt to beat the market are unskilled, investing in an index fund with low fees is arguably a preferable choice for an investor. These findings are in line with similar research conducted on the same and different markets. In the paper of Barras et al. (2010), their research was conducted on an earlier period (1975-2006), focusing on Growth and Growth & Income funds in the US market. Their findings reached the same conclusion as ours: the vast majority of active funds do not manage to overperform the market. In addition, Cuthbertson et al. (2012) used the same method as Barras et al. (2010), but on the UK market. They reached similar results where most mutual funds did not manage to exhibit stock-picking skills well enough to cover their costs. Another study focused on the US market in 1982-1991 and concluded that the sample of funds had in aggregate underperformed their benchmark portfolios net of fees (Malkiel 1995). Fama and French's (2010) studied the US market 1984-2006 and the results show the difficulties of fund managers in producing benchmark-adjusted expected returns well enough to cover their costs. Thus, prior research supports the results of our study.

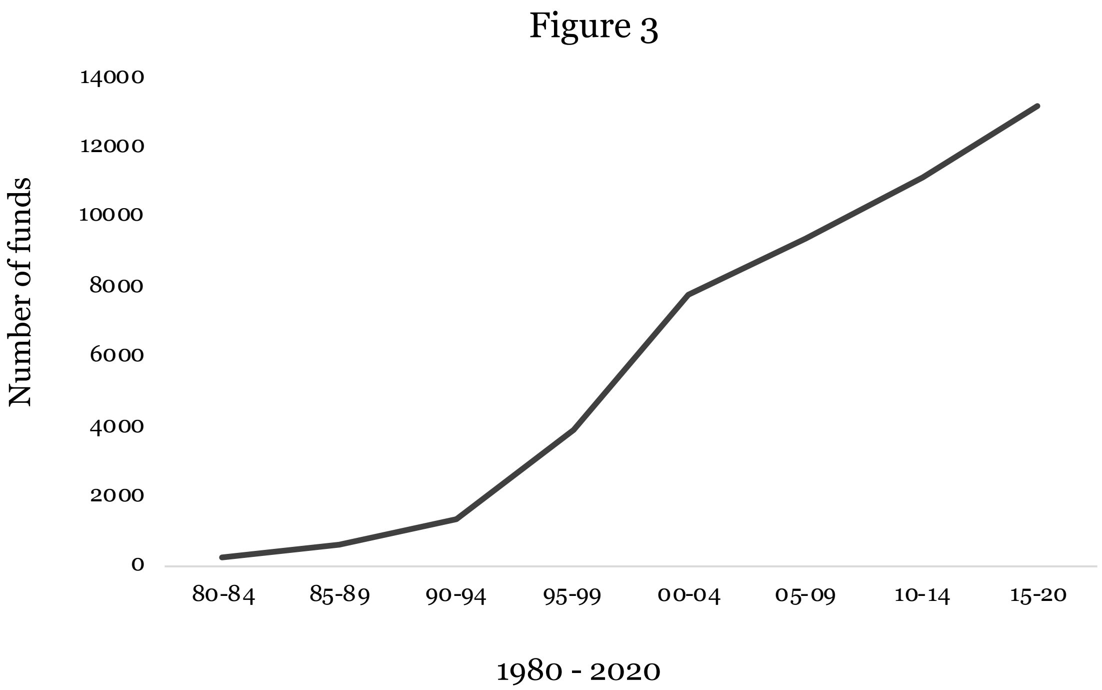
The results from table 2 show that the proportion of unskilled funds and zero-alpha funds accounts for 100% of all actively managed mutual funds in the US market. Prior studies discuss the non-existence of skilled fund managers (Fama & French 2010). However, there exists evidence suggesting the opposite (Kosowski 2006 & Barras et al. 2010). There are some important differences that can explain these inconsistencies. Our results come from a sample of all domestic US equity funds while other studies (Kosowski 2006, Barras et al 2010. and Fama & French 2010) use samples of roughly 2.000-3.500 funds. In other words, we have included more funds and subsequently also different fund categories. When including a larger amount of funds, also including every fund category within active management, the proportion of skilled funds diminishes in that group setting. When we only include Growth and Growth & Income funds as Barras et al. (2010), our results are consistent with theirs (see table 5). On the contrary, our results contradict the results from the dollar-value added method, at least in regard to finding skill (Berk & Binsbergen 2015). However, their finding that there are more negative alpha funds than positive alpha funds is in line with our results. With that said, we can conclude that the essence of our results is consistent with prior literature – the proportion of skilled funds are small, sometimes even zero, compared to the proportion of unskilled- and zero alpha funds.

