Mutual Fund Performance in Norway and its Effect on Investor Capital Allocation

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Preface

This master's thesis concludes our Master of Science degree in Applied Finance at the University of Stavanger. We decided early on that we wanted to explore a topic that provided opportunities for large gains in knowledge. Our common interest for analytical programming lead us to undertake a quantitative subject. The thesis proved far more challenging and laborious than any of our previous academic work. It has been a thoroughly rewarding learning experience, that has given rise to many inside jokes.

We thank our thesis adviser Bernt Arne Ødegaard for his valuable guidance and feedback. Additionally, we thank Verdipapirfondenes Forening and, again, Bernt Arne Ødegaard for providing us with data. Lastly, we would like to thank our wife, Karen, for her patience, support, and cookies.

Stavanger, June 2016

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Sammendrag

Ved hjelp av et datasett uten overlevelsesskjevhet (survivorship bias) undersøker vi hvordan Norske aksjefond har prestert i perioden 2000–2015, og tidligere prestasjoners effekt på fondinvestorenes kapitaldisposisjoner. Vi benytter en rekke forskjellige prestasjonsmål for å evaluere fondenes aggregerte avkastning. Den statistiske signifikansen til individuelle fonds prestasjoner evalueres for å skille mellom ferdigheter og tilfeldigheter. Dette gjøres ved å sammenligne distribusjonen av reelle tre–faktor alfa–estimater med simulerte alfa–distribusjoner, generert ved en bootstrap–prosedyre. Til sist undersøker vi hvordan tidligere prestasjoner påvirker fondinvestorenes kapitaldisposisjoner. Analysen består av korrelasjons– og regresjonsanalyser av kapitalstrømmer til aksjefond og forskjellige prestasjonsmål. Vi finner ikke bevis for at fondene samlet leverer høyere risikojustert nettoavkastning enn markedet. Hvis fondene leverer høyere risikojustert bruttoavkastning enn markedet tilfaller meravkastningen fondsforvalteren i form av forvaltningshonorar, og reflekteres derfor ikke i nettoavkastning. Bootstrap–analysen gir bevis på manglende ferdigheter blant de dårligste fondene, men kun svake tegn på høye ferdigheter blant de beste. Vi finner at fondinvestorers kapitaldisposisjoner påvirkes av fondenes tidligere prestasjoner, men vi finner ikke klare bevis for at noen prestasjonsmål foretrekkes fremfor andre. På tross av svake tegn på ferdigheter blant de beste fondene, finner vi at sammenhengen mellom tidligere prestasjoner og fondenes kapitalstrømmer er sterkere for de beste fondene. Resultatet impliserer at investorer i større grad investerer i tidligere vinnere enn de avhender tapere.

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June 15, 2016

Abstract

Using a survivorship bias–free dataset, we investigate the performance of Norwegian mutual funds in the period 2000–2015, and its effect on investor capital allocation to mutual funds. We evaluate the performance of the aggregate mutual fund industry using a range of different performance metrics. To distinguish skill from luck, we evaluate the statistical significance of individual fund performance, by comparing the distributions of actual and simulated three–factor alphas and t–stats. Simulated distributions are generated using a bootstrap procedure. Lastly, we investigate the effect of past performance on investor capital allocation, using correlation and regression analysis of capital flows on different performance metrics. We do not find evidence that the mutual funds in aggregate outperform the market in risk–adjusted net returns. If the average fund is able to generate abnormal gross returns, the gains accrue to the fund manager in the form of management fees, and is not reflected in net returns. Bootstrap evidence shows strong signs of lack of skill among poor performers, but only weak signs of positive skill among high performers. We find that investor capital allocation is affected by past performance, but we do not find conclusive evidence favoring one measure of performance over another. In spite of weak evidence for skill among high performers, we find that the association between past performance and fund flows is stronger for high than for poor performers. This result implies that investors more readily invest in past winners than they divest from losers.

*University of Stavanger (UiS), NO–4021 Stavanger, Norway. We thank Bernt Arne Ødegaard for his valuable guidance and feedback. Additionally, we thank Verdipapirfondenes Forening and, again, Bernt Arne Ødegaard for providing us with data. Lastly, we would like to thank our wife, Karen, for her patience, support, and cookies.

1 Introduction

Whether mutual funds are able to outperform the market is a hot topic in finance. The topic has sparked the creation of many measures of portfolio performance[1], and methods for identifying skilled performers. Most studies have found little evidence that the aggregate mutual fund industry adds investor value in terms of market beating performance, yet individual fund performance varies a great deal. The bootstrap procedures of Kosowski et al. (2006) and Fama and French (2010) attempt to disentangle skill from luck. While studies find varying evidence for skill, many find stronger evidence for lack of skill (negative skill) among poor performers[2]. A complementary approach to assess the feasibility of identifying winners in advance is to study the persistence of performance. Earlier studies find evidence for persistence in fund performance[3], but Carhart (1997) argues that the evidence disappears after controlling for the momentum effect. Bollen and Busse (2005) suggests that persistence can be a short–lived phenomenon, advocating the use of daily data.

While the extent of previous research on performance in the Norwegian mutual fund market is limited, a few articles have emerged in recent years. Sørensen (2009) and Gallefoss et al. (2015) both examine the performance and persistence of actively managed mutual funds. Sørensen (2009) finds no evidence for abnormal nor persistent performance in the aggregate mutual fund industry. Bootstrap analysis reveals few signs of skill, but more reliable signs of the lack of skill. Gallefoss et al. (2015) expands on Sørensen's findings by examining daily data. They find evidence for worse aggregate performance, yet stronger evidence for positive skill, than Sørensen. They add that the performance of the top and bottom quantiles persists for short time horizons, and cannot be explained by chance.

