Erasmus University Rotterdam

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# Investigating the Determinants of Skilled Mutual Funds


**Abstract**

This paper investigates the determinants of skilled mutual funds using the skill ratio from Berk and Van Binsbergen (2015) as a proxy for skill and MAX from Akbas and Genc (2016) with a sample from the CRSP Mutual Fund Database. In contrast to the authors, this paper finds that the average fund manager destroys value of $350,000 per year. When investigating the individual effects, the analysis provides evidence that MAX is an endogenous variable when skill ratio is added to a regression on monthly and quarterly fund flows. Past performance has a highly significant and positive effect on monthly and quarterly fund flows. A high-minus-low portfolio sorted on MAX, skill ratio and past performance generates $65 million higher Value Added per year. A portfolio of high-skilled funds generates a positive net alpha before transaction costs. Size is negatively associated with MAX, while cash has a positive effect on MAX.



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## 1 Introduction

Investors' demand for mutual funds has grown extensively in the past decade. According to the Investment Company Institute (ICI) factbook, total net assets invested with US-registered investment companies accounted for \$13.1 trillion in 2010. The amount of funds invested in ETF's accounted for \$992 billion, while \$11.8 trillion was invested in mutual funds. Assets invested in mutual funds or ETF's are the most popular type of investments. Throughout 2019, these net assets increased by \$4.6 trillion to reach a year-end level of \$26 trillion. \$21.3 trillion accounted for mutual funds and ETF's represented \$4.4 trillion in assets. The share of household financial assets held in investment companies accounted for 23 percent in 2019. Furthermore, these funds collectively owned 32 percent of US corporate equity, 21 percent of US and foreign corporate bonds and 14 percent of US Treasury and government agency securities (ICI, 2020)[1].

An interesting development is the rise of passive investment solutions offered by the investment management industry. Assets Under Management (AUM) of ETF's in the US increased by over 300 percent in the last 9 years (ICI, 2020). These funds are designed to offer low-cost diversification benefits, simplicity and intraday exchange liquidity to investors (Kosev et al., 2011). The increased popularity of these passive solutions can be a result of increased cost-awareness of investors. An alternative explanation can be that active management is failing to deliver adequate value that justifies the costs.

Given the size and importance of mutual funds in current financial markets, determining whether mutual funds add value for investors is an interesting research area. Mutual funds have been covered thoroughly in the academic literature, with an extensive body of research focusing on the ability of mutual funds to generate abnormal returns or alpha. The first research by Jensen (1968) documented that mutual funds do not outperform a passive benchmark index. However, Grinblatt and Titman (1992) found evidence that is consistent with the ability of fund managers to earn abnormal returns. Hendricks et al. (1993) found short-term performance persistence in mutual funds, but according to Carhart (1997), this result is caused by the momentum factor. After controlling for the momentum factor, the results by Carhart (1997) do not indicate that performance persistence is present. These papers document that the average mutual fund does not outperform a passive benchmark index and if a mutual fund does outperform a passive benchmark, the probability of outperformance in subsequent years is small.

With this evidence, Sirri and Tufano (1998) and Chevalier and Ellison (1997) provided contradictory results where mutual fund investors chase funds that displayed past outperformance, also known as return chasing. Furthermore, both studies found that mutual fund flows do not

[1] All data is retrieved from the ICI 2020 factbook

respond linearly to recent fund performance. The relationship between fund flows and recent performance has convex properties, meaning that the sensitivity of flows to performance increases with performance. Berk and Green (2004) provide a rational model for active portfolio management. In their model, they provide evidence that fund flows rationally respond to past performance even though performance persistence does not exist and active management does not outperform passive strategies on average.

Following the reasoning by Sirri and Tufano (1998) and Chevalier and Ellison (1997), investors want to identify funds that are expected to generate outperformance *ex ante*. An important determinant for outperformance is the skill of the fund manager. If the manager of the fund has stock-picking abilities and/or market timing skills, this manager should be able to predict the market correctly and generate abnormal returns for the investors in the fund.

Berk and Van Binsbergen (2015) are the first to find strong evidence for a level of skill. They propose a new proxy for skill of fund managers by looking at the value added, defined as gross alpha multiplied by total net assets (TNA), instead of net alpha. Investors are able to recognize this skill and reward it by investing more capital with better funds (Berk and Van Binsbergen, 2015).

Akbas and Genc (2016) document a positive and significant relationship between the maximum style-adjusted monthly return (MAX) and future fund flows. The effect of MAX on performance was negative albeit insignificant using risk-adjusted returns. According to Berk and Van Binsbergen (2015), risk-adjusted return is not an accurate proxy for skill because it measures the competitiveness of capital markets rather than skill. Therefore, the results from Akbas and Genc (2016) on maximum style-adjusted returns could also be a sign of fund managers' skill. The abnormal returns generated by funds can be the result of superior stock-picking abilities and/or market timing skills compared to other managers. Because MAX and skill ratio can be correlated, MAX can have endogenous properties.

As Berk and Van Binsbergen (2015) have provided a central insight that value added is a better proxy for skill than risk-adjusted returns, examining the determinants that influence skill is interesting from an academic perspective. This paper aims to provide more insight into the determinants of fund managers' skill. Therefore, the following research question can be formulated:

*What are the determinants of skilled mutual funds?*

Berk and Green (2004) concluded that investors respond rationally to past performance and reward high-performing managers with more funds. Investors will allocate more capital to funds that are expected to generate a positive return. Furthermore, Berk and Van Binsbergen (2015) found that investors are able to recognize skill and reward it by investing more capital with skilled funds. Therefore, it is expected that skill has a positive effect on fund flows.

Akbas and Genc (2016) document a positive and significant effect from maximum style-adjusted return (MAX) on fund flows. This paper will investigate the relationship between MAX and fund flows and expects a positive relationship to hold.

The results from Akbas and Genc (2016) on maximum style-adjusted returns could also be a sign of fund managers' skill. This paper will investigate the relationship between MAX and skill ratio and expects to find that skill ratio and MAX are correlated, which implies that MAX is an endogenous variable.

Using the flow-performance relationship by Sirri and Tufano (1998) and Chevalier and Ellison (1997), which documents that the flow-performance relationship has convex properties and increases with performance, theory suggests that past performance has a positive effect on fund flows.

Berk and Van Binsbergen (2015) argue that funds only actively manage the optimal proportion of funds. Any other funds will be passively managed and earn zero alpha. A deviation in the proportion of actively managed funds will lead to non-zero net alpha investment opportunities, which will be competed away (Berk and Van Binsbergen, 2015). As funds grow in size, the amount of funds that is actively managed decreases. Maximum style-adjusted return is dependent on the performance of all funds in the same objective category. A lower share of active management lowers the probability of a deviation in the style-adjusted returns of the fund. Given that extreme returns are dependent on active management of the portfolio, this paper expects a negative relationship between size and extreme returns.

Most funds allocate a proportion of their funds to cash for liquidity and other purposes. The amount of cash held by the fund lowers the amount of actively managed funds. A lower share of active management lowers the probability of a deviation in the style-adjusted returns of the fund. Given that extreme returns are dependent on active management of the portfolio, it is expected that a higher proportion of cash has a negative effect on extreme returns.

This paper aims to contribute to the current academic literature by providing new insights into the characteristics of mutual funds to obtain a broad perspective on this industry. The results of Akbas and Genc (2016) and Berk and Van Binsbergen (2015) will be investigated simultaneously to create a more thorough understanding of mutual funds and provide alternative explanations for research outcomes. This paper will investigate if the result of Berk and Van Binsbergen (2015) that the average fund manager generates value added equal to $3.2 million per year in the period of January 1962 until March 2011 is similar in more recent time periods. Lastly, multiple investment strategies based on portfolio sorts will be evaluated.

Using the CRSP mutual fund database, this paper obtains abnormal returns by regressing returns on benchmark factors provided by Fama and French (1995) and Carhart (1997). Due to cross-sectional dependence of the data, this paper will employ the methodology of Petersen (2009) to estimate a Ordinary Least Squares (OLS) panel regression with monthly time fixed effects and clustered standard errors per fund and time. After retrieving the abnormal returns, the procedure from Berk and Van Binsbergen (2015) is applied to calculate Value Added. In contrast to the authors, this paper finds that the average fund manager destroys value of $29,000 per month, adding up to a total of $350,000 per year. The sign switch of this average can be attributed to the most recent years, since the average Value Added of Berk and Van Binsbergen (2015) is equal to $3.2 million per year during their sample period of 1962 until March 2011.

The results are mostly in line with previous research. When examining the determinants of monthly fund flows, this paper finds that MAX has a positive and significant effect on fund flows, which is line with Akbas and Genc (2016). The skill ratio of Berk and Van Binsbergen (2015) also has a positive and significant effect on fund flows, providing evidence that skilled funds have higher monthly flows. Adding the skill ratio results in a higher $R^2$ and a decrease in magnitude of MAX, indicating that MAX is an endogenous variable. Fund size has a negative effect on fund flows, whereas fund family size is positively associated with fund flows. Lagged fund flows have a positive effect on fund flows, indicating that funds with high past flows are more likely to receive more inflows. All three groups of past performance, as suggested by Sirri and Tufano (1998), have a positive and significant effect on fund flows. The magnitude of the effect is the largest for the highest quintile, providing evidence for a convex relationship between fund flows and past performance. Funds that are younger, charge lower fees to investors or have a lower turnover ratio have higher monthly fund flows on average. Cash Percentage has a positive effect of fund flows, whereas volatility and skewness of funds do not have a significant effect of fund flows.

Similar results are obtained using quarterly fund flows. MAX has a positive and significant effect on quarterly fund flows, which is line with Akbas and Genc (2016). The skill ratio of Berk and Van Binsbergen (2015) has a positive and significant effect on quarterly fund flows, providing evidence that skilled funds have higher flows. Adding the skill ratio results in a higher $R^2$ and a decrease in magnitude of MAX, indicating that MAX is an endogenous variable. All three groups of past performance, as suggested by Sirri and Tufano (1998), have a positive and significant effect on fund flows. The magnitude of lagged fund flows does increase, finding that funds with high lagged fund flows are more likely to receive them in future periods. The effect of fund size, fund family size, volatility, skewness, expense ratio, turnover, cash percentage and age remains similar.

