What Are the Characteristics of Skilled Mutual Funds?

An Exploration of Determinants and Funds' Life Cycles

JAN-BAS VAN RIEL

ABSTRACT

After the new insight of Berk and van Binsbergen (2015) to use the value added as a proxy for skill, I provide insights about the characteristics of funds that are considered skilled. I firstly find that in contrast to the previous authors, the average fund manager destroys value of $2.9 million per year instead of adding value. This value added is positively related to the fund's family size and lagged monthly flow. No evidence is found for future marketing expenses, turnover ratio and dividends. I also find that both male and female investment managers add the same amount of value, although a female manager decrease the fund's chance of survival with 39%. When I take a more extensive look at a fund's life cycle, I find that skilled funds have around 80% more chance to survive than unskilled funds, hence implying a huge survivorship bias. Nevertheless, both are able to accumulate assets at the start, although only skilled funds are able to maintain them. Unskilled funds try to compensate their shrinking AUM with higher management fees to maintain compensation levels.

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Supervised by: Dr. Ran Xing
Co-reader: Prof. Ingolf Dittmann
Studentnumber: 344202
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Erasmus University
Erasmus School of Economics
Economics & Business
Master Specialisation Financial Economics

ERASMUS UNIVERSITEIT ROTTERDAM

Contents

I. Introduction

Extensive research has already been done trying to prove the existence - or lack - of mutual fund managers' skill. As this is a crucial point for a whole industry, it is most interesting to see that so many papers have contradictory conclusions (see e.g. Hendricks, Patel, and Zeckhauser, 1993; Grinblatt and Titman, 1994; Carhart, 1997; Kosowski, Timmermann, Wermers, and White, 2006; Baker, Litov, Wachter, and Wurglur, 2010). After this long list, Berk and van Binsbergen (2015) are the first to find strong evidence that the average fund manager possesses a certain level of skill. By looking at the value added instead of abnormal returns, they identify persistency in performance (i.e. not generated by luck). The goal of this thesis is to get a broader understanding of what determinants drive this value added. I thereby will not only look at the effect of individual determinants, but also examine how the values of those determinants change over funds' life cycle.

Using the CRSP mutual fund survivor fee database, I first estimate the abnormal returns by regressing returns on the four factors of Carhart (1997). I subsequently calculate the value added as in the world of Berk and van Binsbergen (2015). In contrast to those authors, I find that the average fund manager destroys value of \$2.9 million per year. The sign switch of this average can be attributed to the most recent years, since I find a positive average using the more narrow time frame of Berk and van Binsbergen (2015).

To understand the individual effects of determinants on skill, I test the effect of various determinants on value added. Due to cross-sectional dependence of the data, I use a Ordinary Least Squares (OLS) panel regression with monthly time fixed effects and cluster standard errors per fund and time. In addition, I perform regressions as in Fama and MacBeth (1973) with Newey-West adjusted standard errors.

The results are mostly consistent with prior research on abnormal returns. In line with Chen, Hong, Huang, and Kubik (2004), I find that family size has a positive relation with value added as well as flow. In a portfolio analysis I show that large funds with high flow add \$78 million dollar per year more than large funds with low flow. This differs from papers that use abnormal returns as proxy for skill, which usually find that high inflow is followed by lower or negative abnormal returns (see e.g. Frazzini and Lamont, 2008; Lou, 2012). My finding however is consistent with the findings of Berk and van Binsbergen (2015) that investors can identify skilled funds and invest accordingly.

Matching fund managers' names with a gender database enables me to test the difference in performance between male and female managed funds. In line with Atkinson, Baird, and Frye (2003), I find that those funds do not significantly differ in value added. Furthermore, no evidence is found for the effect of marketing expenses, dividends and turnover ratio. Although size has an ambivalent relation to value added, it doesn't seem to have an effect on value added on its own. It can however increase the magnitude of other effects, since variance in value added increases with size.

Next, I explore the life cycles of mutual funds. Research of mutual funds' life cycles is by my best knowledge new in the academic literature. The closest related (working) paper is by Getmansky (2004), who looks at life cycles in hedge funds. I start by looking at the difference in hazard rates (i.e. the probability of funds dying at a certain age) between skilled and unskilled funds. Skilled (unskilled) funds are defined as the top (bottom) 20% of funds based on the Berk and van Binsbergen (2015) skill ratio, measured over their entire lifetime. To test the effect on hazard rates, I use a Cox model with time dependent effects for variables that do not comply with the proportional-hazard assumption. It shows that skilled funds have 80% higher chance to survive than unskilled funds, implicating a huge survivorship bias. High expenses can also increase hazard rates, while higher income streams (management fee) increases their survival chances. I also find that funds with bigger families, have a 7% better chance to survive. Remarkable is the effect of fund managers' gender and turnover ratio on the hazard rates. Both determinants had no significant effect on value added, but do significantly influence the hazard rates. Funds with female managers have 39% less chance to survive than funds with male managers. Furthermore, higher turnover leads to larger hazard rates, implying that trades are driven by overconfidence rather than proprietary knowledge.

To identify trends in the age development of funds, I calculate the means of various determinants per age year and subsequently average those values per age deciles. Every decile then represents a certain period in the life cycle. This makes it easy to compare different phases of ageing funds. Note that younger funds are present in the first deciles, but not in the last (i.e. the composition of the funds changes per age year). I collect new evidence confirming the findings of Berk and van Binsbergen (2015) that skilled funds receive more compensation. Only skilled funds have stable positive abnormal returns and are able to keep accumulating assets and therefore increase their value added and compensation. I find that skilled funds can on average increase compensation with $584 million over their lifetime. Although flow between skilled funds and unskilled funds is not significantly different at the start, when growing older, unskilled funds experience heavy outflow while skilled funds can keep their level of AUM. This is consistent with the survival analysis of both funds. Cumulative hazard rates tend to be similar the first 2.5 years of their existence, while they start to increase rapidly for unskilled funds when investors had enough time to identify a fund as (un)skilled.

How do funds managers attract capital in the beginning? Both skilled and unskilled funds seem to lure investors with low management fees in the fist months, although this effect for unskilled funds is much bigger. After the fees rise to higher levels, the pattern between both groups divergent. To compensate for the outflow, unskilled funds increase their management fee on average with 18% to maintain their compensation. Not an unexpected move as I showed earlier that higher management fees indeed can increase life expectancy. At skilled funds I observe the opposite pattern. They lower their management fee over age, because increasing AUM allows them to do so. It explains why size does not have a significant effect on value added. In this way, both skilled and unskilled funds can accumulate AUM at the start. The unskilled funds offset the value added of big skilled funds, leaving no linear relation between size and value added.

Finally, to strengthen the outcomes of the life cycle analysis, I perform two robustness checks. Firstly, the change in determinants' means are caused by inherent change of the values and by the different composition per age year. I try to disentangle those effects and create cohorts for funds older than 5, 10 and 15 years. Survival effects cause the trends for unskilled funds to become different, while they remain unchanged for skill funds. This implies the existence of a "winning pattern".

Secondly, the skill ratio could be slightly biased because older funds tend to be larger in size. When calculating the skill ratio for old funds, more observations are taken into account of the larger phase compared to young funds. Since value added is directly dependent on size, this could distort the accuracy of the skill ratio. I therefore test the life cycle patterns again with a skill ratio based on a measurement horizon of the first ten years of the funds existence. I find results that are similar to the first outcomes.

II. Background

A. Evidence for Managers' Skill

Evidence for managers' skill in mutual funds is not easy to find. It is hard to prove that abnormal returns achieved by fund managers are persistent (i.e. not gained by luck). Jensen (1968) is one of the first to conclude that there is no evidence that mutual funds can outperform the market-buy-and-hold policy, hence implicating that managers in mutual funds lack skill. Later on Hendricks, Patel, and Zeckhauser (1993) do find short-term persistent returns, but those are probably fully explained by momentum. In perhaps one of the most influential papers on this topic, Carhart (1997) tries to find persistent abnormal returns in excess of the momentum. He is the first to regress returns on a four factor model to obtain abnormal returns. In his findings only the worst performing funds show some persistency.

The findings of Carhart (1997) are challenged by Kosowski, Timmermann, Wermers, and White (2006). They have a different approach and perform a bootstrap analysis to overcome some biases other research suffered from. They argue that extreme funds exhibit portfolio returns that deviate from normality. Correcting for this distribution problem, they find persistency among the top decile of funds for three years. Fama and French (2010) also performed bootstrap analyses. The drawback they see in persistence tests is that the ranking of funds is based on short-term past performance and hence largely based on noise. Therefore they argue that little evidence of persistency can be concluded from those results. However, with their approach they also do not find evidence for skill or persistent performance. They conclude that just a few active funds can even generate returns that cover their costs. Also, when they take gross returns (returns before cost) as measure for skill, no evidence for this skill is found.

Berk and van Binsbergen (2015, B&B) bring a new view to the table by showing that not the alpha but value added should be used as proxy for skill. Net alpha (abnormal performance from the net returns) as well as the gross alpha (abnormal performance from gross returns) are a bad performance measure to prove skill. They argue that if investors can identify good funds and are fully rational, they will compete away the abnormal returns until the net alpha is equal to zero. Net alpha is therefore not a measure for skill, but for the competitiveness of the markets. Consequently, gross alpha does not measure skill either. Because fund managers will optimise the assets under management (AUM) of the fund, gross alpha will only be a proxy for skill if every fund has AUM of $1. They show that this leads to a gross alpha which is equal to the managers' fee and can therefore be chosen by the manager (see for mathmatical proof Berk and van Binsbergen, 2015, p.5-6). What they do believe to be a proxy for skill is the value added. They define the value added as the alpha multiplied by assets under management to obtain a value in dollars. Strong evidence is found under this assumption that the average mutual fund manager has skill and adds value of $3.2 million per year.

This finding of the existence of skill is contrary to the thesis of Sharpe (1991), which B&B shortly refute. Sharpe stated that the sum of all active investors is the market portfolio, which implies that the average fund manager cannot make abnormal returns. B&B provide two arguments to prove Sharpe's reasoning is wrong. First, Sharpe assumes that all active investors are investors not holding the market which is wider than active mutual funds. So mutual funds as a group could still earn abnormal returns. Second, Sharpe ignores the fact that passive investors must also trade at least twice to get in and out the market portfolio. If active investors are better informed they can earn a liquidity premium over passive investors by trading with them.

If abnormal returns in mutual funds are persistent, the interesting question arises what these abnormal returns is driving. A variety of determinants is identified in the literature of which I will discuss a selection below. For an overview of the different determinants, I refer to Table I.

B. *Picking Stocks and Time the Market*

Typical explanations for abnormal returns are that managers can 'pick stocks' or 'time the market'. Cornell (1979) was the first to suggest an event study methodology to measure performance of mutual funds and to see if managers really can pick stocks. Grinblatt and Titman (1993) use this approach by looking whether the stocks held in the portfolio by fund managers have higher returns than when they are not included. In their study, they find that managers do possess some sort of ability to pick stock. The abnormal investment performance is thereby merely achieved by aggressive growth funds and shows some persistency for the sample period. To address some criticism on this study, Daniel, Grinblatt, Titman, and Wermers (1997) use a larger dataset and characteristic based benchmarking to identify abnormal returns for the stocks held by fund managers. They find weaker evidence for stock picking skill, because according to the authors their benchmark controls for momentum. However, it can still not explain the outperformance of aggressive growth funds. They also note that the average outperformance is rather small and approximately matches the management fee. This is in line with B&B who argue that net alphas are always zero because of market competition.

Lastly, Baker et al. (2010) analyse the buy and sell activity of mutual funds around announcement dates. They find higher subsequent announcement returns for stocks bought by the average fund than matching stocks in the benchmark, while stocks sold earn lower returns. Evidence thus indicates that managers possess a certain skill to pick the right stocks.