Past performance is frequently the primary selling point in the marketing efforts of the industry, yet its merit as a reliable estimator of future performance remains questionable. Several previous studies have documented a strong relationship between past performance and the flow of capital to mutual funds[4]. The link could be seen as an implicit incentive contract, and thus an important factor in ameliorating

[1] For example, the ratios of Treynor (1965) and Sharpe (1966), and the alpha of Jensen (1968).
[2] See, for example, Kosowski et al. (2006), Cuthbertson et al. (2008), Fama and French (2010)
[3] See, for example, Hendricks et al. (1993), Elton et al. (1996)
[4] See, for example, Spitz (1970), Smith (1978), Ippolito (1992), Patel et al. (1996)

the agency problem of mutual fund fees[5] (Chevalier and Ellison, 1997). There are many different measures of past performance, but they are not all created equal, nor do they necessarily lead to the same conclusions. Patel et al. (1996) investigates the rationality of the performance–flow relationship in the context of the efficient market hypothesis. The same investigation is relevant in light of the empirical results on skill and persistence in mutual fund performance.

We contribute to the existing literature by evaluating mutual fund performance and attempting to assess the performance–flow relationship with a recent set of data from Norway. To the best of our knowledge, Norwegian research on investor behavior in response to past performance is non–existent. The analyses are based on a survivorship bias–free dataset consisting of 71 actively managed Norwegian funds from January 2000 to December 2015. We will address the following questions: *i)* Do active equity mutual funds deliver market beating performance in aggregate or individually, and can investors reliably identify skilled managers ex ante? *ii)* Does past performance affect investor capital allocation, and do different measures of performance affect capital allocation differently? *iii)* Does investor capital allocation conform with empirical evidence on the skill and persistence in mutual fund returns?

We investigate the aggregate and individual performance of actively managed funds with a Norwegian mandate. Aggregate performance is assessed using returns, three common performance ratios[6], and alpha. Individual fund performance is evaluated by applying the Fama and French (2010) bootstrap procedure to the Fama and French (1993) three–factor model. As an assessment of robustness, the results are tested using a different reference index, the Carhart (1997) four–factor model, and the Kosowski et al. (2006) bootstrap procedure. The effect of past performance on investor capital allocation is investigated using correlation analysis and a regression model inspired by Chevalier and Ellison (1997). We regress the net flows to funds on the various performance metrics used in the performance analysis. All metrics are re–calculated for 3–year moving windows.

We do not find conclusive evidence that active equity mutual funds deliver market beating performance in aggregate risk–adjusted net returns. Returns and ratios are only marginally better than the market, while multi–factor alphas are negative but

[5] Fees are usually a fixed percentage of assets under management, incentivizing fund managers to focus on increasing assets instead of returns, creating an agency problem.

[6] The Sharpe ratio, Treynor ratio, and Information ratio.

statistically insignificant. The results suggest that the average fund may generate abnormal gross returns, but that the gains accrue to the fund manager in the form of management fees, and is not reflected in net returns. We find evidence for lack of skill among poor performers, but only weak signs of skill among high performers. This implies that past performance is more sensibly used to avoid losers, rather than chase past winners.

We find that past performance affects investor allocation of capital, but do not find conclusive evidence favoring one measure of performance over another. In spite of our bootstrap evidence, and the research of Sørensen (2009) and Gallefoss et al. (2015), we find that the association is stronger for high performers, suggesting that investors more readily invest in winners than they divest from losers.

The remainder of the paper is organized as follows. Section two contains a brief account of the dataset. The performance evaluation in section three discusses performance results for the equally weighted and value weighted aggregate portfolios, and bootstrap evidence for disentangling luck and skill in individual fund returns. Section four contains the analysis of investor capital allocation, utilizing the results from the preceding section. Section five concludes the paper.

2 Data

This section presents the data used in our analysis, including fund returns and capital, along with various benchmarks. All data in the sample consists of monthly observations in a 16–year time period, spanning January 2000 to December 2015.

2.1 Fund returns and investor capital allocation

Data on investor capital allocation includes total assets, along with cash inflow and outflow (purchase and sale of fund shares). The data was obtained from the Norwegian Fund and Asset Management Association[7] (VFF). The raw data consisted of 192 monthly reports, dating back to January 2000. The process of consolidating the raw data involved resolving name changes, mergers and acquisitions, and occasional naming errors. Refer to Appendix A for a more detailed summary of the process.

The figures are reported to VFF by fund managers, as opposed to being derived from indirect calculations, eliminating the potential for miscalculation, yet opening for human error in reporting and data handling. We adopted the VFF classification of Norwegian mutual funds, requiring at least 80 percent of fund capital invested in the Norwegian stock market. The classification of individual funds is reviewed monthly, as some funds have intermittent periods[8] with different classification, whenever their share of assets invested in the Norwegian stock market drops below 80 percent. Funds that change classification are still included in the sample, but observations from periods with different classification are removed.

After correcting for errors and removing index, pension, and savings scheme funds, the VFF dataset consisted of 201 funds, which were further reduced to 113 individual funds after resolving name changes, mergers and acquisitions. Merging funds are kept separate until the time of the merger, while acquisitions and funds with name changes are pooled in a single time series.