The results of the portfolio sorts based on MAX, skill ratio and past performance provide significant outcomes in terms of Value Added. For each decile of MAX, comparing the highest and lowest decile of skill ratio yields a significant difference in Value Added. The same applies for eight out of ten deciles of skill ratio, where a portfolio of high MAX funds generates \$ 36 million higher Value Added per year compared to low MAX funds in the highest skill decile. These differences stress the importance of a double-sorted portfolio to select the best-performing funds. The results of Past Performance show that a double-sort together with skill generates higher Value Added equal to \$60 million a year. A double-sorted portfolio of Past Performance and MAX does not yield significant differences in Value Added. A high-minus-low portfolio sorted on skill ratio, MAX and past performance generates about \$65 million higher Value Added per year.

Estimating the net alpha of portfolios based on skill ratio finds that high-skilled funds generate a positive, significant net alpha before transaction costs using an equal- and value-weighted methodology. Low-skilled funds generate a negative, significant net alpha before transaction costs.

Exploring the determinants of MAX finds that volatility, skewness, expense ratio, turnover and fund flows have a positive significant effect on MAX. Fund family size has a negative effect on MAX, while age did not provide a significant effect. The lowest quintile of past performance displays a negative effect, while the other quintiles have a positive effect on MAX. Furthermore, larger funds generate a lower MAX on average, confirming the hypothesis that size has a negative effect on MAX. There exists a positive relationship between cash percentage and MAX, which is not in line with the hypothesis that cash has a negative effect. Funds with a higher skill ratio are more likely to generate a higher MAX.

The regression on skill ratio provides evidence that MAX has a positive and significant effect, indicating that the abnormal returns can be the result of superior stock-picking abilities and/or market timing skills. Fund size, expense ratio, fund flows, past performance and cash percentage are positively associated with skill ratio. Fund family size and turnover ratio have a negative effect, while age is insignificant.

# 2 Theoretical Framework

## 2.1 Skill of Fund Managers

Finding evidence of fund managers' skill is a complicated process, because proving that fund managers possess persistent ability to obtain abnormal returns is hard. The earliest research on this subject has been performed by Jensen (1968). Using data from 115 open-end mutual funds in the period of 1945-1964, this study finds no evidence that mutual funds can outperform a buy and hold strategy on an individual or aggregate level. Grinblatt and Titman (1989) employ quarterly holdings of a sample of mutual funds to construct an estimate of their gross returns. This sample is combined with a sample that contains net returns of the mutual funds. The results indicate that the risk-adjusted gross returns of some funds were significant and positive. Grinblatt and Titman (1992) construct a multiple portfolio benchmark that was formed on the basis of the characteristics of securities. They provide evidence that performance differences between funds persist over time and that this persistence is consistent with skill of fund managers (Grinblatt and Titman, 1992).

Grinblatt and Titman (1993) introduce a new measure that employs portfolio holdings instead of a benchmark to measure mutual fund performance. The paper finds that especially aggressive growth funds earned significantly positive risk-adjusted returns in the 1976-85 period. However, this does not translate to abnormal returns for investors because of transaction costs and fund expenses. Hendricks et al. (1993) investigate the short-term relative performance persistence in mutual funds. The authors examine quarterly return data over 1975-88 on a sample of open-end growth equity funds constructed to mitigate survivorship bias. They document substantial gains between the top and bottom portfolio. However, this result may be explained by the momentum factor. Carhart (1997) finds that the results of Hendricks et al. (1993) are explained by the momentum effect. Carhart (1997) extends the analysis by trying to find persistent abnormal returns in excess of the momentum factor. Using a four-factor model to estimate abnormal returns, the author concludes that only the worst performing funds show some persistence (Carhart, 1997).

Berk and Green (2004) derive a rational model of active portfolio management. In their model, fund flows rationally respond to past performance even though performance persistence is absent and active funds do not outperform passive investments on average. The main argument is based on the notion that funds experience decreasing returns to scale. Investors will allocate more capital to funds that are expected to generate a positive return. Likewise, investors will withdraw more capital from funds that are expected to generate a negative return.

In equilibrium, all funds manage a certain amount of capital where expected returns are competitive going forward. This process provides an explanation for the co-existence of return chasing and lack of performance persistence. The flow-performance relationship is consistent with high average levels of skills and considerable heterogeneity across managers (Berk and Green, 2004).

Berk and Van Binsbergen (2015) document strong evidence for a level of skill among fund managers. They propose a new proxy for skill of fund managers by looking at the value added, defined as gross alpha multiplied by assets under management (AUM), instead of abnormal returns. They conclude that value added is the best proxy to capture skill. Net or gross alpha (abnormal returns without or with fees) are both inaccurate proxies to measure skill. The authors argue that if investors can identify skilled funds and are fully rational, all non-zero net alpha investment opportunities will be competed away. Therefore, net alpha is a measure for the competitiveness of the markets instead of managers' skill. Consequently, gross alpha does not measure skill either. Because all fund managers optimize their assets under management (AUM), gross alpha can only be an accurate proxy for skill when all managers manage funds of the same size. The outcome of this process is that gross alpha is equal to the fee, which is determined by the fund[2] and therefore a variable unrelated to skill. Skill is a function of how much money the manager decides to *actively* manage (Berk and Van Binsbergen, 2015). Excess capital will be invested in passive instruments. If some of the fund managers lack these skills, outperformance should be attributed to plain luck with regards to asset allocation decisions. This presents an opportunity that mutual fund managers can earn economic rents without possessing a competitive advantage. Such a high compensation for being lucky is not logical from a theoretical perspective (Berk and Van Binsbergen, 2015).

The authors conclude that the average mutual fund manager has skill and adds value of $3.2 million per year in the period of 1962-2011. Large cross-sectional differences in skill persist for as long as ten years. Investors are able to identify this skill and reward skilled funds by investing more capital. As a result of higher AUM, skilled funds earn higher aggregate fees. The cross-sectional distribution of skill is reflected in AUM, not gross alpha (Berk and Van Binsbergen, 2015).

[2]See Berk and Van Binsbergen (2015) for mathematical proof.

## 2.2 Behavioural Evidence

Bali et al. (2011) study the effect of maximum daily returns in the previous month of stocks on expected returns. Their results indicates that stocks with the lowest maximum daily return in the previous month have the highest expected return, providing evidence for a negative and significant effect of maximum daily return on expected returns. This effect remains significant after accounting for risk-adjusted returns as measured by the alphas of the four-factor model by Carhart (1997).

Sirri and Tufano (1998) study fund flows for equity mutual funds. They conclude that retail investors base their fund purchase decisions on prior performance information different for high- and low-performing funds. Investors allocate higher amounts of capital to high performing funds and fail to withdraw capital from low performing funds. Their analysis concludes that search costs are an important determinant of fund flows. High performing funds increase their marketing effort and charge these marketing costs to their investors. Flows are directly related to the fund family size and current media attention (Sirri and Tufano, 1998).

The analysis by Chevalier and Ellison (1997) examines the potential agency conflict between mutual fund investors and mutual funds. Investors aim to generate maximized risk-adjusted fund returns, while the mutual funds aim to maximize their Asset under Management by attracting inflows. Their model estimates the shape of the flow-performance relationship. The results indicate that the shape of the flow-performance relationship is convex, which creates incentives to add or reduce risk in their portfolio. Funds with a strong relative performance provides an incentive to increase their risk and earn higher inflow, while a weak relative performance provides an incentive to decrease your risk to prevent outflow. Younger funds have a stronger incentive than older funds.

Akbas and Genc (2016) research the role of extreme positive payoffs (MAX) in the distribution of monthly fund returns in investors' mutual fund preferences. Using the cumulative prospect theory from Tversky and Kahneman (1992), they conclude that MAX has a positive and significant effect on future fund flows. The effect of MAX on fund flows remains similar after controlling for various variables, such as volatility and skewness of fund returns, past performance and other fund characteristics. Their analysis finds a negative albeit insignificant relationship between MAX and performance by using risk-adjusted returns as performance measure.

Bali et al. (2019) document a relationship between MAX and future fund returns. Hedge funds with a higher MAX generate higher average returns than funds with a lower MAX. This result remains significant after controlling for a large variety of fund characteristics. They conclude that MAX provides additional information on future hedge fund returns (Bali et al., 2019).

### 2.3 Active Management

Chen et al. (2000) review the added value of active mutual funds by exploring the holdings and trades of mutual funds. Stocks that are common amongst funds do not outperform other stocks. However, actively bought stocks generate significant higher returns than stocks that are actively sold. These results are robust for both value and growth stocks and is not influenced by market capitalization of the underlying company. Growth funds display better stock selection skills than income funds. Similarly, funds with a high turnover display better stock selection than low turnover funds (Chen et al., 2000).

The concept of Active Share is introduced by Cremers and Petajisto (2009), which represents the share of the portfolio that deviates from the benchmark. In the period of 1980 to 2003, US equity funds with a higher deviation from the benchmark generate significant outperformance and demonstrate strong performance persistence after accounting for costs. The effect is more present for smaller funds, indicating that smaller funds tend to be more actively managed (Cremers and Petajisto, 2009).

Baker et al. (2010) consider the stock-picking ability of fund managers by combining the Thompson Financial and CRSP mutual fund database. Their focus is on the performance of mutual funds' holdings at subsequent corporate events. Their results indicate that the average fund's recent buys significantly outperform its recent sells around the next earnings announcement. The outcome provides evidence that mutual fund managers are able to trade profitably in part because they are able to forecast earnings-related fundamentals.

## 2.4 Scale in Mutual Funds

Guedj and Papastaikoudi (2003) explore whether mutual fund families affect the performance of their funds. Using a sample of funds within large mutual fund families from the CRSP mutual fund database, the authors confirm the existence of a significant momentum effect within funds based on 1-year lagged fund performance. Furthermore, evidence suggests that funds inside large families have more persistent performance relative to the entire universe and this persistence can be attributed to the amount of mutual funds within the family. The probit regression results reveal that last year's best performing funds have a higher probability of receiving more resources after accounting for costs, size and past performance. To summarize, there exists evidence that fund families allocate resources based on their performance instead of their needs (Guedj and Papastaikoudi, 2003).