Do managers then also have timing abilities? Less evidence is found for this hypothesis. Daniel et al. (1997) test whether mutual funds time certain investment styles (i.e. invest in factors such as high market to book ratio, when those factor returns are expected to be high). They find no evidence for timing abilities. Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014) on the other hand do find weak evidence for market timing abilities. According to them, timing is more dominant in recessions, while stock picking is more observable in booms.

C. Information Advantage

Besides the ability to pick stocks or time the market, a wide variety of other – sometimes less obvious – factors which could affect abnormal returns is identified in the literature. It is not being said that these factors are generating value completely independently. They may affect the level of ability to pick stocks or time the market. For example, if fund managers have connections with the board of a company, they could gain an information advantage which enhances their ability to pick stock. With respect to this topic, Cohen, Frazzini, and Malloy (2008) report positive abnormal returns for stocks held by mutual funds for which there exists an educational connection between the fund manager and one of the board members of the company.

Also, Coval and Moskowitz (2001) find a negative relationship between the distance of an investment and the returns. They argue that managers are better informed about stocks when they are geographically closer.

All skills described above should give the fund manager tools to improve performance. It is however worthwhile to note that when competition rises, the opportunity to outperform the market becomes smaller. As the mutual fund industry grows, more money is used to chase value enhancing opportunities. This leads to higher prices, which erode the value of such opportunities. Pastor, Stambaugh, and Taylor (2015) therefore argue that overall skill of the industry can improve, while the performance can linger.

D. Size and Portfolio Concentration

The literature assumes a negative relation between fund-size and performance. Pollet and Wilson (2013) argue that these diminishing returns to scale are caused by the inability to scale an investment strategy as the fund becomes large. Managers diversify too little because they want to stick to their strategy or are overconfident that they can pick the right stocks. When the fund is growing they have to diversify because of price-impact or liquidity constraints. In line with Chen et al. (2004) they find that small-cap funds can outperform when they are small, because the liquidity constrains when growing bigger are most present here. In contrast, Chen et al. (2004) find that the *family* size of the fund has a positive relation with the returns. This is intuitively explained by better bargaining positions of these funds when negotiating trading commissions and lending fees.

Although diversification is assumed to create better risk-return portfolio's, Kacperczyk, Sialm, and Zheng (2004) find that focusing on industries can lead to abnormal returns. Mutual fund managers tend to have more ability to select stocks when they are holding a concentrated portfolio in just a few industries. This can be intuitively explained because focused fund managers might have information advantages in these focus industries.

E. Deviation from the Benchmark

Another way to look at actively managed funds is introduced by Cremers and Petajisto (2009). They calculate deviation of the portfolio from the benchmark, which they call "active share". If the manager puts more - or less - weight in certain stocks than the benchmark or buys stocks outside the benchmark, the deviation rises. The authors report a positive relation between active share and the fund performance. Funds with the highest active share outperform the benchmark after expenses persistently, even when controlled for momentum. This effect is stronger for smaller funds than for larger funds and seem to confirm the popular statement that smaller funds are more active.

F. Fund Flows

When funds do outperform the market, does this result in higher cash inflow from investors or could it be the other way around? If we follow the assumption of B&B mentioned earlier, investors can identify good funds ex ante and steer their money towards these funds, causing the net alpha to become zero. This would imply that funds with larger positive flows have higher value added afterwards, independently of the raising AUM caused by the flows.

For retail funds, consumers tend to base their investment decisions on the highest recent returns (Sirri and Tufano, 1998). For institutional investors, the same selection criterion seems to apply. Goyal and Wahal (2008) find for plan sponsors however, that this selection of mutual funds does not result in positive abnormal returns. Plan sponsors that changed their investment managers, did not perform better than when they had kept everything unchanged.

Because investors base their investment decision apparently on past performance, it seems that cash inflows should be correlated with prior performance. However, is it also possible that investors can identify good funds ex ante and invest accordingly? This would implicate that cash inflows are correlated with future performance. Gruber (1996) and Zheng (1999) develop such a theory which they call "smart money". They hypothesise that investors possess an ability to predict which funds are better than others and send their money to those funds. They find evidence for their theory, but Sapp and Tiwari (2004) argue that this effect is totally due to the momentum factor.

More robust evidence is found for the hypothesis that fund inflow generates negative abnormal returns (Frazzini and Lamont, 2008). This effect can be explained when looking at the trading level. If funds have to trade for liquidity reasons caused by in- or outflow, Alexander, Cici, and Gibson (2007) report negative abnormal returns. This effect is stronger when managers have to sell their investments because of heavy fund outflow, than when they buy because of heavy inflows.

G. Goal Turnover and Expenses

As mentioned earlier, aggressive growth funds are associated with higher abnormal returns. Volkman and Wohar (1995) confirms that the goal of a fund has a relation to the performance. They find that maximum capital gain funds do better than income funds. Most likely, the more aggressive funds also have the highest expenses.

Table I

The Predicted Effects on Abnormal Returns for Different Determinants

This table summarizes the different determinants from the literature. The sign in column "Effect" shows the predicted effect on the abnormal returns, where '+', '-' and '#' indicate positive, negative and no or unknown effect.

Panel A: Fund Characteristics

Determinant	Effect	Existing literature
Size	#	Diseconomies of scale causes a negative effect on returns. (Chen et al., 2004; Pollet and Wilson, 2013) Value added is however also influenced by size directly causing the total effect to become ambiguous.
Family size	+	Bigger family size can lead to a better market position (Chen et al., 2004)
Turnover	+	Higher turnover can indicate trading on advantages (Grinblatt and Titman, 1994)
Expense ratio	+	Higher expense ratio can lead to more information advantages (Grinblatt and Titman, 1994)
Age of the fund	-	Although Carhart (1997) does not find a significant effect, a negative relation could exists Howell (2001)
Deviation from the benchmark	+	Deviation can indicate more information advantage (Cremers and Petajisto, 2009)
Goal (more aggressive)	+	More aggressive funds do better (Grinblatt and Titman, 1994; Volkman and Wohar, 1995)
Load	#	No evidence is found for a relationship between load and performance (Volkman and Wohar, 1995)
Industry concentration	+	Industry concentration can lead to information advantage (Kacperczyk et al., 2004)
Geographical distance	-	Managers can have information advantage over geographically near stocks (Coval and Moskowitz, 2001)
12b-1 fee	+	"Good" funds are expected to have higher marketing expenses (Sirri and Tufano, 1998)

Panel B: Manager Characteristics

Determinant	Effect	Existing literature
SAT Scores	+	SAT scores are positively related to fund performance (Chevalier and Ellison, 1999)
Female Manager	#	No significant relation has yet been found (Atkinson et al., 2003)

Furthermore, funds that spend most on research are expected to create more abnormal returns. Grinblatt and Titman (1994) find that better performance is related to higher turnover, load and higher management fee. No relation was found for expense ratios. Volkman and Wohar (1995) also find a positive relation between turnover and performance, but do not find evidence for load. In the light of Sirri and Tufano (1998) it can be expected that higher marketing costs (or higher 12b-1 fees) would indicate better past performance, since funds tend to spend more on advertising if they have a better track record. It could also be argued that "good" funds spend more on marketing and these expenses relate to better performance in the future.

H. Fund Age

Carhart (1997) states that age cannot explain the difference in performance between mutual funds. However, Howell (2001) finds a negative relation between returns and age in the hedge fund industry. He states that new discovered niches can be arbitraged away suppressing returns of older funds still focused on this niche. The same can apply to investment strategies of mutual funds, although expected to be less present.

I. Manager Characteristics

Chevalier and Ellison (1999) look at the effect of some manager characteristics on the performance of mutual funds. They find that the SAT scores of these managers have a significant relation with higher returns. This relationship is however not significantly stronger for women or men. Atkinson et al. (2003) do not find significant differences between male and female fund managers either, but limit their research to fixed-income funds.

III. Methodology

A. Definition of Skill

As in the previous section described, many determinants for *abnormal returns* have already been researched. A summary of these determinants and effects on abnormal returns can be found in Table I. Before explaining the methodology to test the effects of different determinants on *value added* as a proxy for skill, I will first define skill as in the world of B&B.

Because the net alpha does not measure skill, but rather the competitiveness of the market (as explained earlier), I will use fund's gross returns, which can be estimated as

$$R^g_{it} = R^n_{it} + f_{i,t-1} \tag{1}$$

where R^n_{it} is the return in excess of the risk free rate (or net return) at time t for fund i and $f_{i,t-1}$ the expense ratio of the previous period. The gross abnormal returns can then be obtained by subtracting the benchmark R^b_{it} from the fund returns. In the final step to define value added V_{it}, I multiply the gross abnormal returns by the AUM of the previous period in dollars $q_{i,t-1}$:

$$V_{it} \equiv q_{i,t-1}(R^g_{it} - R^b_{it}) \tag{2}$$

The skill is then the expected value of V_{it}. Thus, for a fund that exists for T_i periods, the estimated skill is given by:

$$\hat{S}_i = \sum_{t=1}^{T_i} \frac{V_{it}}{T_i} \tag{3}$$

B. Benchmarking and Added Value

One important step in determining the value added is defining the benchmark. As most common in the search for abnormal returns, I use the four factor model of Carhart (1997) and Fama and French (1995). Returns are in this model regressed on four factors, which can be shown as

$$R^g_{it} = \alpha_{it} + \beta_{it}MKT_t + \beta_{it}SML_t + \beta_{it}HML_t + \beta_{it}UMD_t + \epsilon_{it} \tag{4}$$

where MKT_t, SML_t, HML_t capture the risk factors for respectively excess return on the market, size, book-to-market equity and UMD_t is adjusting for momentum. Furthermore, β_{it} captures the exposure to each factor.[1] When regressing excess gross returns on the factors, gross abnormal returns $\alpha^g_i t$ are estimated by the unexplained values in the equation given by

$$\alpha^g_{it} = \alpha_{it} + \epsilon_{it} \equiv R^g_{it} - R^b_{it} \tag{5}$$

To obtain the value added and the skill, respectively Equation 2 and Equation 3 are used. Note

[1]Data for all factors and risk free rate is obtained from the website of French: `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

that the skill is observed on a fund level and not on a manager level, since i stands for the fund in both equations.

C. Regression Specifications

The first approach to test effects of determinants on value added, is to perform panel regressions. This allows for a quick overview of (significant) effects on the skill of mutual funds. I take the value added or V_{it} as dependent variable which results in

$$V_{it} = \beta_1 x_{it} + (\alpha_i + u_{it}) \tag{6}$$

where β_1 is the effect of factor x_{it} on the value added. $(\alpha_i + u_{it})$ is the unobserved term where α_i stands for the effect per fund and u_{it} for the idiosyncratic factor.

Petersen (2009) highlights some important issues encountered with these regressions on panel data. Since the fund data is likely to be cross-sectional dependent and has a time effect, I follow his line to include monthly time fixed effects and cluster standard errors per fund and time in my Ordinary Least Squares (OLS) regressions. As long as there are a sufficient number of clusters, the standard errors should then be unbiased (see also Thompson, 2011). Petersen (2009) advises in this case datasets with over hundred observations in time-series and firm dimensions. My dataset contains over 200 time-series observations and 7000 funds, which sufficiently fulfil this requirement.

In addition to OLS, I perform regressions as Fama and MacBeth (1973). Because this regression is designed to account for time dependency only, it might have difficulties with the cross-sectional dependence in this data. For some determinants, such as flow and compensation, previous research found evidence for being persistent over time. This can cause serial correlation between coefficients and I therefore correct standard errors with Newey-West adjustments.

IV. Data

My primary data for fund returns and characteristics come from the Center of Research in Security Prices (CRSP) survivor bias free mutual fund database, which is widely used by authors including Carhart (1997) and B&B. This database holds monthly observations for Total Net Assets

Table II

Distribution and Statistics on Mutual Funds

The table shows the distribution of skill $\hat{S}_i$ for two time periods. The second column shows the skill for the time span B&B used in their paper, which is until March 2011. The third column shows the current skill distribution until Januari 2016. Real Total Net Assets (TNA) q and age are displayed in column 4 and 5 based on data until January 2016. Real TNA is given in million Y2015$. The weighted mean is the skill weighted by the number of observations T the fund exists in the dataset.