This intermediate list of funds was used for gathering data on fund total returns, originating from two sources: Oslo Stock Exchange[9] (OSE), and Thompson Reuters Datastream for the funds that were missing from the former dataset. We were unable to find returns data for 11 out of the 113 funds, possibly due to unresolved name

[7]Verdipapirfondenes Forening (VFF)
[8]Includes temporarily interrupted time series, and permanent re-classifications.
[9]The data was provided by Professor Bernt Arne Ødegaard.

changes, mergers and acquisitions. Funds without at least 36 months of corresponding data on capital and returns were excluded from the sample, amounting to the exclusion of 31 funds. This left us with a sample of 71 funds, for a total of 10,461 fund months. The dataset from OSE reports total returns, while Datastream reports the total return index. Fund returns from Datastream are calculated as the percentage change in the total return index.

$$r_t = \frac{TRI_t}{TRI_{t-1}} - 1 \qquad (1)$$

Where TRI_t is the fund's total return index at the end of month t, and TRI_{t-1} is the total return index at the end of the previous month, $t-1$. We were unable to fully match the total returns calculation of the OSE dataset, but using the last day of the month proved to be the closest match. Unless otherwise stated, returns are *presented* as annualized geometric returns[10], which is the average compounded return that would be realized per year.

Table 1 Summary fund statistics

The table presents summary statistics on number of funds, fund assets, and performance. Columns two to four show the end of year number of funds, along with the number of funds in and out of the sample. Columns five to eight show aggregate assets under management, capital inflow and outflow, and net inflow. The penultimate column reports active returns of the equally weighted portfolio of sampled funds. Active returns are defined as the return in excess of a reference index (OSEFX). The final column reports the three-factor alpha of the equally weighted portfolio, also using the OSEFX as benchmark index. Monetary values are in millions NOK, performance is in percent.

	Number of funds			*Capital (MNOK)*				*Performance - EW (%)*	
Year	End of year	In	Out	AUM	Inflow	Outflow	Net Inflow	Active Returns	3-Factor Alpha
2000	52			27,361	6,876	8,803	-1,928	2.4	-3.5
2001	56	4		23,462	5,105	5,495	-390	0.6	-0.7
2002	62	6		16,141	5,531	6,112	-581	-2.4	1.8
2003	62	2	2	24,173	4,199	4,202	-4	-0.7	-7.0
2004	60		2	28,411	6,244	10,558	-4,314	-2.1	-5.3
2005	57		3	34,266	9,926	15,828	-5,902	4.2	1.9
2006	55	3	5	45,152	14,033	13,100	933	-2.5	-3.6
2007	53		2	47,509	10,669	12,986	-2,316	1.8	1.0
2008	53			22,652	11,407	11,528	-121	6.0	-4.7
2009	53			48,874	15,997	8,083	7,914	2.1	5.9
2010	54	1		63,308	16,779	15,853	926	-0.9	2.2
2011	56	2		48,861	12,398	13,621	-1,223	-0.8	-0.3
2012	55		1	55,747	12,526	11,984	543	-4.1	-4.9
2013	52	1	4	66,209	11,229	12,363	-1,135	-0.9	0.8
2014	47		5	66,081	17,819	22,001	-4,182	1.2	2.2
2015	45		2	59,330	14,127	19,656	-5,529	-0.6	-0.9

[10]Note that *calculations* of, for example, performance ratios use arithmetic mean returns.

Table 1 reports descriptive statistics on the Norwegian active equity mutual fund market. The table shows that investors have divested from actively managed funds with a Norwegian mandate since 2000. The same trend is evident for all funds with a Norwegian mandate, as investors have shifted more capital to bond and money market funds (refer to Figure 6 in Appendix B).

A notable weakness of the dataset is that it is exclusively comprised of VFF members. To be sure, most fund managers involved in the Norwegian stock market *are* members, but we were unable to acquire an exhaustive account of non-members. In comparing our sample of funds with that of Gallefoss et al. (2015), which is from a comprehensive database[11] at the Norwegian School of Economics (NHH), we find that we have accounted for all 64 funds from their analysis, covering the period 2000-2010. As far as we can gather, the members of VFF are representative of fund managers involved in the Norwegian stock market.

There are a few possible explanations for the end of a time series: *a*) Re–classification; *b*) discontinuation due to merger; and *c*) liquidation. Re–classification is only relevant to one fund, and the fund was closed 2 years later. We will refer to all time series of returns ending before December 2015 as dead funds. Omitting dead funds could be a source of bias, as they could be associated with bad performance. Sørensen (2009) found that survivorship bias accounted for a difference of 3.2 percent annual return in his sample from 1982 to 2008. In our sample there are 26 dead funds. They provided mean returns of 5.2 percent, compared to 8.8 percent for the 45 live funds, for a 3.6 percent return differential. This illustrates the importance of using a dataset free of survivorship bias.

2.2 Benchmark data

Relative performance measurement requires an appropriate benchmark. Three candidates are the Oslo Stock Exchange All Share Index (OSEAX), the OSE Benchmark Index (OSEBX), and the OSE Mutual Fund Index (OSEFX), of which we use the latter. The OSEAX contains all shares listed on Oslo Stock Exchange. This includes highly illiquid stocks that might make replication infeasible due to transaction costs. The OSEBX consists of the 50-60 largest capitalization stocks on the exchange. It is constructed as a representative, investable index of the Norwegian stock market, adjusted