Chen et al. (2004) study the effect of scale on performance in mutual funds. Data is retrieved from CRSP for the sample of 1962 to 1999 and the CDA Spectrum Database. Lagged fund size has a negative effect on performance after accounting for multiple benchmarks. This effect is most pronounced for small-cap funds, where liquidity can be a severe issue for the fund's performance. The authors conclude that family size have a positive impact on a fund's return, indicating that the organization of the fund is important for performance. Furthermore, organisational diseconomies related to hierarchy costs also influence fund performance because of its interaction with liquidity (Chen et al., 2004).

Pástor et al. (2015) conduct a similar analysis on the effect of scale on performance in mutual funds. Although the effect on a fund level is negative albeit insignificant, the authors finds similar results compared to Chen et al. (2004) at the industry level. However, the authors also conclude that average skill in the mutual fund industry has increased over time. This trend happened simultaneously with industry growth, which explains why fund performance has not improved despite the increase of skill. As funds are active for a prolonged time period, the performance of these funds deteriorate due to new entrants having a higher level of skill.

Clifford et al. (2014) find that the top 5 percent of actively managed U.S. equity mutual funds in 2012 had greater aggregate AUM than the remaining 95 percent of funds combined. This skewness has several implications for mutual fund research. Fund characteristics are largely dependent on the size of the fund. The authors find that the relationship between fund flows and performance is linear for the top decile of funds sorted on size, which is not line with the result by Sirri and Tufano (1998) that this relationship is convex. In their opinion, more emphasis is needed on the average dollar to understand the importance of the industry to investors (Clifford et al., 2014).

# 3 Data

The primary data source for fund returns and characteristics is the Center of Research in Security Prices (CRSP) Survivor Bias Free Mutual Fund Database (WRDS, 2020). This database is frequently used by other authors like Carhart (1997) and Berk and Van Binsbergen (2015). The main focus of this paper is on examining the determinants of skilled mutual fund managers. Value Added is defined as the gross alpha multiplied by the size of the fund. Berk and Van Binsbergen (2015) require funds to have at least 24 observations to calculate Value Added in their analyses. This paper will apply the same criterium. Maximum style-adjusted returns are defined as the maximum style-adjusted monthly return in the previous 12 months. Style-adjusted monthly returns are calculated by subtracting the average monthly returns of all funds with the same style from a fund's monthly returns. Using the definition by Chen et al. (2004), fund family size is defined as the cumulative TNA of the other funds in the fund's family for the respective period.

The database contains information on total net assets (TNA), monthly returns and other characteristics that are needed to conduct the analysis. The most relevant variables are the size, monthly returns and the expense ratio of the fund. Returns on the benchmark portfolio will be gathered from the Kenneth R. French Data Library (French, 2020). The sample ranges from January 1962 to December 2019. The initial dataset consists of 7 million monthly return observations and 2,2 million fund-year observations. Given that mutual funds are tracked over a time horizon, this paper employs a panel data procedure to conduct the analysis. As some funds will disappear as a result of a liquidation or a merger, the dataset is an unbalanced panel dataset.

The expense ratio, net return and TNA are required to calculate Value Added. All observations that lack one of these variables are removed from the dataset. All observations are dropped before funds reach real assets under management (AUM) of 5 million[3]. Because the expense ratio is reported on a yearly basis, observations for this ratio are extended to the entire fiscal year if they are reported in another period of the corresponding fiscal year. Furthermore, the objective code[4] of the fund is necessary to calculate the maximum style-adjusted return (MAX). These observations of objective codes are extended to other periods in case the next non-missing observation reports the same objective. All observations that do not report the objective code are removed from the dataset.

[3]The real AUM is calculated as the nominal AUM adjusted by the non-food and energy dollar inflation in the US with 2000 as base year

[4]This code refers to the focus of the fund, e.g. market capitalization, geographic area and investment style.

Berk and Van Binsbergen (2015) restrict their analysis to equity funds. This paper employs the same procedure, keeping funds that hold on average more than 50 percent equity and less than 20 percent cash. Funds that employ short-selling and/or leverage are identified by screening fund names for terms like "Long-Short" and "Leverage" and excluded from the dataset. Funds that contain "Fixed Income" or "Money Market" in their name are also removed from the dataset. In addition to this selection, the names of the funds are screened for terms that indicate index funds[5] and dropped consequently. The focus of this paper is on both international and domestic funds.

The CRSP mutual fund database suffers from a known bias that return histories of the same fund are present under different identifiers. This bias is caused by funds that split into multiple shares classes during their lifetime. Consequently, those new share classes inherit the history of the fund's return. In order to account for this bias, share classes are aggregated by weighing their TNA. They can be identified by splitting the names by colons (":") or slashes ("/"), since share class information is reported after such symbols in the CRSP database. In some cases other information is given after the sign and funds thus should not be aggregated. These observations are identified with keywords and kept as an individual fund[6].

The sum of total net assets (TNA) of the share classes is obtained to compute the fund's TNA. Fund age is defined as the age of the oldest share class of a fund. For other quantitative variables (i.e., returns, expense ratio, MAX, etc.), the weighted averages of each variable from individual share classes are used. Weights are determined by the total net assets of the individual share classes for the corresponding period. For qualitative fund characteristics such as name and objective, the data from the largest share class of the fund is used.

Fund incubation is a strategy for initiating new funds. Multiple funds are started privately, and at the end of the evaluation period, some are opened to public investors. Consistent with incubation being used by fund families to increase performance and attract inflows, funds in incubation outperform non-incubated funds by 3.5% on a risk-adjusted basis (Evans, 2010). This outperformance disappears after the incubation period. To control for incubation bias, this paper uses the procedure from Evans (2010). The incubation bias can be minimized by using returns only after funds receive a ticker symbol from NASDAQ, which typically means they are available to the public. Therefore, all observations before CRSP has assigned a ticker to the fund are removed from the dataset.

[5] A fund is coded as an index fund if the "index fund flag" in CRSP is "D," indicating a pure index. Furthermore, an index fund is identified if its name contains any of the following strings: "Index," "Idx," "Indx," "Dow Jones, "Index", "S&P 500," or "BARRA,"

[6] This information usually refers to the style of the fund, e.g. "small-cap value fund".

### Table 1: Descriptive Statistics

The table below displays the descriptive statistics of the relevant variables. Value Added is calculated by multiplying gross alpha with TNA of the previous period and inflation-adjusted with 2000 as base year in millions. Funds are required to have at least 24 months of consecutive data to be included in the dataset. MAX refers to the maximum style-adjusted return of the previous 12 months. Log(TNA) refers to the logarithm of total net assets for a fund. Log(Family TNA) is the logarithm of the TNA for the other funds within the fund family. Gross alpha is equal to the unconditional mean of the benchmark deviation plus the expense ratio of the previous period. Net alpha refers to the unconditional mean of the benchmark deviation. $Flow_M$ and $Flow_Q$ are defined as the money in- or outflow of the fund per month and quarter respectively and winsorized at the 1 and 99% level. VOL and SKEW are defined as the standard deviation and skewness of monthly returns over the previous 12 months. Turnover represents the portfolio transactions' value as a percentage of total portfolio value and is winsorized at the 1 and 99% level. Percentage Cash is the mean percentage of cash for each fund. Fund age is reported in years and equal to the period since the inception date. Expense ratio is equal to the cost of the fund.

| Statistic | Value Added | MAX | Log(TNA) | Gross alpha | Net alpha |
|---|---|---|---|---|---|
| Mean | 0.830 | 0.023 | 4.959 | 0.001 | 0.0001 |
| Median | 0.006 | 0.018 | 4.873 | 0.0002 | 0.00002 |
| Maximum | 2,691.614 | 0.549 | 11.274 | 0.382 | 0.335 |
| Minimum | -2,725.239 | -0.183 | 1.610 | -0.413 | -0.407 |
| Std. Deviation | 34.670 | 0.021 | 1.720 | 0.021 | 0.020 |
| Skewness | 6.490 | 3.413 | 0.324 | 0.484 | 0.311 |
| Kurtosis | 1,043.89 | 26.840 | 2.676 | 14.580 | 15.263 |
| **Statistic** | **Log(Family TNA)** | **$Flow_M$** | **$Flow_Q$** | **Turnover** | **Expense ratio** |
| Mean | 2.337 | 0.013 | 0.030 | 0.736 | 0.012 |
| Median | 0 | 0.007 | 0.013 | 0.56 | 0.012 |
| Maximum | 10.766 | 0.344 | 0.670 | 17.62 | 0.053 |
| Minimum | 0 | -0.180 | -0.259 | 0 | 0.0001 |
| Std. Deviation | 2.739 | 0.075 | 0.134 | 0.708 | 0.005 |
| Skewness | 0.633 | 1.102 | 1.753 | 4.869 | 0.361 |
| Kurtosis | 1.987 | 6.946 | 9.095 | 62.61 | 3.529 |
| **Statistic** | **VOL** | **SKEW** | **Percentage Cash** | **Age** | |
| Mean | 0.043 | -0.148 | 3.099 | 8.70 | |
| Median | 0.038 | -0.129 | 2.384 | 8.12 | |
| Maximum | 0.337 | 2.444 | 19.988 | 88.08 | |
| Minimum | 0.000 | -2.750 | 0 | 0.08 | |
| Std. Deviation | 0.022 | 0.541 | 2.633 | 8.12 | |
| Skewness | 1.772 | -0.246 | 2.259 | 3.67 | |
| Kurtosis | 8.676 | 3.729 | 10.315 | 25.07 | |

The descriptive statistics of the relevant variables are reported above in Table 1. The final dataset contains 7,221 funds, which is a larger sample than Berk and Van Binsbergen (2015). This is due to the longer sample of this analysis and the increased popularity of mutual funds in recent years. The mean Value Added per month is equal to $830,000 for this dataset. TNA and Family TNA are transformed into a logarithmic distribution to account for skewness in these variables. The majority of funds does not belong to a fund family. The cross-sectional difference of the expense ratio is relatively small, while the cross-sectional difference in TNA is much larger. This is an important insight from Berk and Van Binsbergen (2015) and one of the main reasons for using Value Added as a measure of skill. The average maximum style-adjusted return of the previous 12 months for a fund is equal to 2.3%. Following the procedure from Akbas and Genc (2016), the flow variable is winsorized at the 1 and 99% to mitgate the impact from outliers. The funds in this data sample have a mean allocation to cash of 3.1%. Fund age ranges from one month to 88 years, with the mean fund being active for eight years and eight months.