Variable	Skill (pre-2011)	Skill (current)	Real TNA	Age
Mean	0.26	−0.24	955.0	12.5
Weighted mean	0.67	0.18		
Standard deviation	3.70	4.43	4,671.3	11.2
1st percentile	−5.27	−10.66	0.6	1.5
5th percentile	−1.75	−2.82	3.4	2.1
10th percentile	−0.84	−1.40	6.2	2.8
25th percentile	−0.21	−0.38	20.1	4.9
50th percentile	−0.01	−0.06	90.6	9.5
75th percentile	0.17	0.05	442.9	17.2
90th percentile	1.08	0.63	1,674.8	24.0
95th percentile	2.83	1.80	3,632.2	30.8
99th percentile	11.03	8.65	14,066.3	61.1
Kurtosis	148.3	185.3	321.5	13.7
Number of funds	6,670	7,566	7,566	7,561

(TNA), returns and some characteristics.[2]

In line with B&B, I restrict my analysis to equity funds. However, they define such funds simply as funds holding more than 50% equity and less than 20% cash.[3] In addition to this selection, I search for terms like "Money Market" and "Fixed Income" in the fund names and drop certain Lipper classifications and objectives to further eliminate non-equity funds. I also drop all full index funds and observations in months before funds reach real assets under managment (AUM) of $5 million.[4]

Because the expense ratio, net returns and TNA are necessary to calculate the value added, I drop all the observations that miss values for those variables. Because the expense ratio is reported on a yearly basis, I extend observations for this ratio to the entire fiscal year, if they are reported

[2]Throughout my thesis I will use Total Net Assets (TNA) and Assets Under Management (AUM) as synonyms referring to the TNA values in the CRSP database.

[3]Funds with more than 20% cash are considered money market funds.

[4]The real AUM is calculated as the nominal AUM adjusted by the non-food dollar inflation in the US with 2015 as base year

Figure 1: Fund distribution trends

This graph is taken from B&B and updated until 2015. The solid black line in the graph shows the logarithm of the number of funds between 1975 and 2015. The dashed lines represent the 1st, 25th, 50th, 75th and 99th percentile of the fund size distribution measured as the logarithm of assets under management (AUM) in Y2015$.

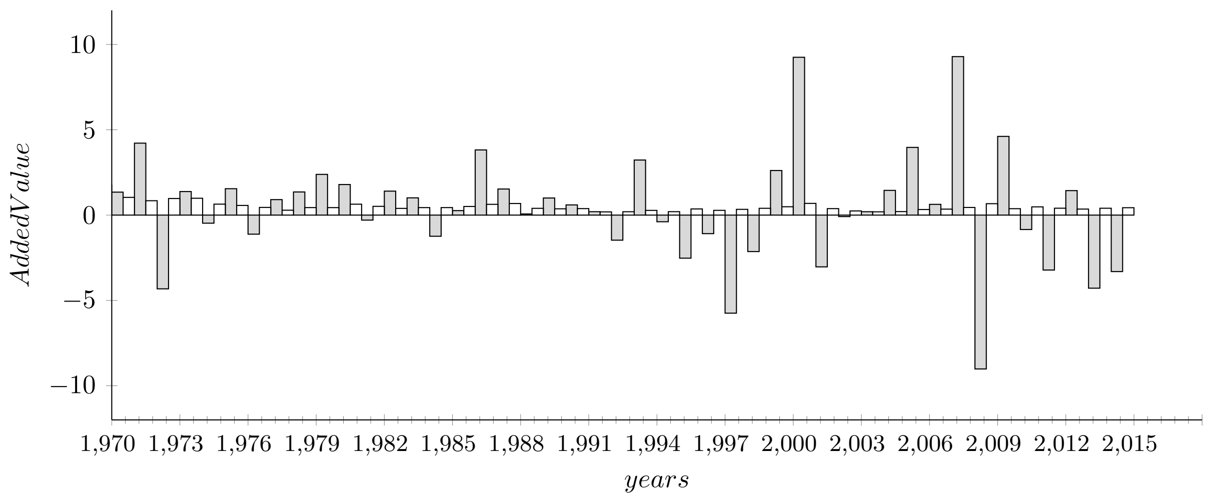


Figure 2: Difference in added value over the years

This figure shows the differences of the added value over the years. The light gray bars indicate the value added for all observations that year, while the white bars represent the standard error of the mean of the contemperious years.

in another period of that year. In 12.7% of the cases I was not able to fill in the expense ratio.[5]

Because the returns are regressed against risk factors for benchmarking to obtain the abnormal returns, a minimum number of observations per funds is necessary. B&B require funds to have 24 observations to be included in their analyses. This mainly excludes smaller and new funds. Since

[5]Negative expenses ratio's are treated as missing.

I do not want to exclude these funds in the effects of determinants, I loosen the restriction to 12 observations per funds. This is consistent with the approach of Chen et al. (2004).

Although widely used, the CRSP mutual fund database has the known bias that histories of the same fund are present under different identifiers. This is due to funds that split into multiple shares classes during the observation period. Each new share class is then permitted to inherit the return history of the entire fund. Some characteristics are different across these share classes (such as load and TNA), but gross returns are the same. Therefore, I aggregate these share classes, weighted by TNA. They can be identified by splitting the names by colons (":") or slashes ("/"), since share class information is always reported after such symbols in the CRSP database. There are cases in which other information is given after such sign and funds thus should not be aggregated. I identify these cases with keywords and keep them as individual funds.[6]

In the end, I am left with 7,566 funds. This represents a larger sample than the one of B&B, but this is probably due to the looser constrained on the minimal amount of observations per fund (12 instead of 24). Furthermore, mutual funds experience increasing popularity. The number of funds rise every year (see Figure 1). The sample is similar to prior studies for other variables. The average factor for market exposer - or beta - of 0.95 is consistent with findings of Chen et al. (2004). The slight increase in assets under management (AUM) relative to other studies can also be explained by trends in the mutual funds industry shown in Figure 1.

I find a slightly different distribution for the skill variable than B&B (see Table II). They find a similar median (here -0.06), but a positive unweighed mean (here -0.24). If the mean is weighted by the number of observations the funds exist in the database, the mean is like B&B's also positive but smaller (0.18). If I use the same timespan as B&B however, the mean turns to a positive number of 0.25, while the median remains slightly negative. This is very similar to their results. In contrast with B&B, I thus demonstrate that with the most recent data, investment managers destroy value of $2.9 million per year. That this sign switch is due to the most recent years is confirmed by Figure 2, which shows that the value added in 2011, 2013 and 2014 is negative with small standard errors.

[6]This other information is mostly the style of the fund e.g. "small cap growth fund".

V. Determinants of Skill

From the wide list of determinants, I first test the effects on value added for the most general ones. I take the log of age, size and the expense ratio (*Logage*, *Logsize* and *Logexpenseratio*) to proxy for these respective effects. These common adjustments are made because the log scale is better estimated in regression for these sort of variables. *Logfamilysize* represents the size of the family the fund belongs to (e.g. the Vanguard STAR fund is part of the Vanguard family). In the spirit of Chen et al. (2004) this family size is calculated as the sum of the assets under management (AUM) of the whole family subtracted by the AUM of the individual funds.[7] The last variable included in the first regression is *compensation*, which is the management fee multiplied by the AUM.

The results of the pooled OLS and the Fama MacBeth regressions are shown in the first column of Table III. In both cases, I use monthly observations as a time frame, but obtain similar results if I use quarterly data. I also adjust the MacBeth standard errors with Newey-West adjustments of five lags. With this adjustment, I obtain similar standard errors between the pooled OLS and Fama MacBeth for most factors.

The outcomes are mostly in line with previous research. The size of the fund's family has a significant positive effect on the value added. This is also what Chen et al. (2004) find. Remarkable is the negative relation with size. This effect has already been found by prior research on abnormal returns, but value added is of course directly related to size (see Equation 2). I will further discuss the effects of size in Section VI and VII.

I also find a positive relation between age and value added, which becomes stronger when I adjust for future compensation. The effect of age is in the current literature not extensively explained, but in prior research sometimes included as control variable. In these regressions, often a negative relation is found with abnormal returns (e.g. Fang, Peress, and Zheng, 2014). This could be due to the fact that older funds suffer from a survivorship bias. I will discuss the effect of age on performance more extensively in Section VII, when I go deeper into the life cycles of mutual funds.

One can think that funds with superior information trade more on this information. I therefore expected the turnover ratio to have a positive significant effect on value added. However, I do not

[7]Since expense ratio and family size can be zero, I add one percent to the expense ratio and one million dollar to the family size before taking the log.

Table III

Effect of Determinants on Value Added

In this table, both panel A and B show the regression results on value added V_{it}. Panel A shows the results of a pooled OLS. For each of those regressions, monthly fixed effects are included and standard errors are clustered by months and funds. In panel B the outcomes for the same variables are shown, but coefficients and standard errors are now calculated as in Fama and MacBeth (1973). The Fama MacBeth standard errors are adjusted with Newey-West standard errors including five lags. $Logsize_{t-1}$ represents the log of the assets under management (AUM) lagged by one month. Age, expense ratio and turnover ratio are also lagged by one month, while the log is taken from age and expense ratio. $Logsizefamily_{t-1}$ is the inflation-adjusted size of the fund's family lagged by one month. $Compensation$ is the management fee multiplied by AUM. $Flow$ stands for the in- or outflow of money in the fund lagged by 1, 2 and 3 months. $Log12b1fee_{t+1}$ are the forwarded actual marketing expenses. $Logsize_{t-1}$, $Logsizefamily_{t-1}$ and $Compensation$ are presented in Y2015$. Standard errors are shown between parentheses. The ***, ** and * indicate p-values of below 0.01, 0.05 and 0.10 respectively.

Panel A: Pooled OLS; Value Added as Dependent Variable						
	(1)	(2)	(3)	(4)	(5)	(6)
$Logage_{t-1}$	0.78**	0.78**	0.38	1.21**	0.92***	0.93**
	(0.33)	(0.34)	(0.34)	(0.55)	(0.34)	(0.39)
$Logsize_{t-1}$	-0.75*	-0.82**	-0.72	0.18	-1.1***	-0.59*
	(0.39)	(0.38)	(0.46)	(0.47)	(0.42)	(0.34)
$Logsizefamily_{t-1}$	0.11**	0.11**	0.09**	0.09	0.12***	0.02
	(0.04)	(0.04)	(0.04)	(0.06)	(0.04)	(0.05)
$Turnoverratio_{t-1}$	-0.08	-0.08	-0.03	-0.09	-0.07	0.00
	(0.05)	(0.05)	(0.17)	(0.06)	(0.05)	(0.10)
$Logexpenseratio_{t-1}$	-2.11**	-2.25**	-2.61*	-2.28	-2.34**	-2.60
	(0.94)	(0.94)	(1.51)	(1.50)	(0.95)	(1.70)
$Compensation$	0.14	0.16	0.17	0.03		0.19
	(0.16)	(0.15)	(0.13)	(0.18)	(0)	(0.13)
$Flow_{t-1}$		0.03**				
		(0.01)				
$Flow_{t-2}$		0.02				
		(0.02)				
$Flow_{t-3}$		0.04***				
		(0.01)				
$ManagerGender$			-0.26			
			(0.61)			
$Dividend$				1.49*		
				(0.90)		
$Compensation_{t+1}$					-1.55	
					(1.60)	
$Compensation_{t+2}$					-1.65	
					(1.86)	
$Compensation_{t+3}$					3.38**	
					(1.56)	
$Marketing_{t+1}$						1.71
						(1.48)
Periods	216	216	216	216	216	216
Number of funds	6,947	6,947	3,902	6,502	6,903	4,706

(continued)