Furthermore, our results in table 4 and 5 Panel A & B present the recent estimates of the proportions of skilled- and unskilled funds up until 2020 regarding Growth and Growth & Income funds. These results contradict Kosowski et al. (2006), where the authors concluded that managers could pick stocks well enough to cover their costs. A potential factor contributing to the discrepancy is that our results cover an entirely different time period. Important to note is that our time period includes the recovery from the financial crisis in 2008 as well as the more recent crisis during the ongoing Corona pandemic. Kosowski (2011) examines the hypothesis that recessions drive underperformance of funds and concludes that 3%-5% of the funds perform better during a crisis. On the other hand, a more recent study on the corona pandemic during 2020 showed that actively managed mutual funds tend to underperform (Pástor and Vorsatz 2020). Our results, however, imply that the inclusion of periods of crises coincides with underperformance. Therefore, the absence of skilled fund managers during 2010-2020 could be due to the inclusion of a crisis in combination with a shorter investigated period of time. Figure 2 presents the development of the proportions during 1980-2020 and displays the argument that crises drive down fund performance.

As shown in figure 2, the recent trend in the proportion of skilled funds is declining and close, or equal, to zero. Further, the decline of skilled funds is replaced by an increase in the proportion of unskilled funds, while the proportion of zero alpha funds is fairly consistent. One explanation for the decline in skilled fund managers is due to funds closing down. Most of these funds are closing down because of underperformance (Rohleder et al. 2011). Another explanation could be the increase in competition in the mutual fund industry during the last decade. In our research and in that of Barras et al. (2010), the competition for finding positive alphas has increased over time. By comparing the size of the mutual fund sample at the beginning of our period to the end; the number of mutual funds has increased significantly (see figure 3). This phenomenon of a growing fund industry could be a sign of market efficiency. When the asset management industry grows, it does so due to lower information costs for the managers, implying an efficient market (Gˆarleanu and H. Pedersen 2018). Hence, a greater proportion of actively managed funds leading to efficient markets could make it challenging for managers to discover investment opportunities to beat the market.

Figure 3 – Development of the proportions of the three skill-groups during 1980 - 2020

Figure 3 displays the development of number of funds during January 1980 to December 2020. The number of funds is based on nine non-overlapping 5-year periods and funds are only included if they have existed for at least half of the 5-year period.



The development of technology in the last decade could also explain why we see a decrease in skilled fund managers. As computer technology improves, today's systems can act on new information in nanoseconds (Hendershott 2010). This indicates that it is even more difficult for fund managers to distinguish themselves from competitors. These are powerful results but are consistent with prior research demonstrating that most active fund managers underperform the market. We can conclude that an increase in competition due to a growing industry and the rapid technological development has most likely made it more difficult to exhibit stock-picking skills.

Another reason why the proportion of skilled funds are zero, could be the costs and fees involved. The high expense ratios that actively managed mutual funds charge are, in general, high compared to the passive segment in the market. Since we measure performance net of fees, this is a plausible explanation for the large proportion of underperformance. Additionally, Barras et al. (2010) argued that the significant funds in the left tail charge even higher expense ratios, which could also explain our results. However, studies have shown that the existence of skilled- and unskilled managers before costs is not sufficiently different from what our results suggest (Fama & French 2010). Hence, the proportion of skilled- and unskilled managers is consistent before- and after the published expense ratio, indicating that the expense ratio is probably not the only cost contributing to our result. The true cost of an actively managed mutual fund is often significantly greater than its published expense ratio, which is known to the investor (M. Miller 2007). The author concluded that the mean active expense ratio was almost six times higher than the published expense ratio. However, estimations of the trading costs and other additional costs is subject to large errors (Fama & French 2010). What research has shown, however, is that actively managed mutual funds face higher costs. This is due to the nature of actively managed mutual funds tending to trade more, contributing to higher costs and subsequently lower performance (Champagne et al. 2018). Actively managed mutual funds also, on average, demand immediacy (Rinne & Suominen 2014) which is, in addition to high transaction costs (Wermers 2000), a factor that contributes to higher costs. Therefore, the high expense ratios can possibly explain our results, but it is primarily the non-reported costs that make it challenging for fund managers to pick stocks well enough to cover their costs.