Table 2 reports the values of the skill variable. The data displays a different distribution for the skill variable compared to Berk and Van Binsbergen (2015). The cross-sectional mean is equal to -0.029, meaning that the average manager destroys value equal to $29,000 per month. The alternative measure is the average added value of surviving funds. This cross-sectional weighted mean is equal to 0.63. To create a meaningful comparison with Berk and Van Binsbergen (2015), the third column of Table 2 displays the results using the same timeframe as Berk and Van Binsbergen (2015). The cross-sectional mean and cross-sectional weighted mean in this dataset increase to 1.02 and 1.84 respectively, where Berk and Van Binsbergen (2015) reported values of 0.10 and 0.25. However, when comparing the amount of funds in the sample, there is a clear difference between both analysis in terms of amount of funds.[7] Moreover, the same restrictions apply for funds with respect to the amount of observations needed to be included in the analysis.

[7] 6,054 funds are included in the sample from Berk and Van Binsbergen (2015), whereas this paper's sample includes 3,968 funds that were active during 2011.

**Table 2: Cross-Sectional Skill and Weighted Skill**

This table reports the cross-sectional mean ($\bar{S}$) and cross-sectional weighted mean ($\bar{S_w}$) of skill. For every fund in the database, the average monthly value added is estimated, denoted by $\hat{S}_i$. The cross-sectional mean, standard error of the cross-sectional mean, percentiles and t-statistic of the mean represent the statistical properties of this variable. The cross-sectional weighted mean, standard error of the cross-sectional weighted mean and t-statistic of the weighted mean are calculated by weighing the number of observations $T$ the fund exists in the dataset.

| Variable | Skill | Skill (until March 2011) |
|---|---|---|
| Cross-sectional mean | -0.029 | 1.016 |
| Standard error of the mean | 0.159 | 0.171 |
| t-statistic | -0.18 | 5.93 |
| | | |
| Cross-sectional weighted mean | 0.633 | 1.84 |
| Standard error of weighted mean | 0.019 | 0.029 |
| t-statistic | 33.40 | 62.61 |
| | | |
| 1st percentile | -11.24 | -6.15 |
| 5th percentile | -2.17 | -1.44 |
| 10th percentile | -0.95 | -0.63 |
| 25th percentile | -0.21 | -0.11 |
| 50th percentile | -0.02 | 0.04 |
| 75th percentile | 0.13 | 0.40 |
| 90th percentile | 0.83 | 1.81 |
| 95th percentile | 2.00 | 4.68 |
| 99th percentile | 12.14 | 20.22 |
| | | |
| Number of funds | 7,221 | 3,968 |

# 4 Methodology

In the theoretical framework, a wide variety of determinants for fund managers' skill have been discussed. Furthermore, a number of behavioural explanations have been proposed for maximum-style adjusted returns (MAX), while also analyzing previous literature on active management and scale in mutual funds. This paper will use the methodology of Berk and Van Binsbergen (2015) to measure skill of fund managers. The methodology of Akbas and Genc (2016) will be used to construct the maximum style-adjusted return measure (MAX). This section will discuss the methodology used to conduct the statistical analysis and answer the hypotheses.

### 4.1 Skill of Fund Managers

Berk and Van Binsbergen (2015) concluded that Value Added is better at capturing skill than gross- or net alpha. Using the same procedure, Value Added will be obtained. The first step is retrieving the gross returns ($R^g$), which can be estimated as

$$R_{it}^{g} = R_{it}^{n} + f_{i,t-1}$$

In this equation, $R_{it}^{n}$ is the return in excess of the risk free rate (or net return) at time $t$ for fund $i$ and $f_{i,t-1}$ is the fund's expense ratio of the previous period. The gross abnormal returns are estimated by subtracting the benchmark return ($R_t^B$) from the fund's gross return for each month the fund is active. In the final step to define Value Added $V_{it}$, the gross abnormal returns are multiplied by the inflation-adjusted TNA of the previous period:

$$V_{it} = q_{i,t-1}(R_{it}^{g} - R_t^B)$$

The next step is calculating the skill of the fund. Skill is defined as the expected value of $V_{it}$. The estimated skill for a fund that exists for $T_i$ periods is given by:

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

Estimating the average skill of funds can be done in two ways. The first procedure simply estimates the mean of all funds in the sample, referred to as the ex-ante distribution:

$$\bar{S} = 1/N * \sum_{i=1}^{N} \hat{S}_i$$

,

where N refers to the amount of mutual funds in our database. Alternatively, the focus is on the mean of surviving funds, which is known as the ex-post distribution. In this case, the average skill is estimated by weighing each fund by the amount of observations in the database:

$$\bar{S_w} = \frac{\sum_{i=1}^{N} \hat{S}_i T_i}{\sum_{i=1}^{N} T_i}$$

Berk and Van Binsbergen (2015) have concerns about the validity of the t-statistic for the skill measure. In order to account for these concerns, they have constructed the skill ratio. This ratio is basically the t-statistic of the estimated Value Added for fund $i$ until time $\tau$, denoted by the following equation:

$$SKR_i^\tau \equiv \frac{\hat{S}_i^\tau}{\sigma(\hat{S}_i^\tau)}$$

where $\hat{S}_i^\tau = \sum_{t=1}^{\tau} V_{it}/\tau$ denotes the mean Value Added for fund $i$ until time $\tau$ and $\sigma(\hat{S}_i^\tau) = \sqrt{\sum_{t=1}^{\tau}(V_{it} - \hat{S}_i^\tau)^2/\tau}$ denotes the standard error of the Value Added for fund $i$ until time $\tau$.

### 4.2 Abnormal Returns

Abnormal returns are required to compute Value Added. The four-factor model of Carhart (1997) is used as the benchmark to calculate abnormal returns. This model is widely used by other academic authors. Excess gross returns in this model are regressed on four factors:

$$R_{it}^g = \alpha_{it} + \beta_i^{mkt} * MKT_t + \beta_i^{smb} * SMB_t + \beta_i^{hml} * HML_t + \beta_i^{umd} * UMD_t + \epsilon_{it}$$

$MKT_t$, $SMB_t$, $HML_t$ and $UMD_t$ capture the factor premium for respectively market risk, size, book-to-market ratio and momentum. The corresponding $\beta_i$ captures the exposure to each factor. A seperate regression is estimated for each month a fund is active after 24 months to accurately capture the factor loadings. When regressing excess gross returns on the factor premia, gross abnormal returns are estimated by the unexplained values in the equation:

$$\alpha_{it}^g = \alpha_{it} + \epsilon_{it} = R_{it}^g - R_{it}^B$$

### 4.3 Maximum Style-Adjusted Returns

Maximum style-adjusted return (MAX) is defined as the maximum style-adjusted monthly return in the previous 12 months. Style-adjusted monthly returns are calculated by subtracting the average monthly returns of all funds with the same style from a fund's monthly returns (Akbas and Genc, 2016).

The maximum style-adjusted return is calculated using the following equation:

$$MAX_{it} = max(R_{it} - \mu(R_{n,t})) \in t$$

where $R_{it}$ represents the return of fund $i$ at time $t$ and $n$ refers to the amount of funds with the same objective code in the corresponding time period. $\mu(R_{n,t})$ is the mean return of funds with the same objective code in the corresponding time period and $t$ refers to the previous 12 months. Because mutual funds often hold stocks that belong to their style, there will most likely be high cross-sectional correlation between funds within the same style. Likewise, it is expected that the best performing funds are more likely to belong to the same style. Style-adjusted returns control for the time-varying style effect and mitigate concerns related to categorizing funds as high-MAX funds because of the popularity of the style to which they belong (Akbas and Genc, 2016).

### 4.4 Fund Flows

Mutual fund flow is defined as the in- or outflow of a fund for each time period. Following the procedure from Sirri and Tufano (1998), fund flow can be calculated using the following equation:

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} * (1 + R_{i,t})}{TNA_{i,t-1}}$$

In this equation, $TNA_{i,t}$ represents total net assets in the current time period for fund $i$, $TNA_{i,t-1}$ is equal to total net assets in the previous time period for fund $i$ and $R_{i,t}$ is the return in the current time period for fund $i$. $Flow_{i,t}$ equals the growth percentage of TNA for fund $i$ per time period in excess of the return.

### 4.5 Regression specification

The analysis on mutual funds will be estimated using panel data regressions. Petersen (2009) highlights some important issues encountered with panel data regressions. Since the fund data is expected to be cross-sectional dependent and has a time effect, an adjustment for monthly time fixed effects and clustered standard errors per fund and time are included in the OLS regressions. The advice for the dataset by Petersen (2009) is more than hundred observations in time-series and firm dimensions, which is satisfied in this paper. The pooled OLS regression will be estimated as follows:

$$FLOW_{it} = \beta_n * X_{it} + (\alpha_i + \epsilon_{it})$$

where the dependent variable $FLOW_{it}$ is the fund flow for fund $i$ on time $t$ and $\beta_n$ is the effect of independent variable $X_{it}$ on value added. The unobserved term $(\alpha_i + \epsilon_{it})$ consists of the fund-specific effect $\alpha_i$ and the idiosyncratic effect $\epsilon_{it}$. The main independent variables are maximum style-adjusted returns, skill ratio and past performance. The control variables volatility, skewness, fund size, fund family size, expense ratio, turnover, lagged fund flow, age and cash percentage are added to the pooled regression to increase the explanatory power and to answer hypotheses. Furthermore, this paper will apply portfolio sorting procedures to discover potential differences within different deciles.

In order to estimate the effects of size, skill ratio and cash on maximum-style adjusted returns, a similar procedure will be executed. The following pooled OLS regression will be estimated:

$$MAX_{it} = \beta_n * X_{it} + (\alpha_i + \epsilon_{it})$$

where the dependent variable $MAX_{it}$ is the maximum style-adjusted return for fund $i$ on time $t$ and $\beta_n$ is the effect of independent variable $X_{it}$ on the maximum style-adjusted return. The unobserved term $(\alpha_i + \epsilon_{it})$ consists of the fund-specific effect $\alpha_i$ and the idiosyncratic effect $\epsilon_{it}$. The main independent variables are fund size, skill ratio and cash percentage. The control variables volatility, skewness, fund family size, expense ratio, turnover, past performance and age are added to the pooled regression to increase the explanatory power and to answer hypotheses.