Table III - *Continued*

Panel B: Fama MacBeth; Value Added as Dependent Variable						
	(1)	(2)	(3)	(4)	(5)	(6)
$Logage_{t-1}$	0.48	0.58*	0.31	0.57	0.65***	0.71**
	(0.29)	(0.30)	(0.24)	(0.45)	(0.21)	(0.32)
$Logsize_{t-1}$	-0.74**	-0.78**	-0.58	0.51	-0.75***	-0.48
	(0.30)	(0.31)	(0.42)	(0.51)	(0.27)	(0.32)
$Logsizefamily_{t-1}$	0.09*	0.09**	0.07	0.02	0.11**	0.06
	(0.04)	(0.04)	(0.04)	(0.06)	(0.05)	(0.05)
$Turnoverratio_{t-1}$	0.01	0.06	0.11	0.01	-0.07	0.02
	(0.07)	(0.12)	(0.17)	(0.08)	(0.05)	(0.09)
$Logexpenseratio_{t-1}$	-1.43*	-1.82**	-3.47***	-0.79	-1.70**	-1.59
	(0.83)	(0.81)	(1.32)	(1.29)	(0.79)	(1.28)
$Compensation$	0.22	0.2	0.14	0.03		0.19
	(0.15)	(0.15)	(0.14)	(0.19)		(0.13)
$Flow_{t-1}$		1.68**				
		(0.76)				
$Flow_{t-2}$		0.37				
		(0.48)				
$Flow_{t-3}$		1.21***				
		(0.39)				
$ManagerGender$			-0.26			
			(0.49)			
$Dividend$				0.75		
				(0.59)		
$Compensation_{t+1}$					-1.36	
					(1.29)	
$Compensation_{t+2}$					-3.18	
					(2.21)	
$Compensation_{t+3}$					4.84***	
					(1.67)	
$Marketing$						0.45
						(0.98)
$Constant$	-4.12	-5.72*	-11.6**	-6.91*	-5.31*	-4.06
	(3.24)	(3.1)	(4.72)	(4.03)	(2.96)	(3.44)
Periods	216	216	216	216	214	215

find any evidence for this. In contrary, the expense ratio is significant and negatively related to value added. This is line with some other research, but against the hypothesis that more expenses (e.g. cost for research) lead to better performance after controlling for compensation. In Chapter VII, I will explain another reason for this negative relationship.

A. *Flow and compensation*

The flow of mutual funds is defined as the money in- or outflow of the fund per month and is tested in column 2 of Table III. The flow variable is calculated following previous literature (Sirri and Tufano, 1998; Lou, 2012) as

$$flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} * (1 + RET_{i,t}) - ACQ_{i,t}}{TNA_{i,t-1}} \tag{7}$$

where $TNA_{i,t}$ represent the assets under management (AUM) and $RET_{i,t}$ the return at time t. $ACQ_{i,t}$ are the assets acquired in mergers. I use the last available date of the acquired fund in the database initially as merger date, since the CRSP database does not include these dates. In line with Lou (2012), I smooth this process by calculating flows without acquisition assets in the surrounding months of the initial date. I do this for five months after the initial date and for one month before. Then I identify the month with the highest flow for these seven observations. I assume that this month is most likely to be the true acquisition date and match the acquired TNA to this month.

I include three lags of monthly flow in the regression. Both in the pooled OLS and the Fama MacBeth regression, past flow is positively related to value added. Although flow is a process with longer horizons than a few months, this is the first indication that investors can identify funds which add value and send their money to them.[8] This is confirmed by the positive effect of future compensation on value added and in line with findings of B&B. They state that the management fee itself does not differ across funds. Investors can however choose which fund earns the most compensation, by allocating their capital to the funds with most skill (Berk and Green, 2004).

B. *Gender*

The CRSP database does not provide gender of fund's managers, but does include their names. To obtain a gender variable, I check those names with a name-gender-database. To find out whether an investment manager is male or a female, I first split the names into first and second names. I assume that when a "/" is used in the manager name variable, the fund is co-managed. For every

[8]See also Frazzini and Lamont (2008), who estimate the total effect of flow to be complete over a horizon of three years.

single managed fund I match the first name of the manager to a name database from Census to identify the gender.[9] For every single-managed fund I then create a dummy variable which is 1 when the fund manager is a male and include it in the regression. The results indicate that the gender of investment managers does not seem to have a significant effect on value added. This is in line with Atkinson et al. (2003), who came to the same conclusion for fixed income funds.

C. Dividend and marketing

To test whether the goal of the fund is of influence on the performance, I identify funds that are in the top 10% dividend payout. I assume that these funds have a goal more related to income than capital gains. No significant effect is found for this difference between these funds.

Future marketing expenses do not have a significant relation with value added as well. Sirri and Tufano (1998) hypothesise that better current performance would increase future marketing expenses, because it is easier to launch a good campaign with a better recent track record. This relationship does not seem to hold for value added. Furthermore, including more forwards (both in a monthly or quarterly time frame) does not lead to significant results.

VI. Notes on Size and Flow

Because value added is directly related to size, the characteristics of this relation are ambivalent. In the previous chapter, I found that size has a negative effect on value added. To obtain a more broader understanding of this relationship, I perform a portfolio analysis. This analysis has the advantage that it does not depend on statistical assumptions, but just shows whether or not there is a linear relationship between variables. Because the number of observations per month before 1990 is very small, I perform the analysis with data from 1990 and beyond. This prevents months being included with less than five observations. Every observation is assigned to a portfolio based on its characteristics each month. In the spirit of Fama and MacBeth (1973), I first calculate the cross-sectional means for every portfolio per month and then take the time-series mean as average per quintile. For the high-minus-low-portfolio I monthly subtract the lowest quintile from the highest quintile. Results are shown in Table IV.

[9] The Census name database is acquired from `https://www.census.gov/topics/population/genealogy/data/1990_census/1990_census_namefiles.html`.

Table IV

Value Added of Portfolios Sorted by Size

This table shows two different portfolios sorted by size. Panel A shows the value added of a single sorted portfolio on size, while panel B represents the value added of porfolios double sorted by size and one month lagged flow. Observations are assigned into quintiles for each month. In the spirit of Fama and MacBeth (1973), I first calculate the cross-sectional means per month and then take the time-series mean as average per quintile. I create a zero cost high-low portfolio where I substract the lowest quintile from the highest quintile every month. Size is defined as the assets under management (AUM). Added value is shown in Y2015$. The standard errors are given in parenthesis and the ***, ** and * indicate p-values for the high-low-portfolio of below 0.01, 0.05 and 0.10 respectively.

Panel A: Value Added for Portfolios Sorted by Size

	Size quintiles					
	Small	Q2	Q3	Q4	Large	Large - Small
	-0.022	-0.074	-0.022	-0.168	1.232	1.255
	(0.01)	(0.03)	(0.17)	(0.33)	(2.35)	(2.34)

Panel B: Value Added for Portfolios Sorted by Size and One Month Lagged Flow

	Size quintiles					
	Small	Q2	Q3	Q4	Large	Large - Small
Low flow	-0.061	-0.178	-0.375	-1.049	-2.93	-2.919
	(0.01)	(0.05)	(0.13)	(0.54)	(1.91)	(1.9)
Q2	-0.031	-0.07	0.047	0.061	0.585	0.748
	(0.01)	(0.04)	(0.16)	(0.36)	(2.13)	(2.1)
Q3	-0.022	-0.092	-0.329	-0.243	2.107	2.256
	(0.01)	(0.04)	(0.16)	(0.39)	(3)	(2.99)
Q4	-0.018	0.008	-0.16	0.319	2.499	2.454
	(0.01)	(0.04)	(0.21)	(0.47)	(3.18)	(3.17)
High flow	-0.011	-0.037	0.319	-0.331	3.695	3.279
	(0.01)	(0.04)	(0.33)	(0.48)	(2.3)	(2.27)
High - Low	0.047***	0.192***	0.545*	0.566	6.473***	
	(0.01)	(0.06)	(0.31)	(0.64)	(2.17)	

Size alone does not seem to have an significant effect on value added. If I create five different portfolios based on size, the value added of these portfolios does not differ significantly (see panel A of Table IV). Despite the absence of a direct effect on value added, size can however increase the volatility in value added since it is an absolute measure. If a big and small fund make the same return in percentage, the large fund has a larger value added compared to the small fund since its AUM is larger. Size thus does not have an effect alone, but can strengthen other relations. In Chapter VII, I will demonstrate that unskilled funds are to some extent able to acquire assets in their early years. It are these funds that offset the value added by large skilled funds to drive down the average of all funds.

To further test the effects of flow on value added, I created portfolios double sorted on one month lagged flow and size. Panel B shows that funds add more value when their lagged flow is higher. Value added of large funds is even \$78 million per year higher when receiving high lagged flow compared with the smallest flow quintile. This is the second indication that investors can identify skilled funds and invest accordingly.

Although small funds with high lagged flow add 0.56 million dollar per year more compared to low flow small funds, they surprisingly still destroy value of 0.13 million dollar per year. As we will see in section VII, this could be due to the fact that unskilled funds are not able to accumulate assets. Small funds are therefore more often unskilled and cannot add value on average.

VII. Life Cycle of Mutual Funds

In this chapter, I will dive deeper into the age effect on mutual funds. I will describe the development of these funds when they grow older and differentiate life cycles between skilled and unskilled funds. Before getting to the results, I will first describe my hypotheses and explain the used methodology.

A. Hypotheses

Section V already described a positive relation between age and value added. Two possible effects could explain this relation. First, older funds could have advantages over younger funds and therefore add more value. Old funds could for example have an established name, which attract higher skilled managers. It is also possible that this effect is due to the way mutual funds develop themselves during their life cycle. It are these developments that are the focus of this section.

The first development which could explain the positive relation between age and value added is the survivorship bias. This bias describes a world where only the best performing funds stay alive and the unskilled funds die out. It can explain the positive relation between age and value added, because when only the skilled funds remain, the value added of older - and thus more skilled - funds is on average higher. To test whether this is true, I therefore hypothesise:

Hypothesis 1 (H1)**.** *Unskilled funds have a higher probability of dying than skilled funds.*

Second, it is also possible that older funds add more value because they have more assets under management. Following Berk and Green (2004), money will flow to funds with positive expected excess returns until the equilibrium is reached and excess returns of all funds are zero. I expect skilled funds to create more opportunities and therefore have more often positive expected excess returns. This leads to the expectation that skilled funds accumulate more capital when they grow older than unskilled funds. This phenomenon should be observable in assets under management (AUM) (H2) as well as in flow (H3). Because funds are expected to reach a certain optimal AUM, the flow difference should be more pronounced under young funds.

Hypothesis 2 (H2)**.** *Skilled funds accumulate more capital over age than unskilled funds*

Hypothesis 3 (H3)**.** *Young skilled funds gain more flow than young unskilled funds, but in both cases flow will decrease over age*

Furthermore, B&B pose that the gross return can be chosen by the manager and set equal to the management fee by choosing the amount of assets he wants to actively manage. It is therefore expected that the abnormal returns start high at skilled funds, but become stable over time when growing older and funds reach their optimal AUM.

Hypothesis 4 (H4)**.** *Skilled mutual funds start with high abnormal returns, but these returns stabilise over time when they grow older*

When skilled funds accumulate more capital than unskilled funds, skilled funds will also generate more value added when growing older. Although the abnormal returns might stay the same, when AUM increase over age, the value added will also increase. Since unskilled funds are not expected to acquire a lot of assets, their value added is likely to be constant over age.

Hypothesis 5 (H5)**.** *Skilled funds have increasing value added, while unskilled funds have stable negative value added*

Furthermore, based on the insights of Berk and Green (2004) and B&B, I also expect management fees to slightly decrease over age. Due to the increasing AUM at skilled funds, compensation will increase for these funds. They can therefore compensate with lower fees. B&B stress in their paper that skilled and unskilled funds have equal fees, since investors reward the best performing funds with larger compensation due to their asset allocation, rather than paying higher fees.