The paper of Sharpe (1991) also provides another possible explanation for the high proportion of underperformance and zero-alpha funds. He proposes a simple arithmetic argument. If the return before costs is equal for both active and passive management, assuming efficient markets, the returns after costs must be lower for the active investor. Hence, one reason for the proportion of skilled funds being zero is because costs are high, making it harder to exhibit positive alphas.

Moreover, a further possible reason why there are no skilled funds on a group level in our sample is market timing. Active fund managers use this phenomenon to buy stocks when the market trend is positive and sell when it is negative. Thus, active mutual fund managers try to overperform the market by using their skills to predict market movements in the future. Statistics from J.P Morgan (2021) show that missing the best 30 days of the S&P in 2001-2020 results in a negative annualized return of -1.49%. Instead, being fully invested throughout the whole period would give an annualized return of 7.47%. Hence, this is an example that shows being in and out of the market continuously is a risky method. This is supported by our results as there are no skilled fund managers in our fund sample.

Another aspect of our results is investors' ability to identify the fund managers that can outperform the market. Even if skilled managers exhibit stock-picking skills to cover their costs, these funds are in the fund universe of all managers, including fund managers with insufficient ability to outperform the market. Thus, the process of being able to pick the right mutual funds is difficult. In the study of Gârleanu et al. (2017), the authors discover that there are high research costs related to identifying skilled managers. A further indication and support of research costs being high is the shift of active to passive investing during the last decades. In the US mutual fund and ETF market, passive funds accounted for approximately 41% of AUM in 2020, compared to 3% in 1995 and 14% in 2005 (Anadu et al., 2020). These statistics support the paper of Gârleanu et al (2017) since more capital has been allocated to passive funds, suggesting that search costs are high.

Conclusion

This paper aims to research whether the significant proportion of funds in the US market during 1980-2020 is skilled or lucky by using the method of Barras et al (2010). Our study rejects the first hypothesis that skilled fund managers exist in a small proportion. Further, the results of our study are consistent with our second hypothesis that there is a decline in skilled fund managers, and an increase in unskilled fund managers over time. Hence, the second hypothesis is not rejected.

The results conclude that there does not exist any active managers that exhibit stock-picking skills well enough to cover their costs. Our interpretation of these results is that there are no skilled fund managers on a group level; however, there is a possibility that skilled fund managers exist on an individual level. The reason why there are no skilled fund managers on a group level is because of the method's approach of estimating the proportions. Since the proportion of significant negative alpha funds and zero-alpha funds is significantly greater than the proportion of significant positive alpha funds, the model estimates that all the significant positive alpha funds are due to luck. Hence, there may exist skilled funds individually but of all domestic actively managed funds in the US, the proportion of skilled fund managers are indistinguishable from zero.

The possible explanations for our results are market efficiency, costs and market timing. These variables influence the results by making it more challenging to overperform the market. Since passive investing does not try to beat the market and has low fees in relation to active investing, it is arguably a preferable strategy for an investor.

By measuring the proportion of skill in a multiple fund setting, active fund managers in the US market are not good enough in comparison to the fees they charge.

References

Anadu, Kenechukwu., Kruttli, Mathias., McCabe, Patrick., and Osambela, Emilio, 2020, The Shift from Active to Passive Investing: Risks to Financial Stability?, Financial Analysts Journal, 76:4, 23-39

Andrikogiannopoulou, Angie., and Papakonstantinou, Filippos, 2019, Reassessing False Discoveries in Mutual Fund Performance: Skill, Luck, or Lack of Power?, The Journal of finance (New York) 74.5: 2667–2688

Barras, Laurent., Scaillet, Oliver., Wermers, Russ, 2010, False Discoveries in Mutual Fund Performance: Measuring Luck in Estimated Alphas. The Journal of finance (New York) 65.1: 179–216

Berk, Jonathan B., and van Binsbergen, Jules H., 2015, Measuring Skill in the Mutual Fund Industry, Journal of financial economics 118.1: 1–20.