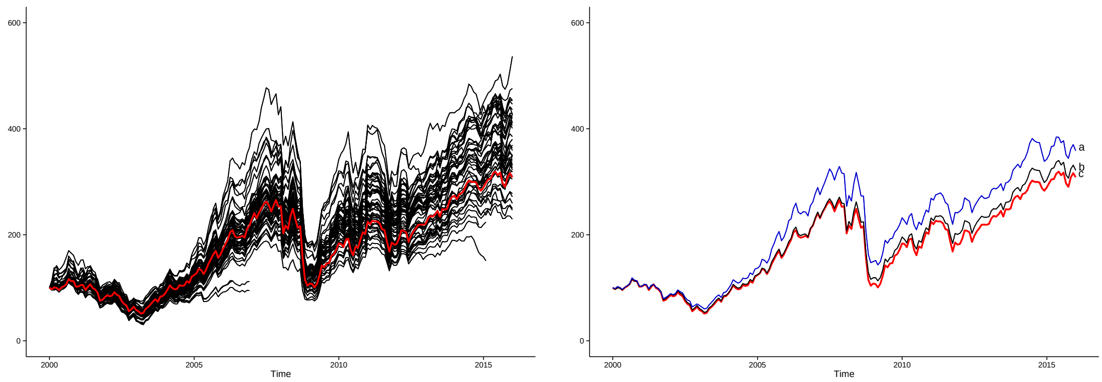
[11] Børsprosjektet

for illiquid stocks and shares. Based on the OSEBX, and adopted as a benchmark by many funds, the OSEFX is designed to reflect the requirements faced by mutual funds in Norway, relating to diversification and risk level. While the fund index complies with the laws and directives applicable to mutual funds, investors are *not* required to conform to these provisions. Its viability as a performance benchmark from the perspective of an investor, who could feasibly engage in investment activities denied to the fund manager, is thus debatable.

Figure 1 Total return index

The figure presents the total return index (TRI) for funds and market indices. Plot A shows the TRI for all funds, relative to the OSEFX mutual fund index (in red). All funds do not start in 2000. The initial value of each fund's TRI equals the OSEFX value at the same month the fund was started. Plot B compares the OSEFX (line c, in red), with two other common Norwegian market indices, the OSEAX (line a, in blue) and OSEBX (line b, in black). The indices in both plots start at an initial value of 100 in January 2000.

Plot A: *Funds and the OSEFX*   Plot B: *Market indices*



Sørensen (2009) showed that the OSEAX exceeded the other two in terms of mean returns by more than 1 percent annually between 1996 and 2008. The same trend is apparent in Figure 1 plot B. Naturally, the OSEBX and OSEFX are close, the difference between them being 0.3 percent annually in both Sørensen's and our data (refer to Table 2). For the sake of not judging fund performance unfairly, we opted for using the OSEFX as a proxy for the market in our analysis. It serves as a minimum requirement, in being the most favorable benchmark for the mutual funds.

Monthly time series on the risk free rate and the remaining risk factors in Carhart's four-factor model (SMB, HML, and MOM) was acquired from Professor Bernt Arne Ødegaard. He estimates a 1-month forward looking risk free rate from a combination of government securities and the NIBOR. Time series on risk factor returns are constructed using portfolios of stocks at the Oslo Stock Exchange. SMB ("small–minus–big") measures the return differential between small capitalization and large capitalization firms, and is constructed as a portfolio with long positions in small firms and short positions in large firms. Similarly, HML ("high–minus–low") is the return differential between firms with high (value stocks) and low (growth stocks) book-to-market values (B/M). It is constructed as a portfolio with long positions in value stocks and short positions in growth stocks. SMB and HML were first introduced by Fama and French (1992, 1993), in their extension of the CAPM. Two alternative approaches to constructing the momentum factor are PR1YR ("prior-1-year), introduced by Carhart (1997) to capture the effect identified by Jegadeesh and Titman (1993), and UMD ("up-minus-down"), as defined by Fama and French (2010). They are both constructed as a portfolio with long positions in firms with high prior returns and short positions in firms with low prior returns. By design, and unlike PR1YR, UMD attempts to correct for firm size, and is calculated in a similar fashion to HML. We will use PR1YR as the momentum factor in calculations of the Carhart (1997) four–factor model. Table 2 reports mean returns on the various market indices and risk factors.

Table 2 Benchmark returns

The table presents simple mean returns on various benchmark portfolios. The portfolios include three market indices: the All Share Index (OSEAX), Benchmark Index (OSEBX), and Mutual Fund Index (OSEFX); and portfolios on the common risk factors: Size (SMB), Book–to–Market (HML), and Momentum (PR1YR and UMD).

	Market indices (%)			Risk factors (%)			
	OSEAX	OSEBX	OSEFX	SMB	HML	PR1YR	UMD
Total	8.3	7.6	7.3	5.6	-0.5	11.8	9.9
2000-2003	-0.4	-2.6	-2.8	15.5	9.3	0.6	-8.5
2004-2007	33.8	30.2	29.9	7.4	1.6	25.3	34.2
2008-2011	-6.1	-5.9	-7.9	-2.1	-7.2	-0.1	3.3
2012-2015	10.1	12.2	14.0	2.4	-4.8	23.9	15.2

3 Performance evaluation

> A common human failing is the desire
> for simple answers to difficult questions
>
> *William F. Sharpe, 1975*

Some would rightly argue that performance is far too complicated to compress into a single number. While this is true, it is also impossible to compare everything with everything. Science inevitably involves simplification and abstraction. Given that performance must be measurable and comparable in some feasible way, what elements should factor into the equation? Portfolio performance can be measured in a variety of ways, accounting for a range of benchmarks and types of risk. As a consequence, the academic literature is full of proposed metrics of varying sophistication.

The evaluation of portfolio performance usually starts with an assessment of absolute and relative returns. The former reveals the actual effect on investor wealth, but is unsuited for measuring performance, in and of itself. Performance measurement requires a benchmark on which to compare results, one that should represent an appropriate alternative investment. Common benchmarks are the risk free rate, and a relevant reference index. The risk free rate represents a zero–risk investment, contrasting the riskiness of the portfolio. Active Portfolio Management is based on the idea that it is possible to outperform the market by use of costly private information. The market portfolio represents the market average, available to any passive investor at low cost, contrasting active versus passive portfolio management.