Hypothesis 6 (H6). *The management fee slightly decreases when funds grow older but is equal between skilled and unskilled funds*

Hypothesis 7 (H7). *Compensation increases more over age for skilled than for unskilled funds*

B. Methodology

To test for survivorship bias, I use a statistical method often used in medical environments and known as survival analysis. This method is - to the best of my knowledge - infrequently used in financial papers but fits the purpose of this study perfectly.[10] It tries to estimate the probability that an individual will experience the event (also known as hazard rate) and can be used to identify effects of different factors on this probability. More traditional approaches such as probit models are less useful since they ignore timing of the fund's death (Lui, 2012).

Before explaining the model, some general assumptions for survival analysis have to be made. Every funds is t months in the database, which I will call duration. The current status of every fund can be dead, still alive or can be unknown because the track of that fund is lost during the observation period. If the fund died, it lived for T months, which I will call the event time. When the probability T is smaller than t no event occurs, which can be shown as

$$F(t) = Prob(T \leq t) = \int_0^t f(u)du \tag{8}$$

where $f(t)$ represents the probability density function of event time T and $F(t)$ the cumulative distribution function over time interval (0,t).

The fact whether an event occurs or not, is of course binary. This causes the complement of this function to describe when an event does occur. The survival function can thus be shown as

$$S(t) = Prob(T > t) = 1 - F(t) \tag{9}$$

[10]The only known paper which combines survival analysis and mutal funds is from Lunde, Timmermann, and Blake (1999) who perform a nonparametric approach to find the determinants of closure distribution and decisions of mutal funds.

Finally, the probability that a fund dies in period t is defined as hazard rate given by

$$\lambda(t) = \frac{f(t)}{S(t)} \tag{10}$$

Given the unknown distribution of the data, I use the semi-parametric Cox proportional hazard model (Cox, 1972). This has the advantage that it uses hazard rates instead of the distribution function, which makes it also easier to interpret. The independent variable $\lambda(t)$ represents these hazard rates in the model as

$$\lambda(t) = \lambda_0(t) * exp\left(\sum_{i=1}^{p} \beta_i x_i\right) \tag{11}$$

where $\lambda_0(t)$ is a known baseline hazard function for T and β represents the coefficients for explanatory variables x_i, where $x_i = (x_1, x_2, ..., x_p)$. Note that the explanatory variables have a multiplicative or proportional effect. The baseline hazard is multiplied with the exponential effect of the explanatory variables. A constant base line over time is thus an important assumption for this model. I therefore test the different variables on the proportional hazards-assumption on the basis of Schoenfeld residuals (Schoenfeld, 1982). Variables that have time-varying baselines are added as time variant coefficients as follows,

$$\lambda(t) = \lambda_0(t) * exp\left(\sum_{i=1}^{p} \beta_i x_i + g(t)\sum_{i=1}^{q} \gamma_k z_k\right) \tag{12}$$

where a variable can vary over time as $z_k(t) = z_k g(t)$. γ_k is then the coefficient for variable z_k, where $z_k = (z_1, z_2, ..., z_q)$.

To further identify trends in fund's life cycles, I try to show the developments funds undergo when ageing. To reveal this effect, I first calculate the mean of various determinants for every year of age. In this way, the effects of being t years old are captured in one mean as

$$D_t = \frac{1}{N}\sum_{i=1}^{N} D_{it} \tag{13}$$

where D_t is the mean of a determinant for all funds at age t. N is the number of observations when a fund is t years old and D_{it} is the value of the determinant for funds i at age t. Note that the oldest funds are present in all means of age years. Every age year however represents a different phase in its life cycle. The age years are subsequently assigned into deciles. Every decile thus represents equally weighted means of the averages of the age years. In this way, differences can be observed between funds being in the beginning of their life cycle compared to funds that are at the end of their life cycle.

In all analysis of life cycles, I want to make a distinction between skilled an unskilled funds. This contributes to the understanding of the development of funds over their life time and the survivorship bias. I therefore rank funds by skill ratio. I use the same measure as B&B defined as,

$$SKR_i = \frac{\hat{S}_i}{\sigma(\hat{S}_i)} \tag{14}$$

where $\hat{S}_i$ represents the skill of fund i and $\sigma(\hat{S}_i)$ the standard deviation as $\sqrt{\sum_{t=1}^{t}(V_{it} - \hat{S}_i)^2/t}$. Different than B&B, I take the total period of the fund's existence into account to calculate the skill ratio. Now B&B proved persistency of skilled and unskilled funds, I want to identify the differences of these funds by measuring their skill over their entire life.

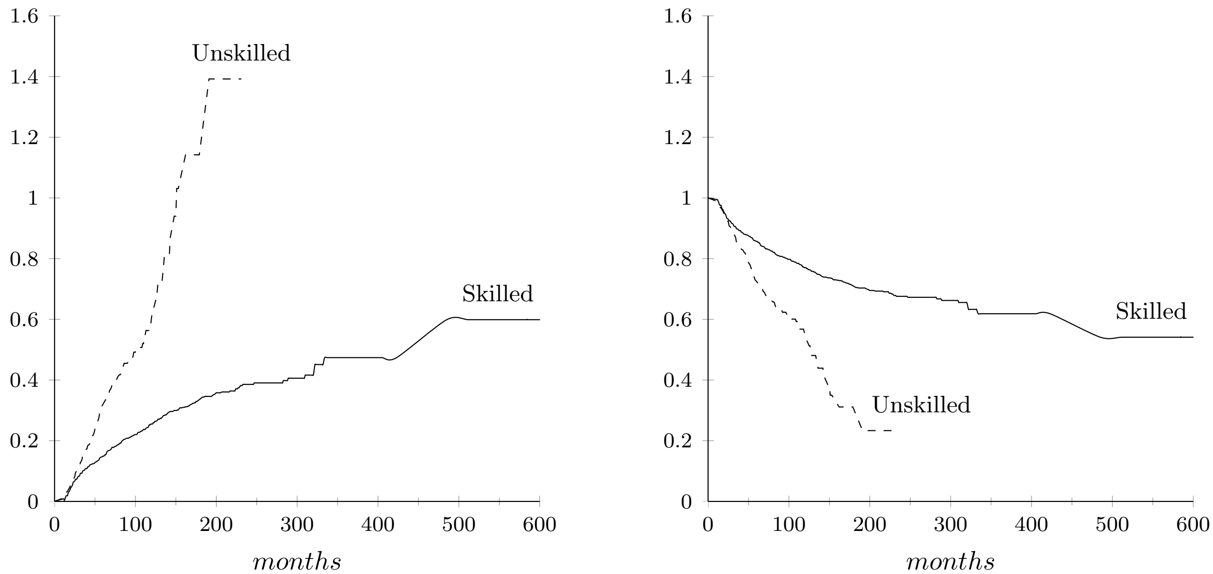
C. Results

The results are divided into two different sections. First, I discuss the survival analysis and the effect of some determinants on the hazard rates. Second, I will show the life cycles of skilled and unskilled funds.

Survival analysis

As expected, a huge survivorship bias exists among mutual funds (H1). Figure 3 shows the cumulative hazard rates in figure (a) for skilled and unskilled funds over time. Unskilled funds have a much larger probability to die than skilled funds. This difference starts to become increasingly bigger after around 30 months. This pattern is confirmed in figure (b). It shows that unskilled funds can approximately survive the first 2.5 years as good as skilled funds, but after this they die more often. After 150 months, skilled funds have 74% chance to survive compared to only 39% for unskilled funds.

Table V also confirms the survivorship bias. In model (1), the Cox model shows that one jump in skill-ratio decile, increases the chance of survival with 8%. The lowest skilled funds thus have



(a) Hazard rates

(b) Survival rates

Figure 3: Fund distribution trends

This graph shows the survival distrubtion for funds in the database. Figure (a) shows the cumulative hazard function at time t, calculated by summing up the hazard functions over time. Figure (b) shows the Kaplan-Meier estimator of the survivor function, which indicates the probability of survival at time t. The solid line represents skilled funds, where the dashed line shows the distribution of unksilled funds.

approximately 80% less chance of survival than the most skilled funds. Flow does not seem to have that much impact, while the expense ratio has a very large magnitude. An increase of one in the log of expense ratio, rises the chance of dying with 76%. On the other hand, management fee has a lowering effect on the chance of dying. One percent increase in management fee decreases the chance to die with 14%.

It is not very surprising that the expense ratio has such a large effect on a fund's chance of dying. An easy explanation is that funds with high expenses cannot make enough return to compensate for these and therefore sooner go out of business. Higher management fee on the other hand increases the chance of survival, since it enlarges the income of funds. Later, I will show that unskilled funds will increase management fee to keep their funds alive.

Not surprisingly, higher family size decreases the chance of dying. Big families tend to have more resources to keep the fund alive. The increasing effect of turnover ratio on the chance of dying, indicates that fund managers tend to trade on overconfidence rather than on knowledge.

Notable is the effect of gender. If the fund's manager is a woman, the chance that fund will die is 39% higher than when the fund's manager is a male. It is unclear whether this is due to the

Table V

Effect of Determinants on the Chance Funds Die

This table represents the outcomes of the semi-parametric Cox model (Cox, 1972). In the first model (1) *Ranking* represents which decile the fund is in based on its skill ratio. *Flow* is the cumulative flow over the lifetime of a fund (in Y2015$), while $Expenseratio$, $Managementfee$ and $Turnoverratio$ are the respective averages of a fund (in %), where the log is taken of the expense ratio. $Logsizefamily$ is the log of the fund's family size in Y2015$ at the time of closing. The second model (2) also includes the gender of the fund manager at the time of closing, $ManagerGender$. This dummy equals 1 if the fund manager is a male and zero if she is a woman. All variables are tested on the proportional-hazards assumption on the basis of Schoenfeld residuals (Schoenfeld, 1982). This assumption is violated with *Ranking* in both models. Therefore, this variable is given a time dependent effect in addition to its main effect as $z_k(t) = z_k g(t)$. The coefficients for $z_k(t)$ are not shown in this table due to their extreme small magnitude. The standard errors are given in parentheses and the ***, ** and * indicate p-values of below 0.01, 0.05 and 0.10 respectively

Cox models for the chance a fund dies				
	(1)		(2)	
	Coefficients	Hazard rates	Coefficients	Hazard rates
Ranking	-0.08***	0.92***	-0.07**	0.93**
	(0.02)	(0.02)	(0.03)	(0.03)
Flow	-0.00003***	0.99997***	-0.00001	0.99999
	(0.00001)	(0.00001)	(0.00002)	(0.00002)
Logexpenses	0.57***	1.76***	0.52***	1.69***
	(0.07)	(0.11)	(0.14)	(0.24)
$Managementfee$	-0.15***	0.86***	-0.32***	0.73***
	(0.01)	(0.01)	(0.03)	(0.02)
$Logsizefamily$	-0.07***	0.93***	-0.09***	0.91***
	(0.01)	(0.01)	(0.01)	(0.01)
$Turnoverratio$	0.05***	1.05***	0.15***	1.16***
	(0.01)	(0.01)	(0.03)	(0.03)
$ManagerGender$			-0.49***	0.61***
			(0.16)	(0.1)
Number of funds	6926	6926	1249	1249
Number of closures	1487	1487	418	418

performance of the female fund managers or that other underlying explanations cause this result. Sometimes the manager's name is omitted from the database in the last year(s) before closing. This causes a missing value in the Cox model. It could be that those missing names are mostly men's. Furthermore, causality and selection bias could skew the outcome and further research is needed to explain this remarkable phenomenon.