# 5 Results

In this section, the main results will be displayed and discussed. The hypotheses from this paper will be discussed and answered. Furthermore, some robustness checks will be performed to test the validity of the results.

## 5.1 Regression results on monthly fund flows

In the first section, a regression on the relationship between monthly fund flows and MAX is performed. The results of the pooled OLS-regression with monthly time fixed effects and standard errors clustered by funds and months are presented in Table 3. The analysis contains similar control variables used by Akbas and Genc (2016) and the skill ratio of Berk and Van Binsbergen (2015). Fund size and fund family size are transformed into a logarithmic distribution to account for skewness in these variables. The variables *LOWPERF*, *MIDPERF* and *HIGHPERF* denote the different quintiles of past performance based on the fund relative performance within the style category of the previous 12 months. *LOWPERF* represents the lowest quintile, *MIDPERF* combines the middle 3 quintiles and *HIGHPERF* refers to the highest quintile. These variables are the result of a piecewise linear regression to estimate the sensitivity of each category separately.

The first analysis finds that maximum style-adjusted returns (MAX) has a positive and significant effect on monthly fund flows, which is a similar result compared to the effect of quarterly fund flows by Akbas and Genc (2016). The magnitude of the effect is equal to 0.148, which implies that a 1-standard-deviation increase in MAX yields additional flows of approximately 0.148% over the next month. This result provides evidence that funds with a high style-adjusted return are rewarded with more capital from investors. The effect of volatility is positive albeit insignificant, while skewness is negatively related to fund flows at the 10%-level. Fund size has a significant and negative effect on fund flows, whereas fund family size positively influences fund flows. Both these results are in line with previous research from Akbas and Genc (2016) and Chevalier and Ellison (1997). Funds that generated higher inflows in the previous month are more likely to gain more inflow in the next month. This effect is also observed in the quarterly flow regression of Akbas and Genc (2016). All measures of past performance are positive and highly significant with t-statistics equal to 13, indicating that strong past performance has a positive effect on capital received from investors. Furthermore, there exists a convex relationship, confirming insights from research by Chevalier and Ellison (1997).

Age, turnover and cash percentage have a significant effect on fund flows, although the magnitude of the effect is rather small compared to other variables. The overall $R^2$ of the regression is equal to 0.42, which is higher compared to Akbas and Genc (2016).

The second analysis expands on the first model by incorporating the skill ratio of Berk and Van Binsbergen (2015) to control for the effect of skilled funds. The result of including this variable in the model has a profound impact on the coefficient of MAX, which decreases to 0.127. The significance of MAX remains at the 1%-level with a t-statistic of 3.8. The effect of skill ratio is positive with a magnitude of 0.06 and highly significant with a corresponding t-statistic of 11.74. Hence, funds with a higher skill ratio are rewarded with more capital by investors, which is line with the results of Berk and Van Binsbergen (2015). The other variables in the pooled OLS-regression are not impacted significantly by incorporating the skill ratio. The signs of the coefficients are similar to the first regression. The magnitude of volatility, expense ratio, lagged fund flow and past performance are influenced on a marginal level. The significance of cash percentage decreases to 5%. The explanatory power of the regression improves when the skill ratio is added, as the $R^2$ increases to 0.45.

Overall, the results indicated that MAX has a positive, significant effect on monthly fund flows at 1-% significance level. Funds with a higher MAX generate more inflow than funds with a low MAX. When the skill ratio is added to the regression model, the magnitude of MAX decreases by 0.021. The skill ratio of Berk and Van Binsbergen (2015) is positive and highly significant. This implies that MAX is an endogenous variable in the regression on fund flows, as the true effect of MAX can only be captured after adding the skill ratio to the regression. Furthermore, the results indicate that larger funds exhibit lower inflows on average. Funds being part of a larger fund family enjoy larger inflows from investors. Funds that generate higher inflows are generally younger, charge lower fees to their investors and have a lower turnover within the portfolio. All measures of past performance have a significant effect on monthly fund flows, providing evidence that funds with the highest past performance attract more capital from investors. The explanatory power of the regression models does not cause concerns on the validity of the results.

### Table 3: **Regression results on monthly fund flows**

This table displays the pooled OLS regression parameters on monthly fund flows. The regression contains monthly time fixed effects and standard errors clustered by funds and months. In each month, fund flow is defined as the money in- or outflow of the fund per month and winsorized at the 1 and 99% level. MAX represents the maximum style-adjusted return in the previous 12 months, which is calculated by subtracting the average monthly returns of all funds with the same style from a fund's monthly returns. All observations that contain 11 or less months of MAX are not considered in the analysis. Skill ratio represents the skill of fund managers and is calculated using the procedure from Berk and Van Binsbergen (2015). VOL and SKEW are defined as the standard deviation and skewness of monthly returns over the previous 12 months. $Log(TNA)_{t-1}$, $Log(FamilyTNA)_{t-1}$ and $Expenseratio_{t-1}$ are defined as the fund size, fund family size and expense ratio lagged by one month. TURNOVER represents the portfolio transactions' value as a percentage of total portfolio value. Following the procedure from Sirri and Tufano (1998), funds are sorted into quintiles based on the previous 12-month relative performance within the style category for each month. LOWPERF represents the lowest quintile, MIDPERF combines the middle 3 quintiles, and HIGHPERF refers to the highest quintile. Cash Percentage is defined as the mean cash percentage of the fund over its lifetime. Age represents the time the fund has been active. $Log(TNA)_{t-1}$ and $Log(FamilyTNA)_{t-1}$ are inflation-adjusted with 2000 as base year. Standard errors are reported in parentheses. P-values below 0.01, 0.05 and 0.10 are labeled with ***, ** and * respectively.

| Variable | (1) | (2) |
|---|---|---|
| $MAX$ | 0.148*** | 0.127*** |
| | (0.04) | (0.04) |
| *Skill ratio* | | 0.060*** |
| | | (0.00) |
| $VOL$ | 0.017 | 0.021 |
| | (0.08) | (0.08) |
| $SKEW$ | -0.002* | -0.002* |
| | (0.00) | (0.00) |
| $Log(TNA)_{t-1}$ | -0.001*** | -0.001*** |
| | (0.00) | (0.00) |
| $Log(FamilyTNA)_{t-1}$ | 0.000*** | 0.000*** |
| | (0.00) | (0.00) |
| $Expenseratio_{t-1}$ | -0.595*** | -0.661*** |
| | (0.07) | (0.07) |
| $TURNOVER$ | -0.002*** | -0.002*** |
| | (0.00) | (0.00) |
| $Flow_{t-1}$ | 0.249*** | 0.244*** |
| | (0.01) | (0.01) |
| $LOWPERF$ | 0.007*** | 0.006*** |
| | (0.00) | (0.00) |
| $MIDPERF$ | 0.005*** | 0.004*** |
| | (0.00) | (0.00) |
| $HIGHPERF$ | 0.010*** | 0.009*** |
| | (0.00) | (0.00) |
| *Cash Percentage* | 0.000*** | 0.000** |
| | (0.00) | (0.00) |
| *Age* | -0.001*** | -0.001*** |
| | (0.00) | (0.00) |
| Number of funds | 6,549 | 6,549 |
| Number of periods | 298 | 298 |
| $R^2$ | 0.42 | 0.45 |

### 5.2 Determinants of quarterly fund flows

In the previous section, the determinants of monthly fund flows were investigated. This section will repeat the previous analysis while changing the dependent variable to quarterly fund flows. By doing so, this paper tries to replicate Table 2 of Akbas and Genc (2016) while adding the skill ratio variable of Berk and Van Binsbergen (2015) to the regression.

The results of the analysis are reported in Table 4. The first analysis finds that maximum style-adjusted return (MAX) has a positive and significant effect on quarterly fund flows, which is a similar result compared to Akbas and Genc (2016). The overall magnitude of the effect is lower in this analysis, indicating that fund flows have become less sensitive to MAX in recent periods. Nevertheless, this result provides evidence that funds with a high style-adjusted return are rewarded with more capital from investors. The effect of volatility is positive albeit insignificant, which is not in line with the negative, significant effect of Akbas and Genc (2016). The effect of skewness of previous fund returns is insignificant, which is confirmed by Akbas and Genc (2016). Fund size has a significant and negative effect on fund flows, whereas fund family size positively increases fund flows. Both these results are in line with previous research from Akbas and Genc (2016) and Chevalier and Ellison (1997).

Similarly to the analysis of monthly fund flows, funds that generated higher inflows in the previous period are more likely to gain more inflow in the current period. The effect is highly significant and has a larger magnitude compared to Akbas and Genc (2016). All measures of past performance are positive and highly significant with t-statistics above 10, indicating that past performance has a positive effect on fund flows. Akbas and Genc (2016) reported similar t-statistics for all three variables of past performance. Furthermore, there exists a convex relationship, confirming insights from research by Chevalier and Ellison (1997). Age, turnover and cash percentage have a significant effect on fund flows, although the magnitude of the effect is rather small compared to other variables. The overall $R^2$ of the regression is equal to 0.60, which is higher compared to Akbas and Genc (2016).