While returns are indeed relevant, by providing a basis for comparison, they fail to account for risk. Harry Markowitz (1952) is widely recognized as the founder of Modern Portfolio Theory, by providing the first mathematically precise definition for risk, and a theoretical justification for diversification. In Markowitz's definition, risk is the variance of returns. All else equal, a rational investor will prefer higher returns and lower variance. The essence of his reasoning is that there exists an optimal portfolio offering the maximum possible expected return for any level of risk. This universe of optimal portfolios is what constitutes the "efficient frontier". An optimally efficient portfolio utilizes mean–variance optimization, requiring that assets are combined in such a way that no other combination would provide higher returns for the same level of risk, or lower risk for the same returns.

Herein lies the justification for diversification. By combining assets with less than perfect correlation it is possible to achieve higher overall return–to–variance, than for any asset in isolation. This also provides the basis for separating risk in two subparts. While some return variance is idiosyncratic, the rest is related to the market (or system) as a whole, and will affect every asset. This systematic risk cannot be ameliorated by diversification. Markowitz provided the idea for William Sharpe's doctoral thesis, and became his unofficial adviser, as he attempted to simplify the portfolio model. Sharpe's thesis birthed the notion of the stock index fund, as he questioned what would happen if everyone in the market played by Markowitz's rules. The answer was that the investor's efficient portfolios would collapse into one—the market portfolio.

Risk is thus defined as something manageable, perhaps even simple. The basis for this simplicity is the normal (or Gaussian) distribution—not for its realism, but for mathematical convenience. The normal distribution conveniently places risk within boundaries that are predictable, quantifiable, and manageable. It enables the use—and abuse—of analytical methods in statistics and probability. In assuming that price changes in the stock market are normally distributed one risks grossly underestimating the probability of huge fluctuations (Mandelbrot and Hudson, 2004). The ultimate objective of this paper is in evaluating how performance (and the measurement of performance) affects investor capital allocation in the mutual fund market. Common methods for performance measurement are therefore relevant irrespective of deficiencies.

In the following we will consider fund performance in aggregate and individually. Although performance metrics are justified on predicted relationships, they are usually calculated using historical results. This implicitly assumes that historical data have at least some predictive power (Sharpe, 1994).

3.1 Mean Returns

The simplest way to measure the performance of a portfolio is to consider its mean returns. The analysis will consider three such metrics, all of which are calculated for individual funds along with equally weighted (EW) and value weighted (VW) portfolios on aggregate fund returns: *a*) Simple returns ($\bar{r}$); *b*) excess returns over the risk free rate ($\bar{r}^e$); and *c*) active returns[12], relative to the benchmark index ($\bar{r}^a$).

[12] Active returns are returns in excess of a reference index.

Table 3 Aggregate mean returns

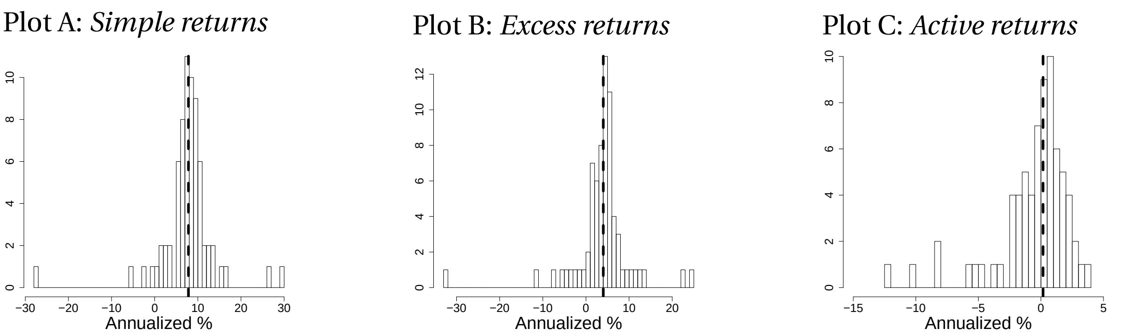
The table reports means on simple returns ($\bar{r}$), excess returns over the risk free rate ($\bar{r}^e$), and active returns relative to the benchmark index OSEFX ($\bar{r}^a$), for equally weighted (EW) and value weighted (VW) aggregate fund portfolios. The returns are computed for the total sample period and in four-year intervals.

	Equally weighted (%)			*Value weighted (%)*		
	Simple	Excess	Active	Simple	Excess	Active
Total	7.82	4.02	0.17	7.69	3.89	0.00
2000-2003	-2.80	-8.81	-0.04	-3.07	-9.06	-0.36
2004-2007	30.30	26.57	0.34	31.60	27.83	1.39
2008-2011	-5.47	-8.68	1.54	-6.20	-9.38	0.56
2012-2015	12.89	11.07	-1.13	12.41	10.60	-1.57

Table 3 reports aggregate mean returns. Our sample covers the dot–com bust and the recent financial crisis, both of which are easily identifiable on simple and excess returns. Comparatively stable active returns reveal that most of the variability in simple and excess returns is explained by changing market conditions. The VW portfolio delivered returns equal to the market index (OSEFX) in the sample period, while the EW portfolio performed slightly better. Using OSEAX or OSEBX as the market index would have turned both portfolios negative in terms of active returns.

Figure 2 Mean returns sample distribution

The figure presents sample distribution histograms of mean simple returns (plot A), excess returns (plot B), and active returns (plot C), for the entire sample period, 2000–2015. The dotted lines are the mean of the equally weighted (EW) portfolio. The returns are in annualized percentages, on the x–axis. The y–axis reports frequencies.