Life cycles

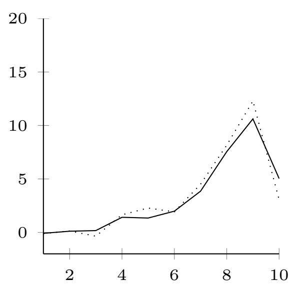
The life cycles of funds can be described by the changing values of determinants over their life time. I try to reveal this, by taking the average of different age deciles as described in section VII.B. These averages are presented in Table VI, while Figure 4 graphically expose the trends that

Table VI

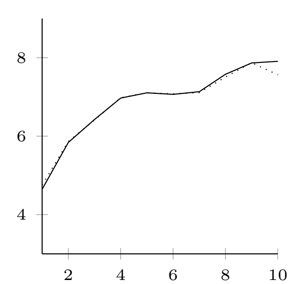
Means and Medians for Fund Characteristics by Age Deciles

For every decile of age, the means (medians) of the characteristics are shown in this table. The age deciles represent equally weighted means of the averages per age year, with the averages per age year as the means of the monthly observations of that age year. Thus, if funds A is 90 years old, it is present in every decile mean, but every decile mean represents another phase of its life cycle. TNA represents the real assets under management (AUM) and V_{it} the added value, both in Y2015\$. $Expenses$ and $Compensation$ are respectivily the $Expenseratio$ and the $Managementfee$ multiplied with the real AUM. Ratios, flow and returns are in %. The total number of funds is the average total in that decile. Note that despite being alive, a fund may only be present in the first decile due to his low current age.

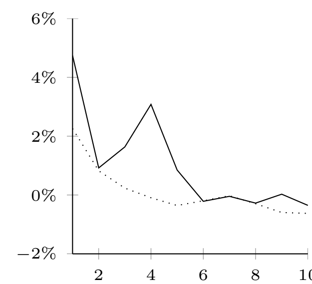
Variable	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
TNA	4.65 (4.75)	5.84 (5.87)	6.43 (6.41)	6.97 (6.98)	7.11 (7.1)	7.07 (7.08)	7.13 (7.11)	7.58 (7.51)	7.87 (7.87)	7.91 (7.57)
$Addedvalue$	-0.08 (-0.1)	0.11 (0.13)	0.17 (-0.35)	1.41 (1.65)	1.35 (2.28)	1.99 (1.92)	3.86 (4.51)	7.55 (8.16)	10.61 (12.3)	5.04 (3.06)
$Abnormalreturn$	0.003 (-0.014)	0.029 (0.026)	0.013 (-0.004)	0.004 (0.001)	-0.012 (-0.027)	0.063 (0.083)	0.012 (-0.009)	0.069 (0.088)	0.045 (0.046)	0.049 (0.036)
$Expenseratio$	1.32 (1.33)	1.25 (1.25)	1.14 (1.14)	1.08 (1.09)	1.01 (1)	1 (1)	1.02 (1.01)	1.02 (1.02)	0.96 (0.96)	0.89 (0.93)
$Expenses$	4.6 (4.3)	14.1 (14.2)	23.3 (23.5)	37.3 (37.6)	47.2 (47.1)	48.5 (49.4)	36.4 (34.5)	51.5 (44.8)	78 (74.2)	35.5 (34.3)
$Managementfee$	0.35 (0.53)	0.73 (0.73)	0.69 (0.7)	0.64 (0.65)	0.63 (0.63)	0.64 (0.64)	0.6 (0.6)	0.52 (0.52)	0.52 (0.53)	0.5 (0.53)
$Compensation$	2.7 (2.5)	9.2 (9.2)	16.4 (16.4)	24.7 (24.1)	38.3 (38.6)	35.9 (36.6)	28 (27.6)	26.2 (25.4)	35.9 (34.3)	20.8 (23.9)
$Flow$	4.74 (2.26)	0.92 (0.82)	1.64 (0.23)	3.08 (-0.09)	0.85 (-0.36)	-0.21 (-0.2)	-0.05 (-0.03)	-0.28 (-0.3)	0.03 (-0.59)	-0.35 (-0.63)
Age	5	14	23	33	42	51	61	70	79	88
Number of funds	5162	2583	931	341	199	122	81	49	30	6
Number of deads	1110	422	91	30	15	9	5	3	3	0



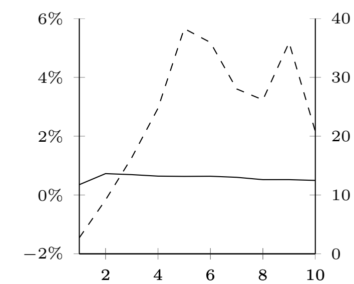
(a) Added value



(b) AUM



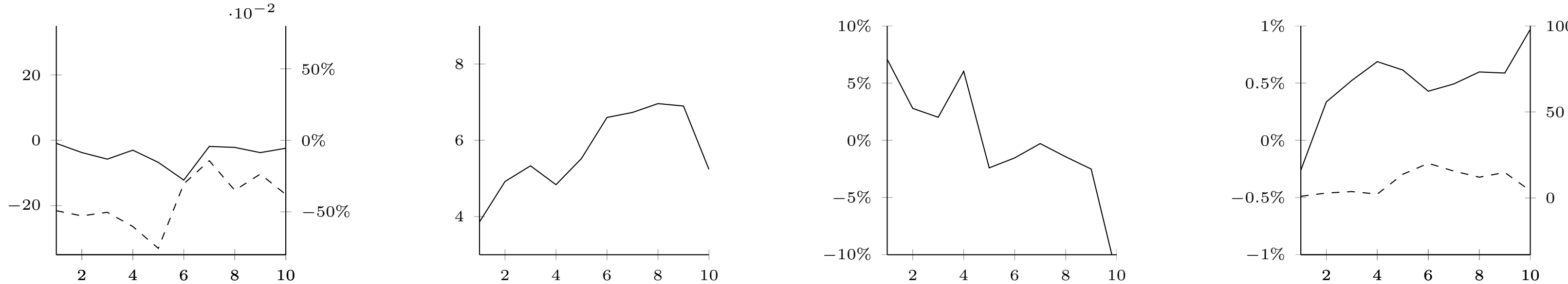
(c) Flow



(d) Management Fee and Compensation

Figure 4: Life Cycle Trends

The graphs shown above depict the means and medians of age deciles for four different characteristics. The age deciles represent equally weighted means of the averages per age year, with the averages per age year as the means of the monthly observations of that age year. The solid lines represent the mean per decile, while the dotted lines represent the median. For graph (d) the compensation is shown as the dashed line and no median is given. The added value, assets under management (AUM) and compensation are in Y2015\$.

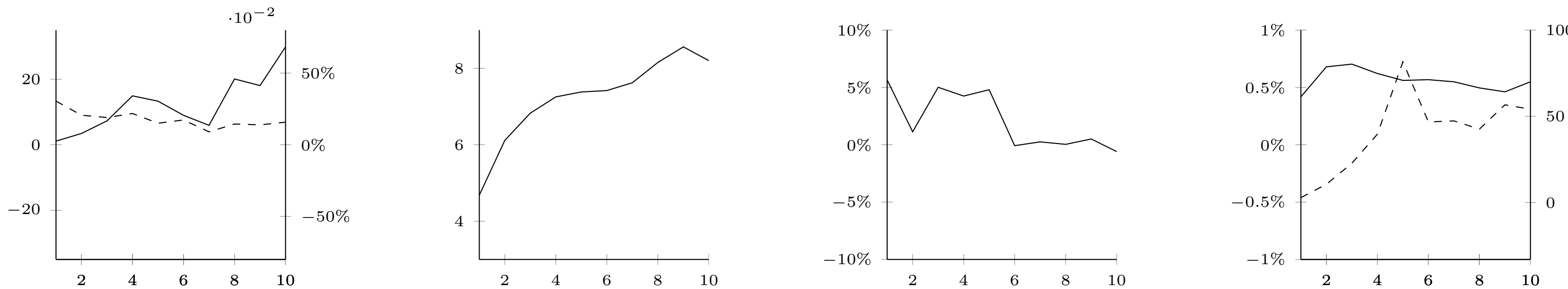


(a) Added value (unskilled)

(b) AUM (unskilled)

(c) Flow (unskilled)

(d) Management Fee and Compensation (unskilled)



(e) Added value (skilled)

(f) AUM (skilled)

(g) Flow (skilled)

(h) Management Fee and Compensation (skilled)

Figure 5: Life Cycle Differences Between Skilled and Unskilled Funds

The graphs above show the means of age deciles for four different characteristics. Graphs (a)-(d) show the life cycle for the unskilled funds, while (e)-(h) does the same for the skilled funds. The skilled (unskilled) funds are the top (bottom) 20% ranked on SKR_i. The age deciles represent equally weighted means of the averages per age year, with the averages per age year as the means of the monthly observations of that age year. Thus, if fund A is 90 years old, it is present in every decile mean, but every decile mean represents another phase of its life cycle. In graph (a) and (e) the solid line represents the added value, while the dashed line represents the abnormal returns in %. For graph (d) and (h) the compensation is shown as the dashed line, while the solid line represents the management fee in %. The added value, assets under management (AUM) and compensation are in Y2015$.

those averages describe.[11] In line of expectations, funds acquire more capital when they grow older. Furthermore, flow is declining over age and compensation increasing. The interesting question is: how do these trends differ between skilled and unskilled funds?

From Table VI it can be observed that a large number of funds die in the first decile. Figure 6 shows that the number of unskilled funds in the database decreases more drastically over age than it does for skilled funds. This again confirms the existence of a survivorship bias.

Also interesting is the difference in development of AUM between skilled and unskilled funds (H2). The graphs (b) and (f) in Figure 5 show a big difference in the accumulation of capital. Unskilled funds seem to a lesser extent be able to build AUM, while skilled funds grow larger over age. This pattern is confirmed in Panel A of Table VII. The two bottom quintiles for skill do not show any significant difference between the youngest and oldest funds. However, in the middle phase of the unskilled fund's life cycle (Q3) there is a peak in AUM observable. Unskilled funds do seem to accumulate capital at the start, but have trouble keeping these assets. This pattern is confirmed by the flow (H3), Figure 5 (c) and (d) show that both skilled and unskilled funds begin with periods of inflow. The difference is that unskilled funds experience heavy outflow after a period of time,

while skilled funds can hold their money and end in constant flow around zero. Panel B of Table VII shows this pattern in more detail. Under young funds, there is no significant difference in flow between lowly and highly skilled funds. This difference begins at the fourth age quintile, where lowly skilled funds experience outflows, while highly skilled funds move to a flow around zero. It thus seems that investors need time to distinguish between skilled and unskilled funds before adjusting their flow accordingly. Across all skill quintiles, flow does decrease over age (H3). Lastly, highly skilled funds moving to a flow of zero over age, confirms the assumption of B&B that mutual funds choose an optimal amount of assets to actively manage and move to this optimum.

Looking at Figure 5 (a) and (e), abnormal returns seem fairly stable over time (H4). It also appears that the skilled funds have a slightly higher start. This is confirmed in Panel C of Table VII. The highly skilled funds have decreasing abnormal returns over age, but stay positive over their lifetime. For unskilled funds, abnormal returns are negative over their entire period of existence. There seems to be a jump in abnormal returns in the graph from decile five to six, but this can be

[11]Figure 7 in the appendix shows the number of skilled and unskilled funds per year of age

due to the survivorship bias. These jumps also do not lead to significant differences in abnormal returns for these funds (see Table VII).

In contrast to returns, the value added increases for most skilled funds when they grow older (H5). Because their AUM increases and returns just slightly decrease, the value added heavily increases. Panel D of Table VII shows that only the best funds can increase their value added significantly over age. Apparently, less skilled funds are not able to acquire enough AUM together with positive abnormal returns to make increasing value added over their life times. The most skilled funds can increase their value added with \$256 million per year between the start and the latest phase of their life cycle.

The third age quintile in panel D shows that there exists a large group of medium aged funds that destroy a lot of value. These funds can accumulate capital at the start, but subsequently destroy value with these assets. This is confirmed by the low percentage of funds that die because of being unskilled. It are these funds that offset the value added of large skilled funds, resulting in the fact that size has no direct effect on value added.