### Table 4: Regression results on quarterly fund flows

This table displays the pooled OLS regression parameters on quarterly fund flows. The regression contains monthly time fixed effects and standard errors clustered by funds and months. In each quarter, fund flow is defined as the money in- or outflow of the fund per quarter and winsorized at the 1 and 99% level. MAX represents the maximum style-adjusted return in the previous 12 months, which is calculated by subtracting the average monthly returns of all funds with the same style from a fund's monthly returns. All observations that contain 11 or less months of MAX are not considered in the analysis. Skill ratio represents the skill of fund managers and is calculated using the procedure from Berk and Van Binsbergen (2015). VOL and SKEW are defined as the standard deviation and skewness of monthly excess returns over the previous 12 months. $Log(TNA)_{t-1}$, $Log(FamilyTNA)_{t-1}$ and $Expenseratio_{t-1}$ are defined as the fund size, fund family size and expense ratio lagged by one month. TURNOVER represents portfolio transactions' value as a percentage of total portfolio value. Following the procedure from Sirri and Tufano (1998), funds are sorted into quintiles based on the previous 12-month relative performance within the style category for each month. LOWPERF represents the lowest quintile, MIDPERF combines the middle 3 quintiles, and HIGHPERF refers to the highest quintile. Cash Percentage is defined as the mean cash percentage of the fund over its lifetime. Age represents the time the fund has been active. $Log(TNA)_{t-1}$ and $Log(FamilyTNA)_{t-1}$ are inflation-adjusted with 2000 as base year. Standard errors are reported in parentheses. P-values below 0.01, 0.05 and 0.10 are labeled with ***, ** and * respectively.

| Variable | (1) | (2) |
|---|---|---|
| *MAX* | 0.150*** | 0.130*** |
| | (0.05) | (0.05) |
| *Skill ratio* | | 0.050*** |
| | | (0.00) |
| *VOL* | 0.024 | 0.028 |
| | (0.11) | (0.11) |
| *SKEW* | -0.02 | -0.02 |
| | (0.02) | (0.02) |
| $Log(TNA)_{t-1}$ | -0.001*** | -0.002*** |
| | (0.00) | (0.00) |
| $Log(FamilyTNA)_{t-1}$ | 0.001** | 0.001*** |
| | (0.00) | (0.00) |
| $Expenseratio_{t-1}$ | -0.583*** | -0.654*** |
| | (0.08) | (0.08) |
| *TURNOVER* | -0.002*** | -0.002** |
| | (0.00) | (0.00) |
| $Flow_{t-1}$ | 0.639*** | 0.636*** |
| | (0.00) | (0.00) |
| *LOWPERF* | 0.006*** | 0.006*** |
| | (0.00) | (0.00) |
| *MIDPERF* | 0.005*** | 0.004*** |
| | (0.00) | (0.00) |
| *HIGHPERF* | 0.011*** | 0.010*** |
| | (0.00) | (0.00) |
| *Cash Percentage* | 0.000*** | 0.000*** |
| | (0.00) | (0.00) |
| *Age* | -0.000*** | -0.000*** |
| | (0.00) | (0.00) |
| Number of funds | 6,549 | 6,549 |
| Number of periods | 298 | 298 |
| $R^2$ | 0.60 | 0.62 |

The second analysis expands on the first model by incorporating the skill ratio of Berk and Van Binsbergen (2015) to control for the effect of fund's skill. The result of including this variable in the model has a profound impact on the coefficient of MAX, which decreases to 0.13. The significance of MAX remains at the 1%-level with a t-statistic of 3.0. The effect of skill ratio is positive with a magnitude of 0.05 and highly significant with a corresponding t-statistic of 9.64. Hence, funds with a high skill ratio generate higher inflows from investors than low-skilled funds, which is line with the result of Berk and Van Binsbergen (2015) that investors are able to identify skilled fund managers and reward them with more capital.

Most of the other variables in the pooled OLS-regression are not impacted significantly by incorporating the skill ratio. The signs of the coefficients are similar to the first regression. The magnitude of volatility, fund size, lagged flows and past performance is influenced on a marginal level. Only the effect of expense ratio decreases by 0.08, indicating that funds that charge higher costs are less likely to generate inflows. The explanatory power of the regression increases when the skill ratio is added as the $R^2$ increases to 0.62.

Comparing the regression parameters of the monthly and quarterly fund flows provides a mostly similar result. The effect of MAX is comparable amongst both regressions, while the effect of the skill ratio is higher in the monthly regression. Skewness of fund returns in quarterly fund flows is relatively high compared to the monthly result, but in absolute terms only a marginal effect. The effect of lagged fund flows is higher for quarterly fund flows[8], indicating that this effect increases with longer time horizons. Furthermore, the $R^2$ of the quarterly regression increases with 0.17 for both regressions.

To sum up, the results indicated that MAX has a positive, significant effect on quarterly fund flows at 1%-significance level. Funds with a higher MAX generate more inflow than funds with a low MAX. When the skill ratio is added to the regression model, the magnitude of MAX decreases by 0.02. The skill ratio of Berk and Van Binsbergen (2015) is positive and highly significant. This implies that MAX is an endogenous variable in the regression on quarterly fund flows, because MAX and skill ratio are correlated. The true effect of MAX can only be captured by adding the skill ratio to the regression on fund flows. The variables and significance of this analysis are mostly in line with the results of Akbas and Genc (2016).

[8] Magnitude of 0.636 for quarterly fund flows versus 0.244 for monthly fund flows when the skill ratio is added to the regression.

Furthermore, the results indicate that larger funds exhibit lower inflows, while funds being part of a larger fund family enjoy larger inflows from investors. Funds that generate higher inflows are generally younger, charge lower fees to their investors and have a lower turnover within the portfolio. Volatility and skewness of fund returns do not significantly influence fund flows. All measures of past performance have a significant and positive effect on quarterly fund flows. The effect of *HIGHPERF* is the strongest of all three, indicating that funds with the highest past performance receive more inflow. The explanatory power of the regression models does not cause concerns on the validity of the results.

## 5.3 Portfolio sorts based on MAX, Skill ratio and Past Performance

In the previous two sections, the determinants of fund flows on a monthly and quarterly basis have been investigated. The effect of MAX was positive and significant at the 1%-level, indicating that funds with a higher MAX generate higher inflows, thereby confirming the result of Akbas and Genc (2016). However, when the skill ratio of funds was added to the regression, the effect of MAX decreased in magnitude. This result shows that both skill ratio and MAX are relevant determinants for fund flows and confirms the result of Berk and Van Binsbergen (2015) that skilled funds attract higher inflows. All quintiles of past performance had a positive and highly significant effect on fund flows, providing evidence consistent with earlier research by Chevalier and Ellison (1997) and Sirri and Tufano (1998). In this section, multiple portfolio sorts will be performed using these three variables.

Portfolio sorts display a possible linear relationship between variables and do not depend on statistical assumptions. A minimum of 11 observations is required for a particular month to be included in the skill ratio portfolio sort. For MAX, a minimum of 11 observations is required for a particular month/objective code combination to be included in the MAX portfolio sort. Past performance requires a minimum of 6 observations for a particular month/objective code combination to be included in the Past Performance portfolio sort. Both MAX and Past Performance require a month/objective code to account for the time-varying style effect and mitigate concerns related to sorting funds based of the popularity of the style. Every observation is assigned to a decile/quintile based on its characteristics in each time period. A procedure comparable to Fama and MacBeth (1973) is performed, which involves calculating the cross-sectional means for each portfolio per time period and then taking the time-series mean as average per decile. The high-minus-low-portfolio is computed by subtracting the lowest decile from the highest decile.

For illustrative purposes, only the results of the high-minus-low-portfolio are reported.

**Table 5: Value Added differences Skill for each MAX decile**

This table displays the mean difference in Value Added for the high-minus-low portfolio (D10-D1) of the skill ratio sorted for each decile of MAX. Observations are assigned into deciles for each month/objective code. Similarly to Fama and MacBeth (1973), the first step involves calculating the cross-sectional means per month/objective code and then taking the time-series mean as average per decile. A zero cost high-low portfolio is created by subtracting the lowest decile from the highest decile every month. Standard errors are reported in parentheses. P-values below 0.01, 0.05 and 0.10 are labeled with ***, ** and * respectively.

| D10-D1 | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | 3.237*** | 4.754*** | 3.206*** | 4.900*** | 4.580*** |
| | (0.854) | (1.010) | (0.517) | (0.794) | (0.671) |
| | (6) | (7) | (8) | (9) | (10) |
| | 3.497*** | 3.531*** | 3.518*** | 10.568*** | 5.027*** |
| | (1.001) | (0.460) | (0.682) | (2.015) | (0.580) |

The first portfolio sort involves a double-sort on the skill ratio and MAX, which is reported in Table 5. This table displays the mean difference in Value Added for the high-minus-low portfolio of the skill ratio sorted for each decile of MAX. All deciles of MAX report a significant difference at the 1%-level in Value Added, providing that funds with the highest skill ratio generate a significant higher Value Added than funds with the lowest skill ratio. This is an interesting result, as this analysis shows that large differences occur amongst deciles and persists until the highest decile of MAX. Funds with the highest MAX generate $60 million higher Value Added per year when they belong to the highest skilled funds compared to the lowest skilled funds. This result displays that even within the highest decile of MAX there is still a major difference in Value Added between funds. Furthermore, these differences show that a single sort on MAX does not provide adequate results when identifying skilled funds.

**Table 6: Value Added differences MAX for each Skill decile**

This table displays the mean difference in Value Added for the high-minus-low portfolio (D10-D1) of MAX sorted for each decile of skill. Observations are assigned into deciles for each month. Similarly to Fama and MacBeth (1973), the first step involves calculating the cross-sectional means per month and then taking the time-series mean as average per decile. A zero cost high-low portfolio is created by subtracting the lowest decile from the highest decile every month. Standard errors are reported in parentheses. P-values below 0.01, 0.05 and 0.10 are labeled with ***, ** and * respectively.

| D10-D1 | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | 1.203* | 2.249*** | 2.868*** | 2.343*** | 2.299*** |
| | (0.717) | (0.823) | (0.533) | (0.443) | (0.537) |
| | (6) | (7) | (8) | (9) | (10) |
| | 1.909** | 8.217*** | 3.370*** | 1.560* | 2.993*** |
| | (0.902) | (1.935) | (0.892) | (0.870) | (0.761) |

Table 6 contains the result of the high-minus-low portfolio of MAX sorted for each decile of the skill ratio. The results show that all deciles except the first and ninth decile of the skill ratio have a significant difference in Value Added at the 5%-level or lower, meaning that funds with the highest MAX add more value than funds with the lowest MAX. The mean differences of Table 6 seem to be a bit lower than Table 5. Funds with the highest skill ratio generate $36 million higher Value Added per year when they belong to the highest MAX decile compared to the lowest MAX decile. Similarly to Table 5, the outcome of this analysis is interesting as it provides evidence that differences occur amongst deciles of the skill ratio. Once again, these differences show that a single sort on skill ratio does not provide adequate results when identifying skilled funds.