Berk, Jonathan B., and Green, Richard C., 2004, Mutual Fund Flows and Performance in Rational Markets, The Journal of political economy 112.6: 1269–1295

Carhart, Mark M., 1997, On Persistence in Mutual Fund Performance, The Journal of finance (New York) 52.1: 57–82.

Champagne, Claudia., Karoui, Aymen., and Patel, Saurin., 2018, Portfolio Turnover Activity and Mutual Fund Performance, Managerial finance 44.3: 326–356.

Cuthbertson, Keith., Nitzsche, Dirk., and O'Sullivan, Niall., 2012, False Discoveries in UK Mutual Fund Performance, European financial management: the journal of the European Financial Management Association 18.: 444–463.

Fama, Eugene F., and French, Kenneth R, 1993, Common Risk Factors in the Returns on Stocks and Bonds, Journal of financial economics 33.1: 3–56

Fama, Eugene F., and French, Kenneth R, 2010, Luck Versus Skill in the Cross-Section of Mutual Fund Returns, The Journal of finance (New York) 65.5: 1915–1947

G'arleanu, Nicolae., and Pedersen, Lasse H., 2018, Efficiently Inefficient Markets for Assets and Asset Management, The Journal of finance (New York) 73.4: 1663–1712

Hendershott, Terrence, 2010, Automated Trading, Encyclopedia of Quantitative Finance

Investment Company Institute, 2020, 60th edition Investment Company Fact Book

J.P Morgan Asset Management, 2021, Guide to Retirement 2021 Edition

Kosowski, Robert., Timmerman, Allan., Wermers, Russ., and White, Hall., 2006, Can Mutual Fund 'Stars' Really Pick Stocks? New Evidence from a Bootstrap Analysis, The Journal of finance (New York) 61.6: 2551–2595

Kosowski, Robert., 2011. Do Mutual Funds Perform When It Matters Most to Investors? US Mutual Fund Performance and Risk in Recessions and Expansions, Quarterly Journal of Finance (QJF), World Scientific Publishing Co. Pte. Ltd., vol. 1(03), pages 607-664.

Malkiel, Burton G., 1995, Returns from Investing in Equity Mutual Funds 1971 to 1991, The Journal of finance (New York) 50.2: 549–572.

Miller, Ross M., 2007, Measuring the True Cost of Active Management by Mutual Funds. Journal of Investment Management, Vol. 5, No. 1, First Quarter 2007

Pástor, Ľuboš., Vorsatz, M. Blair., and Pontiff, Jeffrey, 2020, Mutual Fund Performance and Flows during the COVID-19 Crisis, The Review of Asset Pricing Studies, vol 10(4), pages 791-833

Rinne, Kalle., and Suominen, Matti, 2014. Mutual Funds' Returns from Providing Liquidity and Costs of Immediacy, LSF Research Working Paper Series 14-01, Luxembourg School of Finance, University of Luxembourg.

Rohleder, Martin., Scholz, Hendrik., and Wilkens, Marco., 2011, Survivorship Bias and Mutual Fund Performance: Relevance, Significance, and Methodical Differences, Review of Finance 15.2 (2011): 441–474.

Sharpe, William F., 1991, The Arithmetic of Active Management, Financial analysts journal 47.1: 7–9

Statista, 2019, Number of mutual funds worldwide 2009-2019

Storey, John D., 2002, A Direct Approach to False Discovery Rates, Journal of the Royal Statistical Society. Series B, Statistical methodology 64.3: 479–498.

Wermers, Russ., 2000, Mutual Fund Performance: An Empirical Decomposition into Stock-Picking Talent, Style, Transactions Costs, and Expenses, The Journal of finance (New York) 55.4: 1655–1695

Appendix

Table 6

Table 1 provides clarification of the notations in the formulas used in the method.