Looking at figure 5 (d) and (h), it seems that the management fee is slightly lower for the youngest funds (H6). This could indicate that fund managers lower their beginning fee to sell their starting funds at investors. For the less skilled funds this "starting discount" is the largest. Also of interest is the increasing management fee for unskilled funds and the decreasing fee for skilled funds (see panel E of Table VII). It seems like the unskilled funds want to compensate the loss of AUM with higher management fees to keep their compensation at a certain level, while skilled funds can afford to slightly lower their fee. Panel E shows that if the "starting discount" is disregarded, management fees for unskilled funds increase on average with 18% over their lifetime.

Although unexpected, the unskilled funds also have some increase in their compensation (H7). Panel A of Table VII shows all funds receive more compensation over age. Unskilled funds seem to be able to keep compensation increasing by raising their management fee when accumulation of AUM does not cause this effect. The increase of 18% in management fee translates to a difference of \$113 million compensation per year between the youngest and oldest funds. Due to the climbing AUM for the most skilled funds, compensation does also rise over age for the these funds. On average, skilled funds can increase their compensation with \$584 million per year. This huge difference is closely tight to their ability to acquire large amount of assets. This again confirms

Table VII
Age Effects on Characteristics Between Fund's Skill

This table shows how the means for five age quintiles differ across skilled and unskilled funds. These age quintiles represent equally weighted means of the averages per age year, with the averages per age year as the means of the monthly observations of that age year. Thus, if fund A is 90 years old, it is present in every decile mean, but every decile mean represents another phase of its life cycle. The five quintiles of skill are obtained by ranking the funds by SKR_i. $Addedvalue$, $logAUM$ and $Compensation$ are in Y2015\$. The $Managementfee$, $Flow$ and $Abnormalreturns$ are in %. The standard errors are given in parenthesis and the ***, ** and * indicate p-values for the high-low-portfolio of below 0.01, 0.05 and 0.10 respectively.

Panel A: Log AUM averages

	Age quintiles					
	Young	Q2	Q3	Q4	Old	Old - Young
Lowly skilled	5.894	6.307	7.399	7.397	6.514	0.620
	(0.25)	(0.21)	(0.32)	(0.06)	(0.57)	(0.60)
Q2	6.164	7.199	7.284	6.726	6.364	0.200
	(0.18)	(0.1)	(0.07)	(0.09)	(0.06)	(0.20)
Q3	6.445	7.937	8.06	7.763	8.354	1.909***
	(0.18)	(0.08)	(0.08)	(0.09)	(0.09)	(0.20)
Q4	6.506	8.031	8.861	8.501	7.868	1.362***
	(0.21)	(0.05)	(0.11)	(0.13)	(0.08)	(0.23)
Highly skilled	6.586	8.433	8.911	8.971	9.817	3.231***
	(0.21)	(0.08)	(0.06)	(0.08)	(0.15)	(0.26)
High - Low	0.692*	2.127***	1.512***	1.574***	3.303***	
	(0.35)	(0.18)	(0.23)	(0.12)	(0.44)	

Panel B: Flow averages

	Age quintiles					
	Young	Q2	Q3	Q4	Old	Old - Young
Lowly skilled	5.173	4.022	-1.973	-0.864	-7.133	-12.306***
	(1.72)	(2.61)	(0.46)	(0.39)	(2.97)	(3.34)
Q2	3.304	1.411	-0.443	-0.318	-0.726	-4.029**
	(1.48)	(1.39)	(0.33)	(0.33)	(0.13)	(1.52)
Q3	2.751	0.768	-0.540	-0.282	-0.769	-3.520***
	(1.06)	(0.84)	(0.08)	(0.10)	(0.19)	(1.10)
Q4	3.054	-0.089	3.268	-0.171	0.121	-2.933**
	(1.12)	(0.07)	(3.33)	(0.09)	(0.72)	(1.35)
Highly skilled	3.390	4.630	2.359	0.144	-0.013	-3.402**
	(1.37)	(2.41)	(2.39)	(0.06)	(0.53)	(1.50)
High - Low	-1.783	0.608	4.332	1.008***	7.121***	
	(2.29)	(4.03)	(3.64)	(0.27)	(2.14)	

(continued)

Table VII - *Continued*

Panel C: Abnormal returns averages

	Age quintiles					
	Young	Q2	Q3	Q4	Old	Old - Young
Q1	-0.508	-0.553	-0.53	-0.246	-0.307	0.201
	(0.03)	(0.05)	(0.13)	(0.14)	(0.18)	(0.17)
Q2	-0.161	-0.27	-0.203	-0.137	-0.047	0.114
	(0.02)	(0.04)	(0.06)	(0.06)	(0.23)	(0.22)
Q3	0.004	-0.071	-0.065	-0.067	0.013	0.009
	(0.01)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)
Q4	0.127	0.029	0.035	0.051	0.053	-0.074**
	(0.02)	(0.01)	(0.02)	(0.03)	(0.02)	(0.03)
Q5	0.255	0.204	0.162	0.118	0.148	-0.108**
	(0.02)	(0.02)	(0.02)	(0.03)	(0.05)	(0.05)
High - Low	0.764***	0.757***	0.692***	0.364***	0.455***	
	(0.03)	(0.04)	(0.09)	(0.1)	(0.14)	

Panel D: Added value averages

	Age quintiles					
	Young	Q2	Q3	Q4	Old	Old - Young
Lowly skilled	-2.186	-4.385	-9.458	-2.018	-3.096	-0.91
	(0.55)	(0.67)	(3)	(1.22)	(1.71)	(1.71)
Q2	-1.936	-5.366	-3.322	-1.816	-0.862	1.074
	(0.43)	(1.07)	(1.1)	(0.96)	(1.57)	(1.58)
Q3	-0.964	-4.276	-4.151	-2.428	-1.67	-0.706
	(0.25)	(1.55)	(1.59)	(1.08)	(2.09)	(2.05)
Q4	0.847	0.089	2.785	3.342	0.115	-0.732
	(0.2)	(0.69)	(4.92)	(2.41)	(0.75)	(0.76)
Highly skilled	2.285	11.112	11.152	13.008	23.632	21.346***
	(0.38)	(1.4)	(2.56)	(3.26)	(7.32)	(7.12)
High - Low	4.471***	15.498***	20.61***	15.026***	26.727**	
	(0.66)	(2.16)	(4.35)	(5.01)	(10.85)	

(continued)

Table VII - *Continued*

Panel E: Management fee averages						
	Age quintiles					
	Young	Q2	Q3	Q4	Old	Old - Young
Q1	0.004	0.605	0.521	0.545	0.715	0.711***
	(0.16)	(0.04)	(0.05)	(0.03)	(0.08)	(0.21)
Q2	0.459	0.63	0.755	0.729	0.879	0.42***
	(0.09)	(0.06)	(0.02)	(0.03)	(0.01)	(0.09)
Q3	0.568	0.653	0.679	0.592	0.481	-0.087
	(0.08)	(0.03)	(0.01)	(0.02)	(0.02)	(0.08)
Q4	0.61	0.708	0.616	0.594	0.581	-0.029
	(0.07)	(0.01)	(0)	(0.01)	(0.02)	(0.08)
Q5	0.549	0.662	0.564	0.522	0.503	-0.046
	(0.07)	(0.01)	(0)	(0.01)	(0.02)	(0.07)
High - Low	0.545***	0.057*	0.043	-0.022	-0.212***	
	(0.15)	(0.03)	(0.03)	(0.02)	(0.06)	

Panel F: Compensation averages						
	Age quintiles					
	Young	Q2	Q3	Q4	Old	Old - Young
Lowly skilled	1.811	2.966	16.934	13.833	11.255	9.444***
	(0.38)	(0.41)	(3.47)	(1.03)	(2.6)	(2.13)
Q2	3.24	9.465	13.465	8.374	5.248	2.008***
	(0.54)	(1.13)	(1.08)	(1.04)	(0.35)	(0.65)
Q3	5.235	15.748	20.313	12.527	18.971	13.736***
	(0.68)	(1.03)	(1.51)	(1.04)	(1.47)	(1.59)
Q4	6.141	18.952	44.459	27.005	12.916	6.775***
	(0.88)	(1.02)	(4.8)	(3.46)	(1.01)	(1.33)
High skilled	6.726	31.225	64.164	44.962	55.473	48.747***
	(1.09)	(2.74)	(5.79)	(1.99)	(3.82)	(3.88)
High - Low	4.915***	28.258***	47.23***	31.13***	44.218***	
	(1.58)	(4.17)	(9.07)	(3.08)	(6.7)	

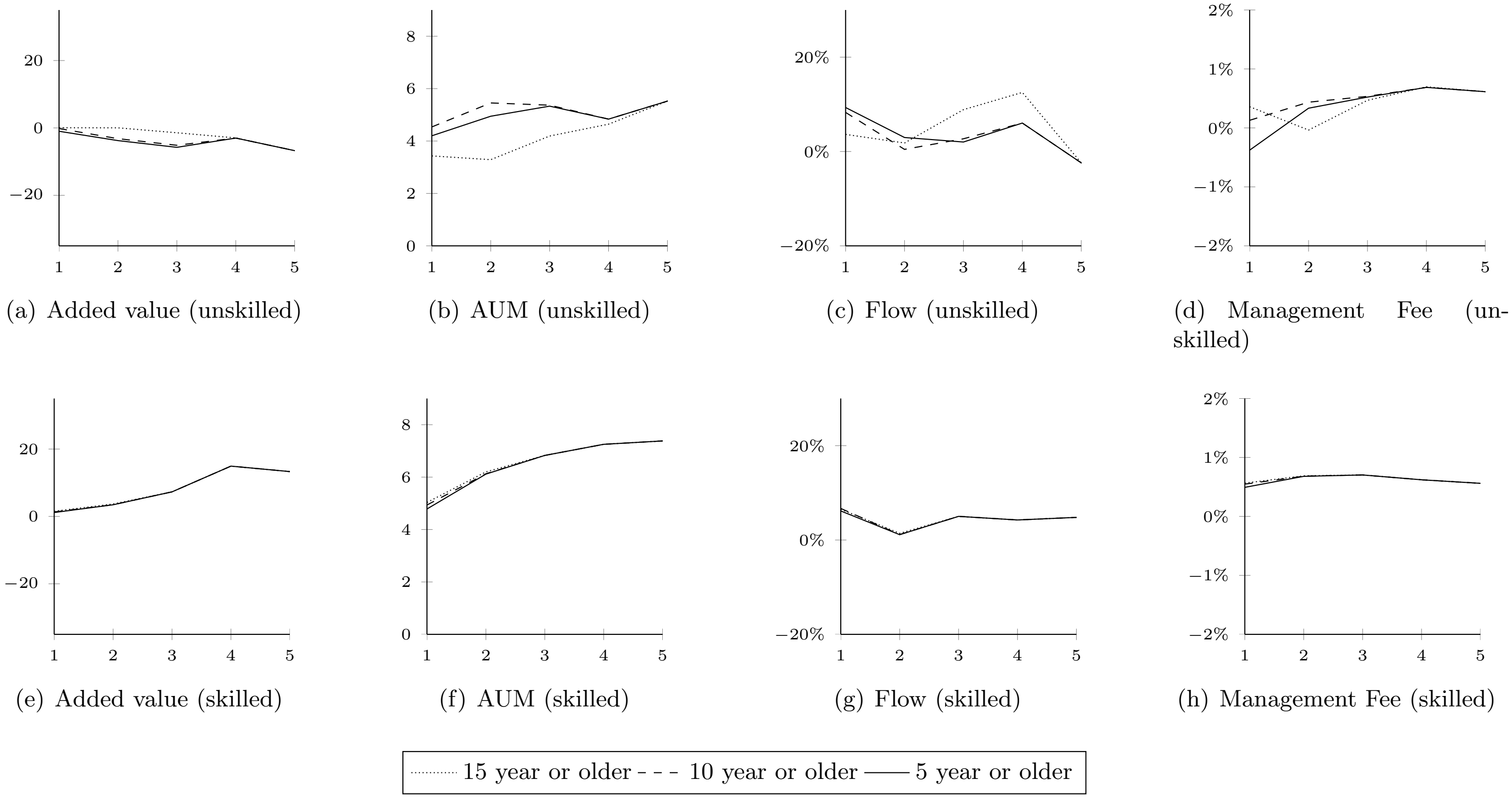
the theory of Berk and Green (2004) that investors identify skilled funds and invest accordingly. It is remarkable to see that unskilled funds also try to increase their compensation by raising the management fee. This might also explain the negative effect of higher expense ratios on value added. The funds with larger expense ratios try to compensate their asset outflow and thus perform worse.