Table 7 involves a double-sort that is based on past performance. All funds that belong to a particular month/objective code are sorted in quintiles based on the 12-month cumulative past performance of the fund. The results are presented below.

**Table 7: Results for Past Performance**

This table displays the mean difference in Value Added for the high-minus-low portfolio (Q5-Q1) of skill and MAX sorted for each quintile of Past Performance. Observations are assigned into quintiles for each month/objective code. Similarly to Fama and MacBeth (1973), the first step involves calculating the cross-sectional means per month/objective code and then taking the time-series mean as average per decile. A zero cost high-low portfolio is created by subtracting the lowest quintile from the highest quintile every month. Standard errors are reported in parentheses. P-values below 0.01, 0.05 and 0.10 are labeled with ***, ** and * respectively.

| Panel A: Differences Skill for each Past Performance quintile | | | | | |
|---|---|---|---|---|---|
| D10-D1 | (1) | (2) | (3) | (4) | (5) |
| | 3.683*** | 2.493*** | 4.023*** | 4.280*** | 5.888*** |
| | (0.609) | (0.592) | (0.688) | (0.543) | (1.216) |
| **Panel B: Differences MAX for each Past Performance quintile** | | | | | |
| D10-D1 | (1) | (2) | (3) | (4) | (5) |
| | 0.895* | 1.324** | 1.011 | 0.262 | 2.797 |
| | (0.476) | (0.614) | (0.612) | (0.791) | (3.846) |

Panel A reports the results of the double-sort based on past performance and skill. All portfolios of Past Performance report a significant difference at the 1%-level in Value Added, providing that funds with the highest skill ratio generate a significant higher Value Added than funds with the lowest skill ratio. The differences display a near-monotonic increase for the quintiles. Funds with the highest Past Performance generate around $6 million higher Value Added per month when they belong to the highest skilled funds compared to the lowest skilled funds.

This results displays that even within the highest quintile of Past Performance there is still a major difference in Value Added between funds. Furthermore, these differences show that a single sort on skill ratio does not provide adequate results when identifying skilled funds.

Panel B reports the results of the double-sort portfolio based on past performance and MAX. This double sort does not yield significant differences in Value Added, except for the second quintile. For the other quintiles of Past Performance, there doesn't exist a significant difference in Value Added when comparing the highest and lowest decile of MAX. Therefore, this double sort does not add much value when trying to identify skilled funds.

Table 8 displays the results of the high-minus-low portfolio based on a triple-sorted portfolio. For each variable, an analysis of the observations belonging to the top and bottom category is performed based on the top category of the other two variables. For skill, this implies that the observations of the top and bottom decile of skill that also belong to the highest decile of MAX and highest quintile of past performance are analyzed. For all three variables, only skill reveals a significant difference in Value Added between the top and bottom decile. Funds with the highest Past Performance and MAX generate around \$54 million higher Value Added per year when they belong to the highest skilled funds compared to the lowest skilled funds. The other analyses do not yield a significant difference in Value Added. There are some concerns about the validity of the result, as the amount of observations in the lowest category for skill, MAX and past performance are around 200. As a robustness check, an analysis of the entire sample will provide more insight.

The result of the entire sample exhibits a large significant difference in Value Added. D10 represents funds belonging to the highest category of skill, MAX and past performance funds, while D1 represents funds belonging to the lowest category of all three variables. Funds in D10 generate about \$65 million higher Value Added per year compared to funds in D1. As both these categories represents more than 1,400 observations, there is no reason for concern over the validity of the results.

### Table 8: **Results for Triple Portfolio Sort**

This table displays the mean difference in Value Added for the high-minus-low portfolio of Skill, MAX and Past Performance respectively. The portfolios are sorted for the top quintile/decile of the other two variables. For the full sample, observations that belong to all three top categories are compared to observations that belong to all three bottom categories. Observations are assigned into the relevant category for each time period combination. Similarly to Fama and MacBeth (1973), the first step involves calculating the cross-sectional means per month/objective code and then taking the time-series mean as average per decile. A zero cost high-low portfolio is created by subtracting the lowest quintile from the highest quintile every month. Standard errors are reported in parentheses. P-values below 0.01, 0.05 and 0.10 are labeled with ***, ** and * respectively.

| Variable | Sorted by: | D10 | D1 | Difference |
|---|---|---|---|---|
| Skill | (MAX/PP) | 4.157 | -0.361 | 4.518*** |
| | | (0.513) | (0.214) | (1.021) |
| MAX | (Skill/PP) | 4.157 | 3.981 | 0.176 |
| | | (0.513) | (1.335) | (3.253) |
| Past Perf. | (Skill/MAX) | 4.157 | 1.366 | 2.791 |
| | | (0.513) | (0.506) | (1.704) |
| Full sample | (Skill/PP/MAX) | 4.157 | -1.277 | 5.433*** |
| | | (3.253) | (1.704) | (0.471) |

To summarize, the results of the portfolio sorts display considerable differences in mean Value Added. For each decile of MAX, there exists a significant difference in Value Added when comparing the highest and lowest decile of skill ratio. The same applies for each decile of skill ratio except the first and ninth, where significant differences in Value Added exists when comparing the highest and lowest decile of MAX. These differences stress the importance of a double-sorted portfolio to select the best-performing funds. The results of Past Performance indicated that a double-sort together with skill generates higher Value Added equal to $70 million a year, while the double-sort of Past Performance and MAX does not yield a significant result. A high-minus-low portfolio sorted on Skill, MAX and Past Performance generates about $65 million higher Value Added per year.

## 5.4 Net alpha estimates for Skill portfolios

The previous section has displayed that portfolio sorts result in considerable differences in mean Value Added. This section will perform an analysis on returns obtained by investors that invest in a portfolio that ranks funds based on their skill ratio. The analysis has an advantage over the Value Added analysis as it directly measures returns obtained by investors. In each month, the monthly return of all funds in the highest and lowest decile of skill are aggregated using an equal- and value-weighted technique. The time series sample is regressed onto the 4-factor model by Carhart (1997). Standard errors are estimated using the Newey-West procedure including five lags. The impact of transaction costs is not considered in the analysis. The results are reported below.

**Table 9: Net alpha estimates of skill portfolios**

This table displays the time-series average net alpha estimates of a monthly regression on the returns of the skill portfolio. In each month, the monthly return of all funds in the highest (10) and lowest (1) decile of skill are aggregated using an equal- and value-weighted technique. EW and VW refer to the equal- and value-weighted technique respectively. Larger funds receive a higher weighting in the value-weighted technique. These average returns are regressed onto the 4-factor model by Carhart (1997). Transaction costs are not considered in the analysis. Standard errors are estimated with the Newey-West procedure including five lags and reported in parentheses. P-values below 0.01, 0.05 and 0.10 are labeled with ***, ** and * respectively.

| Decile | EW10 | EW1 | VW10 | VW1 |
|---|---|---|---|---|
| Net alpha | 0.0055*** | -0.0061*** | 0.0052*** | -0.0052*** |
| | (0.0008) | (0.0007) | (0.0010) | (0.0007) |

The table displays interesting results. A positive and significant net alpha is obtained by the highest decile of skill using both the equal- and value-weighted approach. This implies that a portfolio consisting of the highest skilled funds provides evidence of generating positive abnormal returns equal to 0.55% per month for equal-weighting and 0.52% per month for value-weighting in this data sample. For the lowest decile, the table reports negative and significant net alpha for the both the equal- and value-weighted approach. Funds with the lowest skill ratio generate negative abnormal returns equal to 0.61% per month for equal-weighting and 0.52% per month for value-weighting in this data sample.

Overall, the results indicate that there is a significant difference in net alpha for funds with the highest skill compared to funds with the lowest skill. The outcomes of the equal- and value-weighted approach generate similar positive estimates for net alpha of high-skilled funds and negative estimates for low-skilled funds. The most important consideration of this analysis is that transaction costs are not included in this analysis, which can have a profound impact on net alpha. In the case of high-skilled funds, this might cause the net alpha to be insignificant from zero. For low-skilled funds, this will probably result in more negative net alphas. The above result emphasizes the importance of including skill when identifying funds that are expected to generate strong performance.

### 5.5 Regressions on MAX and Skill ratio

In this section, more emphasis will be put on the relationship between MAX and skill ratio. Previous sections have concluded that MAX has an endogenous effect when skill ratio is omitted from the fund flows regression. In this section, regressions using both variables as dependent variables are performed. Similar control variables are included in the analysis. The results of the analyses are presented in Table 10.

The first regression uses MAX as the dependent variable. Volatility is positive and significant, indicating that funds with more volatile returns have a higher MAX. A similar effect is found for skewness. Skill ratio has a positive and significant effect on MAX, finding that more skilled funds have a higher MAX. This result provides more evidence that MAX is an endogenous variable. Fund size has a negative significant effect on MAX, indicating that larger funds on average generate lower style-adjusted returns. This result is in line with the negative relationship between lagged MAX and fund size found by Akbas and Genc (2016), although the effect of Akbas and Genc (2016) is not significant. Furthermore, the result is consistent with the notion that the amount of actively managed capital decreases for larger funds and leads to a lower probability of a deviation in the style-adjusted returns of the fund.

Fund family size has a negative significant effect on MAX, which is line with the results of Akbas and Genc (2016). However, this finding is not in line with Chen et al. (2004), who find that fund family size has a positive effect on performance. The effect of the expense ratio is positive and significant at the 1%-level. This result is in line with Akbas and Genc (2016), even though a higher expense ratio directly influences the style-adjusted performance of the fund. A potential explanation could be the existence of funds charging higher fees for research-intensive strategies with superior performance. TURNOVER is positive and significant, indicating that more active funds generate higher style-adjusted returns. Similarly to the effect of MAX of fund flows, monthly fund flow is positively associated with MAX. Funds belonging to the lowest quintile of past 12-month relative performance exhibit a negative significant, while the other quintiles exhibit a positive significant effect. Akbas and Genc (2016) take the style-adjusted return of the previous 12 months and find a negative effect on lagged MAX.

A higher mean cash percentage has a positive effect on MAX that is significant at the 1%-level. This result is not consistent with the notion that the amount of cash held by the fund lowers the amount of actively managed funds, which lowers the probability of a deviation in the style-adjusted returns of the fund. The effect of age on MAX is negative and the only insignificant variable. This result is not consistent with the finding by Pástor et al. (2015) that performance of a fund deteriorates as funds get older holds. Akbas and Genc (2016) find a positive albeit insignificant effect of age on MAX. The $R^2$ of the regression is 0.49, providing a decent amount of explanatory power.