Notation	Explanation
π_0, $\hat{\pi}_0$	True proportion- and estimated proportion of zero-alpha funds, respectively
$E(S_\gamma^+)$, $E(S_\gamma^-)$	Expected proportion of significant funds in the right- and left tail, respectively
$E(T_\gamma^+)$, $E(T_\gamma^-)$	Expected proportion of skilled- and unskilled funds, respectively
$E(F_\gamma^+)$, $E(F_\gamma^-)$	Expected proportion of lucky, and unlucky funds, respectively
$\hat{S}_\gamma^+$, $\hat{S}_\gamma^-$	Observed estimated proportion of significant funds in the right- and left tail, respectively
$\hat{T}_\gamma^+$, $\hat{T}_\gamma^-$	Estimated proportion of skilled- and unskilled funds, respectively
$\hat{F}_\gamma^+$, $\hat{F}_\gamma^-$	Estimated proportion of lucky- and unlucky funds, respectively
$\hat{\pi}_A^+$, $\hat{\pi}_A^-$	Estimated proportion of skilled- and unskilled funds in a given group

Figure 4 – Histogram of the Growth and Growth & Income funds' p-values

Figure 1 displays the histogram of the p-values, obtained from the Carhart four-factor regression during the period of January 2010 to December 2020. The histogram represents a sample of 7410 US actively managed mutual funds, in the category Growth and Growth & Income. The threshold for estimating the proportion of zero-alpha funds is set to 0.4 ($\lambda^* = 0.4$).