The plots in Figure 2 show the fund distribution on the three metrics. There are a few outliers on all metrics, but the distribution of active returns has lighter tails. In fact, the heavy right tails of the first two metrics disappear in the distribution of active returns. The top two funds in terms of simple and excess returns are both below average when adjusting for the market index. Both funds started in the immediate aftermath of the dot–com bubble and dropped out of the sample shortly before the financial crisis of 2007–2008. Conversely, the top performing fund on active returns is fairly average on the other metrics. This supports the notion that simple returns tell only half the story. Impressive returns do not necessarily translate into market beating performance.

Risk is the next piece of the puzzle. Mean returns speak of performance, but does not account for what the returns "should have been", considering the level of risk compared to alternative investments. In the following, we will consider three well known ratios, all of which attempt to adjust returns by some measure of variance.

3.2 Ratios

The Sharpe Ratio (SR), Treynor Ratio (TR), and Information Ratio (IR) all adjust returns for a univariate measure of risk, and differ mainly in how this risk is measured. The main strengths of the ratios are simple calculation and interpretation. The only necessary inputs are portfolio returns and either the risk free rate or a reference index.

While simplicity lends to their popularity, there are some important drawbacks. A negative ratio complicates the interpretation, reducing their usefulness. An increase in volatility would then imply an increased ratio, which is hardly intuitive. It is sufficient, however, to conclude that a negative value indicates bad performance, in that the portfolio has performed worse than the benchmark (risk free rate or reference index). While the interpretation of positive ratios is straightforward, they do not quantify value added. Consequently, they are mainly ranking criteria. Refer to Appendix C for a short theoretical presentation of the ratios.

Table 4 presents aggregate results on the performance ratios. The interpretation of the ratios is as follows, exemplified by the equally weighted portfolio: *i)* A Sharpe ratio of 0.085 implies that monthly excess returns increase by 0.085 percent for every 1 percent increase in the total risk (standard deviation of excess returns). *ii)* The observed Treynor ratio implies that monthly excess returns increase by 0.006 percent for every 0.01 unit increase in systematic risk (beta). *iii)* The information ratio implies that monthly active returns increase by 0.019 percent for every 1 percent increase in active risk (standard deviation of active returns).

Both the equally weighted and value weighted portfolio outperform the index on the SR and TR. For the SR, this implies that the aggregate fund market have earned higher returns per unit of total risk, and that investors could have combined the aggre-

Table 4 Aggregate performance ratios

The table reports Sharpe Ratios (SR), Treynor Ratios (TR), and Information Ratios (IR) for equally weighted (EW) and value weighted (VW) aggregate fund portfolios. SR and TR are also calculated for the OSEFX for comparison. The ratios are computed for the total sample period, and in four-year intervals. Note that the IR 2000–2003 for the EW portfolio is positive although active returns from the same period was negative (refer to Table 3). This is because active returns are geometric mean returns, while the IR is calculated from arithmetic returns.

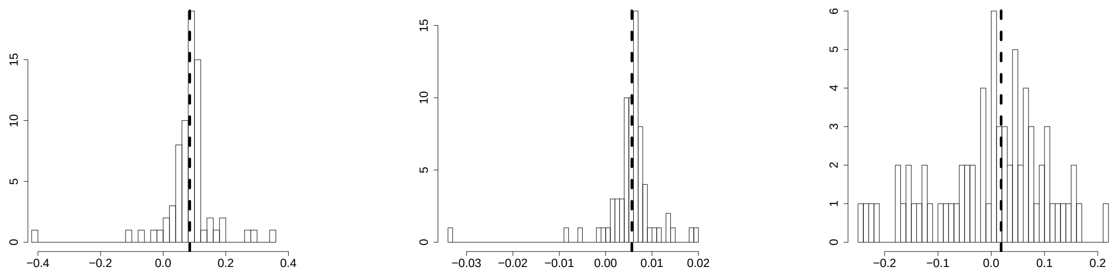
	Equally weighted (#)			*Value weighted (#)*		
	SR	TR	IR	SR	TR	IR
Total	0.085	0.006	0.019	0.084	0.006	0.005
2000-2003	-0.071	-0.005	0.005	-0.076	-0.005	-0.020
2004-2007	0.446	0.021	0.038	0.458	0.021	0.142
2008-2011	-0.044	-0.004	0.113	-0.054	-0.005	0.039
2012-2015	0.303	0.010	-0.113	0.294	0.010	-0.160
OSEFX Total	0.078	0.005	–			

gate portfolio with a risk free investment to earn a higher return for any level of risk. As the TR only accounts for systematic risk, the result implies that a well diversified investor should prefer the aggregate portfolio to the index. By its definition, the IR is undefined for the reference index, invalidating comparison between the aggregate portfolios and the market on a risk–adjusted basis[13]. Although the results are consistently in favor of the aggregate fund portfolios, the difference between them and the index is small.

Figure 3 Performance ratio sample distribution

The figure presents sample distribution histograms of the Sharpe ratio (plot A), Treynor ratio (plot B), and the Information ratio (plot C), for the entire sample period, 2000–2015. The dotted lines are the ratio of the equally weighted (EW) portfolio. The ratios are on the x–axes, while the y–axis reports frequencies.

Plot A: *Sharpe ratio* Plot B: *Treynor ratio* Plot C: *Information ratio*



We noted previously that outperformance in simple and excess returns did not

[13]Although active returns and active risk is relative to the benchmark, the IR will always adopt the sign of the active returns. As such, the active risk will scale the active returns, but cannot change the conclusion regarding market beating performance.

necessarily translate to outperformance in active returns. A similar conclusion can be drawn from the ratios. In general, the top performing funds according to the SR and TR are nowhere near the top on the IR. The rankings seem to be primarily influenced by the performance metric in the numerator, and not so much by the risk measure in the denominator. The IR and active returns alike have lighter tails than their counterparts, as illustrated in Figure 3.