**Table 10: Regression results on MAX-Skill ratio relationship**

This table displays the regression parameters on $MAX_{it}$ (1) and Skill ratio (2). MAX represents the maximum style-adjusted return in the previous 12 months, which is calculated by subtracting the average monthly returns of all funds with the same style from a fund's monthly returns. All observations that contain 11 or less months of MAX are not considered in the analysis. Skill ratio represents the skill of fund managers and is calculated using the procedure from Berk and Van Binsbergen (2015). VOL and SKEW are defined as the standard deviation and skewness of monthly excess returns over the previous 12 months. $Log(TNA)_{t-1}$, $Log(FamilyTNA)_{t-1}$ and $Expenseratio_{t-1}$ are defined as the fund size, fund family size and expense ratio lagged by one month. TURNOVER represents portfolio transactions' value as a percentage of total portfolio value. Following the procedure from Sirri and Tufano (1998), funds are sorted into quintiles based on the previous 12-month relative performance within the style category for each month. LOWPERF represents the lowest quintile, MIDPERF combines the middle 3 quintiles, and HIGHPERF refers to the highest quintile. Cash Percentage is defined as the mean cash percentage of the fund over its lifetime. Age represents the time the fund has been active. $Log(TNA)_{t-1}$ and $Log(FamilyTNA)_{t-1}$ are inflation-adjusted with 2000 as base year. Standard errors are reported in parentheses. P-values below 0.01, 0.05 and 0.10 are labeled with ***, ** and * respectively.

| Variable | (1) | (2) |
|---|---|---|
| *VOL* | 0.541*** | -0.103 |
| | (0.03) | (0.07) |
| *SKEW* | 0.003** | -0.001 |
| | (0.00) | (0.00) |
| *MAX* | | 0.230*** |
| | | (0.04) |
| *Skill ratio* | 0.008*** | |
| | (0.00) | |
| $Log(TNA)_{t-1}$ | -0.000*** | 0.006*** |
| | (0.00) | (0.00) |
| $Log(FamilyTNA)_{t-1}$ | -0.000*** | -0.001*** |
| | (0.00) | (0.00) |
| $Expenseratio_{t-1}$ | 0.078** | 1.565*** |
| | (0.04) | (0.22) |
| *TURNOVER* | 0.001*** | -0.011*** |
| | (0.00) | (0.00) |
| *FLOW* | 0.014*** | 0.016*** |
| | (0.00) | (0.01) |
| *LOWPERF* | -0.001*** | 0.014*** |
| | (0.00) | (0.00) |
| *MIDPERF* | 0.003*** | 0.010*** |
| | (0.00) | (0.00) |
| *HIGHPERF* | 0.011*** | 0.016*** |
| | (0.00) | (0.00) |
| *Cash Percentage* | 0.001*** | 0.001*** |
| | (0.00) | (0.00) |
| *Age* | 0.000 | -0.000 |
| | (0.00) | (0.00) |
| Number of funds | 6,549 | 6,549 |
| Number of periods | 298 | 298 |
| $R^2$ | 0.49 | 0.16 |

In the second regression, skill ratio is used as the dependent variable. The effect of VOL, SKEW and age are all negative and insignificant, indicating that funds' skill is not significantly influenced by these variables. The coefficient of MAX is positive and significant at the 1%-level, indicating that funds with a higher MAX are more skilled. The positive, significant effect provides evidence that abnormal style-adjusted returns generated by funds are the result of superior stock-picking abilities and/or market timing skills compared to other managers. Fund size has a positive and significant effect on skill ratio, indicating that larger funds on average are more skilled. This result is not consistent with the negative relationship between fund performance and fund size documented by Chen et al. (2004). However, given the direct relationship between Value Added and fund size, a significant effect of this variable can be expected. Fund family size has a negative significant effect on skill ratio, which is not in line with previous research by Chen et al. (2004).

Similarly to fund size, the effect of the expense ratio is positive and significant at the 1%-level, which can also be explained using the direct relationship with Value Added. The effect of monthly fund flows on skill ratio is positive and significant, providing evidence for Berk and Green (2004) that investors are able to identify skilled fund managers and reward them with more capital. Chevalier and Ellison (1997) concluded that the flow-performance relationship is convex and increases with performance. All measures of past performance are significant at the 1%-level. Cash Percentage and portfolio turnover have a positive and significant effect, although with a limited magnitude. The $R^2$ of the regression is 0.16, providing a fair amount of explanatory power.

The main outcome of the analyses is that MAX and Skill ratio have a significant, positive effect on the other variable. The regression on MAX confirms that skilled funds generate higher style-adjusted returns. This result directly confirms the hypothesis that MAX is an endogenous variable, because the skill ratio has a positive and significant effect on MAX. Furthermore, more volatile past returns, a higher expense ratio, higher fund flows and the highest past performance are the main characteristics of funds with high MAX. The analysis of Skill ratio provided the result that funds with higher MAX are more skilled. Fund size, expense ratio, fund flows, all measures of past performance and cash percentage also exhibit a positive and significant effect on skill ratio. Funds being part of a fund family and with a higher turnover ratio are associated with lower skilled funds.

# 6 Conclusion

This paper investigates the determinants of skilled mutual funds. This paper aims to contribute to the current academic literature by providing new insights into the characteristics of mutual funds to obtain a broad perspective on this industry. Using a sample from the CRSP mutual fund database, the results demonstrate that the average fund manager destroys \$350,000 value per year in the period of 1962 to 2019.

When investigating the individual effects, this paper finds that maximum style-adjusted return has a positive and significant effect on monthly fund flows, indicating that fund managers with higher MAX attract more capital from investors. Adding the skill ratio from Berk and Van Binsbergen (2015) to the regression provides evidence that skilled funds generate higher inflow from investors while decreasing the effect of MAX, which indicates that MAX is an endogenous variable. This outcome provides evidence that style-adjusted returns are the result of stock-picking abilities and/or market timing skills. All measures of past performance are positive and highly significant, which implies that funds with strong past performance are rewarded with more capital from investors. Furthermore, fund family size, lagged fund flows and cash percentage have a positive significant effect on monthly fund flows. Fund size, expense ratio, turnover and age display a negative significant effect on monthly fund flows.

Repeating the previous analysis using quarterly fund flows provides additional evidence that fund managers with higher MAX attract more capital from investors. Adding the skill ratio from Berk and Van Binsbergen (2015) to the regression yields skilled funds generating higher inflow from investors while decreasing the effect of MAX, confirming that MAX is an endogenous variable. This result indicates that style-adjusted returns are the result of stock-picking abilities and/or market timing skills. Fund family size, lagged fund flows, cash percentage and all measures of past performance have a positive significant effect on quarterly fund flows, while fund size, expense ratio, turnover and age exhibit a negative significant effect on quarterly fund flows.

A series of portfolio sorts on skill ratio, Past Performance and MAX demonstrate significant differences in mean Value Added. For each decile of MAX, there exists a significant difference in Value Added when comparing the highest and lowest decile of skill ratio. The same applies for each decile of skill ratio except the first and ninth, where significant differences in Value Added occur when comparing the highest and lowest decile of MAX. The results of Past Performance indicated that a double-sort together with skill ratio generates higher Value Added equal to $70 million a year within the highest quintile of Past Performance, while creating a portfolio by double-sorting Past Performance and MAX does not yield significant higher Value Added. A high-minus-low portfolio sorted on skill ratio, MAX and past performance generates about $65 million higher Value Added per year.

Estimating the net alpha of portfolios based on skill ratio finds that high-skilled funds generate a positive, significant net alpha before transaction costs using an equal- and value-weighted methodology. Low-skilled funds generate a negative, significant net alpha before transaction costs using both methodologies. This outcome emphasizes the importance of including skill when identifying funds that are expected to generate strong performance.

Exploring the determinants of MAX finds that volatility, skewness, expense ratio, turnover, fund flows, middle and top past performance have a positive and significant effect. Cash Percentage has a positive and significant effect on MAX, lacking evidence that more cash leads to a lower probability of a deviation in the style-adjusted returns of the fund. The negative effect of size on MAX accepts the hypothesis that size has a negative effect on MAX, which indicates that the amount of actively managed capital decreases for larger funds and leads to a lower probability of a deviation in the style-adjusted returns of the fund. Skill ratio has a positive and significant effect on MAX, finding that more skilled funds have a higher MAX.

The regression on skill ratio revealed that funds with a higher MAX are more likely to have a skilled fund manager, providing evidence that style-adjusted returns generated by funds are the result of superior stock-picking abilities and/or market timing skills compared to other managers. Larger funds and funds with higher fees to investors have higher skill on average, although this result could be caused by the direct relationship with Value Added. Furthermore, higher fund flows and strong past performance are also characteristics of skilled funds. Fund family size and turnover are negatively associated with skill.

The empirical results reported herein should be considered in the light of some limitations. First of all, this paper has used the CRSP mutual fund database to retrieve information on mutual funds. Although widely used by academic authors, this data sample only includes a limited amount of mutual funds with sufficient and correct data. As a result, the results in the analysis might not be representative for the entire mutual fund industry. Combining a dataset with well-known data providers such as Bloomberg can mitigate this limitation. Secondly, this paper has incorporated all variables that are available in the database, have been discussed in previous academic research and are deemed relevant to provide explanatory power as a determinant of skilled mutual fund managers. Obviously, there are more factors that can influence the skill of fund managers, but the setup was designed to create a comprehensive analysis.

A possible area for future research could be the translation of these results into investment strategies. Since this paper only tries to investigate the determinants of skilled mutual funds, it remains unclear whether investing in these funds provides investors with abnormal returns. The result on the portfolio sort did provide evidence of significant higher Value Added when selecting funds based on MAX, Skill ratio and past performance, but does not elaborate on the returns obtained by investors. Furthermore, the fund can directly impact the net alpha for investors by setting the management fee. As a result, returns for investors are disentangled from fund managers' skill. The impact of transaction costs and availability of these investment strategies are not considered in this paper.

# 7 List of Tables and Figures

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# Bibliography

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