D. Robustness

To strengthen the outcomes of this section, I explore two robustness checks. Firstly, one could argue that change in the values of determinants over the years, is caused by two different factors. The first factor is the inherent value change of determinants within a fund as it grows older. This shows how funds develop over age. The values presented above however, also change because the composition of the means constantly change over time. Year ten for example only includes funds of ten years and older, because none of the funds below ten years old experienced the 10th year of its life yet. This creates a survival effect. I try to disentangle these effects by calculating the means for funds that are older than five, ten and fifteen years. The results of these different cohorts are presented in Figure 6. For unskilled funds the survival effect is clearly visible. Unskilled funds that managed to live for five or more years, have different life cycles than funds that died before this period. Unskilled funds that lived for example for more than 15 years were better able to keep positive added value and received flow in a later stage, helping them to survive.

For skilled funds the patterns for all cohorts are the same. Survival effect does not play a major role for these funds since skilled funds often survive. This implicates the existence of a “winning life cycle pattern” for mutual funds.

Secondly, in Section VI, I argued that size affects the volatility of value added in absolute terms. This is because size has a multiplicative effect on value added (see equation 2). I also showed that older funds are often larger. Since the skill ratio is based on the fund’s entire existence, more observations are taken into account of the larger phase at older funds compared to young funds. Old funds can thus be ranked higher in skill, because their skill is magnified by their size. To overcome this bias, I rank funds again on SKR_i, but take a measurement horizon of the first 10 year of existence. I argue that ten years is enough to measure skill, but not too long to suffer from the bias (ten years only represent the first decile of age for skilled funds). Although less pronounced,



(a) Added value (unskilled)
(b) AUM (unskilled)
(c) Flow (unskilled)
(d) Management Fee (unskilled)
(e) Added value (skilled)
(f) AUM (skilled)
(g) Flow (skilled)
(h) Management Fee (skilled)

Figure 6: Life Cycle Differences Excluding Younger Funds

The graphs above show the means of age deciles for four different characteristics. Graphs (a)-(d) show the life cycle for the unskilled funds, while (e)-(h) does the same for the skilled funds. The skilled (unskilled) funds are the top (bottom) 20% ranked on SKR_i. The age deciles represent equally weighted means of the averages per age year, with the averages per age year as the means of the monthly observations of that age year. Thus, if fund A is 90 years old, it is present in every decile mean, but every decile mean represents another phase of its life cycle. The solid, dashed and dotted lines show cohorts where funds younger than 5, 10 and 15 years are excluded. The log is taken of assets under management (AUM). AUM and value added are both in Y2015$.

I obtain similar outcomes with this ranking. The results are presented in Figure 8 in the Appendix.

VIII. Conclusion

To summarize, this thesis contributes to the current literature by putting the fund characteristics in a new perspective to obtain a broader understanding of mutual funds and their life cycles. I demonstrate that the average funds manager has not been able to add value between 1962 and 2015 and even destroys value of $2.9 million per year.

When I test the effect of individual determinants, I find that family size and flow have a positive relation with value added, while expenses have a negative effect. In a portfolio analysis I show that large funds with high lagged flow add $78 million dollar per year more than large funds with low flow. No evidence is found for the effect of the investment managers' gender, marketing expenses, turnover ratio and dividends on value added. Although size has an ambivalent relation to value added, it does not have an effect on value added on its own.

With survival analysis, I subsequently provide insights in the effects of determinants on the fund's chance to survive. Remarkably, female managers increase hazard rates with 39%. Higher turnover ratio also decreases the chance of survival, which could imply that managers do not trade on proprietary knowledge. Hazard rates are also negatively influenced by expenses. I find that funds with high expenses go sooner out of business, while higher income streams (management fee) increase their chances. Being part of a big fund family can also help to survive as it causes lower hazard rates. However, being skilled is the best method of staying alive. Skilled funds have around 80% more chance to survive than unskilled funds, hence a huge survivorship bias exists.

In the life cycle analysis, I show that both skilled as unskilled funds are able to accumulate capital at the start. Their flow however turns negative after some time, leading to decreasing AUM. This is consistent with the hazard rates, which start to differentiate only after a period of around 2.5 years. Investors do apparently need some time to identify a fund as (un)skilled. In this starting period, both skilled and unskilled funds try to lure investors with low management fees, but this effect is most pronounced at unskilled funds. In the end, both can increase compensation over their lifetime. Unskilled funds manage to keep their compensation increasing by raising management fees on average with 18% when growing older. Skilled funds lower their management fee, but receive higher compensation because of increasing AUM, which Berk and van Binsbergen (2015) find as well.

Finally, since this thesis only tries to explain the origin of skill as gross value added, translation to investment strategies seems not immediately clear. By setting the management fee, fund managers can directly influence net alpha. This causes the return for investors to be disentangled from fund managers' skill. However, since life cycles of skilled funds follow a certain pattern, it might be possible to "time" a mutual fund's life cycle to optimise returns. Further research is needed to see how these suggestions lead to profitable investment strategies.

Appendix A Distribution of funds in the database

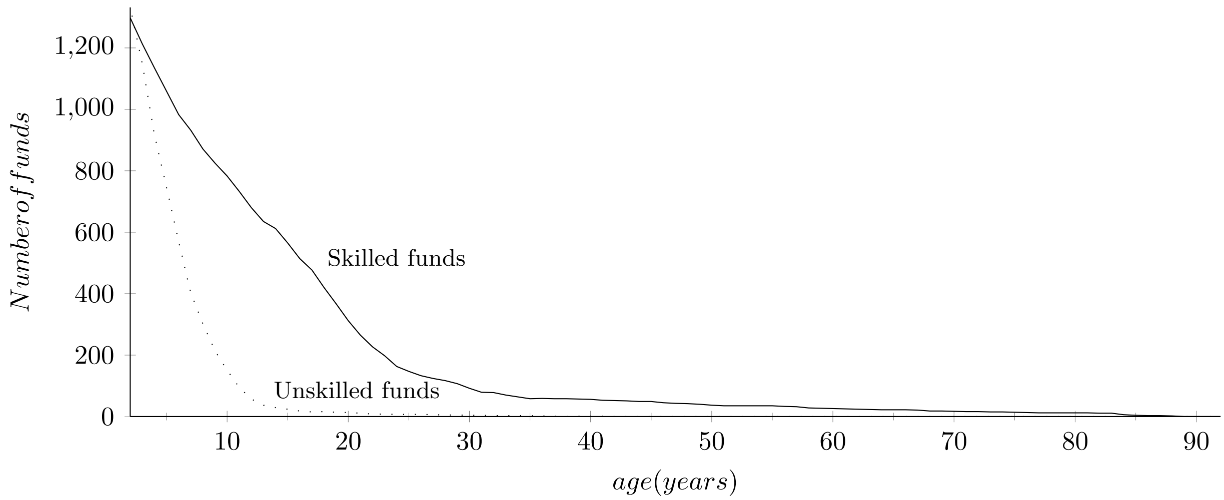
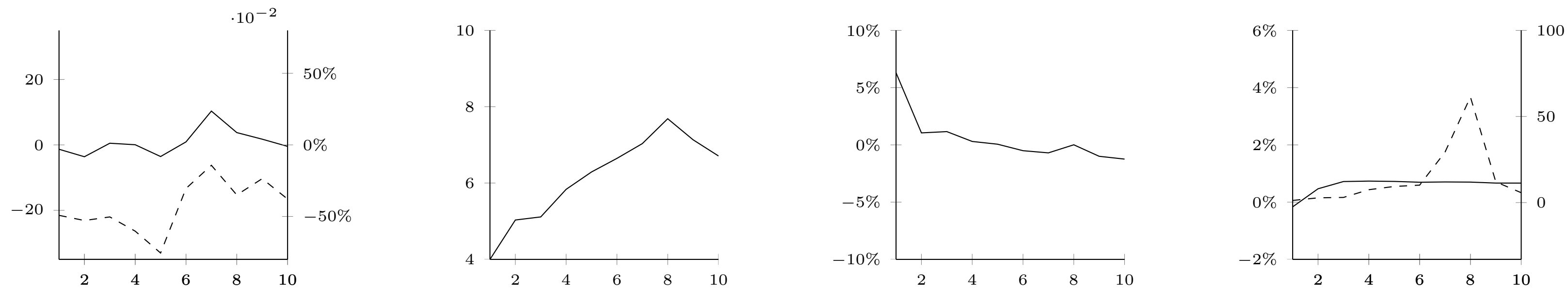


Figure 7: Fund distribution skilled and unskilled funds

The number of funds present in the database per year of age is shown in this graph. The solid line represents the skilled funds, while the dotted line shows the distribution for the unkskilled funds.

Appendix B Robustness Test For Life Cycle Means

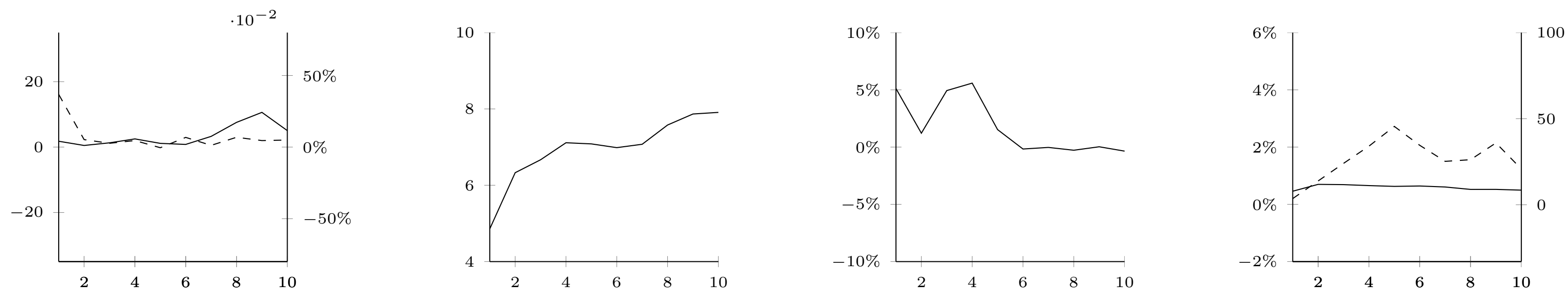


(a) Added value (unskilled)

(b) AUM (unskilled)

(c) Flow (unskilled)

(d) Management Fee and Compensation (unskilled)



(e) Added value (skilled)

(f) AUM (skilled)

(g) Flow (skilled)

(h) Management Fee and Compensation (skilled)

Figure 8: Life Cycle Differences Between Skilled and Unskilled Funds Ranked on First Ten Years

The graphs above show the means of age deciles for four different characteristics. Graphs (a)-(d) show the life cycle for the unskilled funds, while (e)-(h) does the same for the skilled funds. The skilled (unskilled) funds are the top (bottom) 20% ranked on SKR_i based on the first ten years of the fund's existence. The age deciles represent equally weighted means of the averages per age year, with the averages per age year as the means of the monthly observations of that age year. Thus, if fund A is 90 years old, it is present in every decile mean, but every decile mean represents another phase of its life cycle. In graph (a) and (e) the solid line represents the value added, while the dashed line represents the abnormal returns in %. For graph (d) and (h) the compensation is shown as the dashed line, while the solid line represents the management fee in %. The value added, assets under management (AUM) and compensation are in Y2015$.

List of Tables

List of Figures

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