Among other shortcomings, the ratios do not address the significance of the results, and they do not allow for multivariate risk. The following subsections on Jensen's alpha address some of these issues.

3.3 Jensen's alpha

As implied by its name, Jensen's alpha was first described as a performance metric by Michael C. Jensen in 1968. It derives from the works of Treynor (1961) and Lintner (1965), and was originally based on the Capital Asset Pricing Model (CAPM) of Sharpe (1964), a pillar of modern finance. Sharpe (1964) illustrates the important difference between systematic and idiosyncratic risk, where only the former should affect asset prices [14], assuming well diversified investors. Systematic risk is here defined as the slope coefficient of the linear relationship between excess asset and market returns.

$$r^e_{i,t} = \alpha_i + \beta_i r^e_{m,t} + \epsilon_{i,t} \tag{2}$$

Where $r^e_{i,t}$ is excess asset returns, α_i is the constant term, $r^e_{m,t}$ is the market risk premium, β_i is the asset's exposure to market risk, and $\epsilon_{i,t}$ is the error term. The model is appreciated by practitioners in economics and finance due to its simplicity and applicability.

As the theory posits that only systematic risk is relevant, all assets should earn returns proportionate to the market, at the rate of its respective beta (β_i), and the alpha (α_i) is zero in expectation. An alpha deviating from zero implies asset returns above or below what is explained by market risk (abnormal returns). This mechanism is a reasonable measure of performance. If a manager earns more (less) money in expectation, without assuming more (less) risk, he exhibits skill (lack of skill).

Given the CAPM context, alpha is related to all the preceding performance ratios.

[14] Idiosyncratic risk is firm specific and can be reduced (removed) with (perfect) diversification

The SR is directly linked to the theoretical foundation of the CAPM. In accordance with the TR, alpha only considers systematic risk, as measured by the market beta. By taking the expectation of Equation 2, and dividing each side by the market beta, we obtain the following mathematical relationship:

$$\frac{E(r_i^e)}{\beta_i} = \frac{\alpha_i}{\beta_i} + E(r_m^e) \quad = TR(r_i) \tag{3}$$

Where the expectation of the error term equals zero ($E(\epsilon_i) = 0$). Alpha has a positive relation to the TR, proportionate to the market beta. If the true alpha is zero, the TR equals the expected market risk premium, or the Treynor ratio of the market (benchmark) portfolio[15]. Both the IR and alpha is concerned with returns in excess of a reference index. Given certain criteria[16], the two metrics will coincide in what is commonly known as the "appraisal ratio"[17] (Eckbo and Ødegaard, 2015). As the fund manager seeks to achieve abnormal returns, he will need to overweight individual assets which, in turn, incurs idiosyncratic risk. The appraisal ratio accounts for this by adjusting alpha for this incurred risk.

Despite its relationship to the ratios, alpha has certain distinctive qualities. It offers a very simple interpretation, representing abnormal returns, which is a measure of value added. Unlike the ratios, the interpretation of alpha is the same for both positive and negative values. All else equal, a lower alpha is always bad. Instead of risk being a scaling mechanism, the abnormal returns are what is left after subtracting returns that are due to market risk exposure.

Extensions of the CAPM allow for a multivariate risk setup, while maintaining the same methodology and interpretation of alpha. If a fund generates alpha by assuming additional risk from factors that are unaccounted for by the CAPM, it could falsely appear to outperform other funds. The academic literature proposes many different models, of which the most commonly accepted are the three-factor model of Fama and French (1993) and the four-factor model of Carhart (1997). Both are based on the CAPM, but with additional risk factors. An unfavorable characteristic of these extensions is weaker theoretical foundation, where the origin of the risk is not very clear. There is academic discord regarding whether any of these additional risk factors

[15] By definition, the Treynor ratio of the market portfolio will always equal the expected market risk premium, because the market portfolio has a beta of 1.

[16] $\beta_i = 1$ and $\alpha_i \neq 0$

[17] $IR(r_i) = \frac{\alpha_i}{\sigma(\epsilon_i)}$, where α_i is abnormal returns, and $\sigma(\epsilon_i)$ is idiosyncratic risk.

are priced by the market. As Fama and French (1993) argue, however, the components are proxies for common risk factors. The models may appropriately account for risk despite its uncertain source. While American studies show that the three–factor model does not capture the momentum effect of Jegadeesh and Titman (1993), Næs et al. (2008) and Sørensen (2009) find that the factor is not relevant in the Norwegian market. Our analysis will focus on the three–factor model, although some results are reported for all three models for comparison:

$$r^e_{i,t} = \alpha_i + \beta_{i,MKT} MKT_t + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \epsilon_{i,t} \tag{4}$$

$$r^e_{i,t} = \alpha_i + \beta_{i,MKT} MKT_t + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \beta_{i,MOM} MOM_t + \epsilon_{i,t} \tag{5}$$

Where Equation 4 is the three–factor model of Fama and French (1993), and Equation 5 is the four–factor model of Carhart (1997). $r^e_{i,t}$ is excess returns, the intercept coefficient α_i is abnormal returns, and MKT_t is the market risk premium ($r^e_{m,t}$). SMB_t and HML_t are risk factors on firm size and book-to-market value, and MOM_t is the momentum factor, added to the model by Carhart (1997) to account for persistence in returns. All three risk factors represent simple, investable trading strategies, constructed as zero-investment portfolios. The ϵ_i is the error term, and the *betas* are the portfolio's exposure to the respective risk-factors.