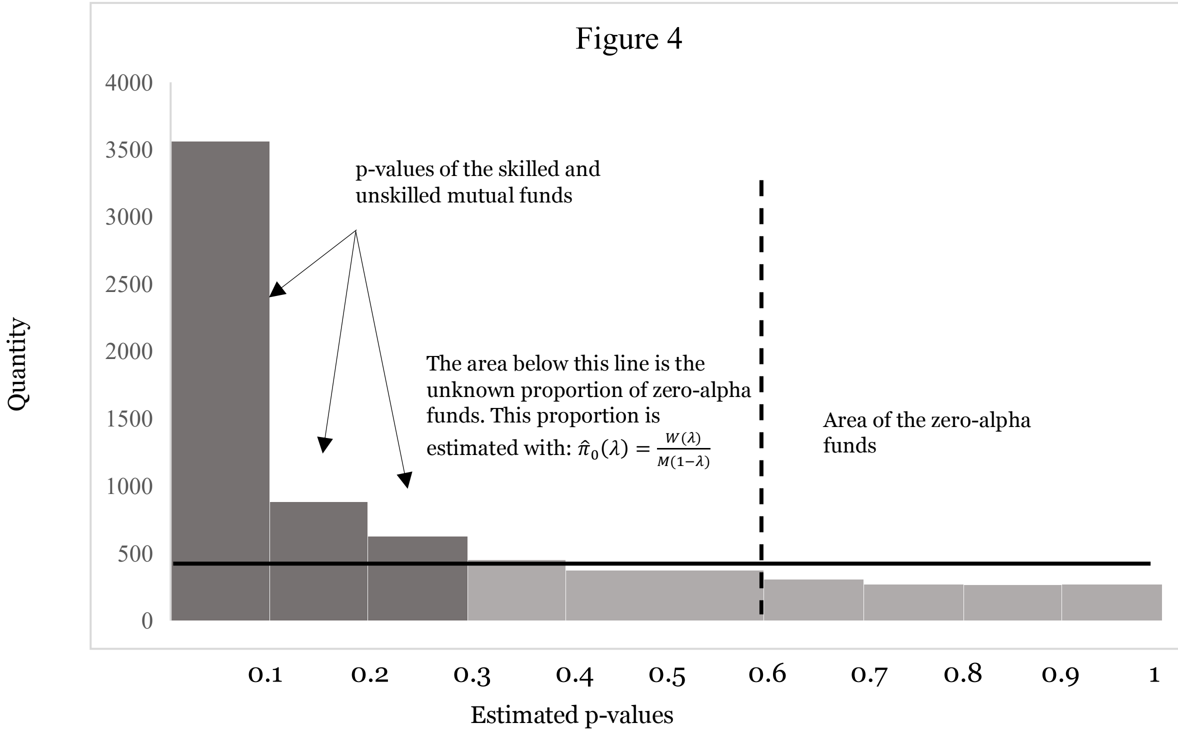


Table 7 – The performance of Equally-Weighted Portfolio of Funds

The descriptive statistics for the Carhart four-factor model regarding the equally weighted portfolio of Growth and Growth & Income funds are shown in table 7. The regression is based on monthly data between January 2010 to December 2020. The portfolio is rebalanced every month to include all funds that exists in the begging of the month. Table 7 consists of the estimated annualized alpha, $\hat{\alpha}$, the estimated exposure to the market, $\hat{b}_m$, size, $\hat{b}_{SMB}$, book-to-market, $\hat{b}_{HML}$, and momentum factors, $\hat{b}_{MOM}$. Also, the adjusted R^2 of the equally weighted portfolio is shown, which includes all the funds at the beginning of each month. The second row of the table depicts the standard error for each factor.

TABLE 7						
	$\hat{\alpha}$	$\hat{b}_m$	$\hat{b}_{SMB}$	$\hat{b}_{HML}$	$\hat{b}_{MOM}$	R^2
All funds (19,689)	-1.90%	0.888	0.025	-0.009	-0.001	0.99%
(Standard error)	0.000	0.010	0.017	0.016	0.012	

Table 8 - Development of the proportions during 1980-2020

The performance is measured with the Carhart four-factor model. The table shows the estimated proportions of zero-alpha, $\hat{\pi}_0$, unskilled, $\hat{\pi}_0^-$, and skilled funds, $\hat{\pi}_0^+$. The estimated proportion is determined at a significance level between 0.35-0.45 and the lambda threshold is 0.6.

TABLE 8

SUMMARY 1980-1984				
	Zero-alpha ($\hat{\pi}_0$)	Non-zero alpha	Unskilled ($\hat{\pi}_0^-$)	Skilled ($\hat{\pi}_0^+$)
Proportion	73%	27%	12%	15%
Quantity	185	70	31	38

SUMMARY 1985-1989				
	Zero-alpha ($\hat{\pi}_0$)	Non-zero alpha	Unskilled ($\hat{\pi}_0^-$)	Skilled ($\hat{\pi}_0^+$)
Proportion	69%	31%	11%	19%
Quantity	405	185	65	112

SUMMARY 1990-1994				
	Zero-alpha ($\hat{\pi}_0$)	Non-zero alpha	Unskilled ($\hat{\pi}_0^-$)	Skilled ($\hat{\pi}_0^+$)
Proportion	78%	22%	20%	2%
Quantity	1035	299	267	27

SUMMARY 1990-1994				
	Zero-alpha ($\hat{\pi}_0$)	Non-zero alpha	Unskilled ($\hat{\pi}_0^-$)	Skilled ($\hat{\pi}_0^+$)
Proportion	78%	22%	20%	2%
Quantity	1035	299	267	27

SUMMARY 1995-1999				
	Zero-alpha ($\hat{\pi}_0$)	Non-zero alpha	Unskilled ($\hat{\pi}_0^-$)	Skilled ($\hat{\pi}_0^+$)
Proportion	67%	33%	33%	0%
Quantity	2593	1284	1284	0

SUMMARY 2000-2004				
	Zero-alpha ($\hat{\pi}_0$)	Non-zero alpha	Unskilled ($\hat{\pi}_0^-$)	Skilled ($\hat{\pi}_0^+$)
Proportion	82%	18%	18%	0%
Quantity	6298	1426	1426	0

SUMMARY 2005-2009				
	Zero-alpha ($\hat{\pi}_0$)	Non-zero alpha	Unskilled ($\hat{\pi}_0^-$)	Skilled ($\hat{\pi}_0^+$)
Proportion	90%	10%	9%	1%
Quantity	8460	918	844	94

SUMMARY 2010-2014				
	Zero-alpha ($\hat{\pi}_0$)	Non-zero alpha	Unskilled ($\hat{\pi}_0^-$)	Skilled ($\hat{\pi}_0^+$)
Proportion	55%	45%	45%	0%
Quantity	6055	5032	5032	0

SUMMARY 2015-2020				
	Zero-alpha ($\hat{\pi}_0$)	Non-zero alpha	Unskilled ($\hat{\pi}_0^-$)	Skilled ($\hat{\pi}_0^+$)
Proportion	63%	37%	37%	0%
Quantity	8285	4844	4844	0