The coefficient estimates of alpha are prone to varying levels of uncertainty (Cogneau and Hubner, 2009), and different levels of idiosyncratic risk across funds (Kosowski et al., 2006), potentially making comparisons between funds unreliable. The t–statistic can be thought of as a *standardized alpha*, by accounting for the degree of confidence in the alpha estimates. Comparing funds on the t–statistics might therefore ameliorate these issues. Our analysis considers both metrics. Results from testing the different pricing models for heteroscedasticity and autocorrelation are presented in Table 14 in Appendix D. Both the Breuch–Pagan and White tests show significant heteroscedastic variance in the aggregate EW and VW portfolios. The Durbin–Watson test for autocorrelation does not show evidence for serially correlated residuals. Reported results use Huber–White heteroscedasticity–consistent standard errors.

The results are presented in Table 5. Both aggregate portfolios have positive CAPM alphas, in concordance with the results on ratios and mean returns. The three– and four–factor alphas are both negative, illustrating a divergence between univariate and

Table 5 Aggregate alpha

The table reports Alpha and t–statistics for equally weighted (EW) and value weighted (VW) aggregate fund portfolios. The statistics are estimated for the CAPM, the Fama–French three–factor model, and Carhart's four–factor model. The t–statistic is calculated using Huber–White heteroscedasticity–consistent standard errors.

	Equally weighted		*Value weighted*	
	α (%)	t–stat	α (%)	t–stat
CAPM	0.58	0.65	0.47	0.52
Three-factor	-0.42	-0.50	-0.62	-0.73
Four-factor	-0.39	-0.45	-0.71	-0.83

multivariate risk setups. The results suggest that the funds in aggregate are reaping risk premiums from sources unaccounted for by market risk, inflating the CAPM alpha. We do not find evidence for significant non-zero abnormal returns from the t–statistics. After also estimating alpha coefficients using the OSEAX and OSEBX, we find that the results are consistently insignificant regardless of reference index. These results support the findings of Sørensen (2009) and Gallefoss et al. (2015), neither of whom find significant alphas on aggregate portfolios.

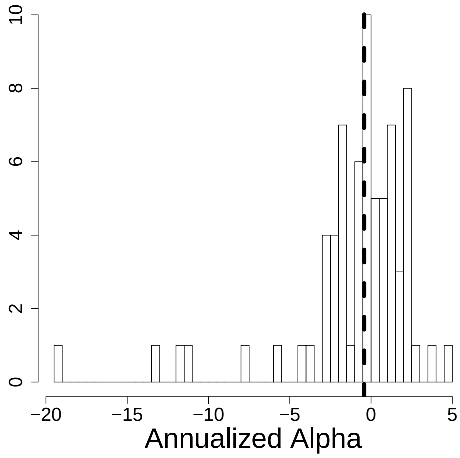
The EW portfolio is consistently better than the VW portfolio on all performance metrics, although the difference is small. As the VW portfolio overweights large funds, these results indicate that smaller funds have performed better than their larger peers in the sample period. Several studies have found evidence for the adverse effect of fund size on performance in the active money management industry (for example Chen et al. (2004); Yan (2008)).

Figure 4 shows the sample distribution of three–factor alphas and the corresponding t–statistics. The distribution of alpha is characterized by heavy left tails, similar to what we have seen in the distributions of other performance metrics. The t–statistics moderate the outliers in plot A, resulting in a more symmetric sample distribution of t–statistics (plot B). Irrespective of metric, the worst performers tend to drop out of the sample at some point (die), and have fewer observations. This observation is no surprise, considering the return differential between dead and alive funds. The non–market–relative metrics have heavy tails in both ends of the spectrum, and both tails are generally populated by funds with fewer observations. None of these metrics adjust for market conditions, and fewer observations will accentuate the market conditions of the time. Consequently, the winners and losers are the funds that have mainly experienced either bull or bear markets. For example, results on simple re-

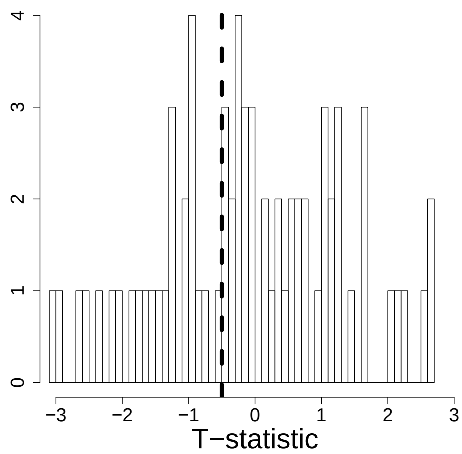
Figure 4 Alpha sample distribution

The figure presents sample distribution histograms of the three–factor alpha (plot A), and t–statistic (plot B), for the entire sample period, 2000–2015. The dotted lines are the metrics of the equally weighted (EW) portfolio. The alpha in plot A is reported in annualized percentage. The metrics are on the x–axes, while the y–axis reports frequencies.

Plot A: *Three-factor alpha*



Plot B: *Three-factor T-statistic*



turns suggest that you'll find the worst performer among the funds that dropped out of the sample shortly after the dot–com bust, and the best performer among those who dropped out shortly before the financial crisis.

Looking at the top funds, the performance metrics separate in two groups in terms of consistent fund rankings between metrics (refer to Table 16 in Appendix E). The dividing line seems to be between market–relative metrics (active returns, IR, alpha) and those that are not (simple returns, excess returns, SR, TR). The latter group is internally consistent in the ranking of funds, but externally inconsistent. The market–relative metrics are less consistent in general, but still internally oriented. For the bottom funds, there is less division between the metrics, as they are all highly consistent—consistently bad.

We do not find conclusive evidence of the mutual fund industry outperforming the market in net returns. The aggregate performance metrics provide conflicting evidence, and alphas indistinguishable from zero. Although we observe individual funds in the far right and left tails of all metric sample distributions, we cannot rule out the possibility that the results are due to chance. There are individual t–statistics in excess of critical value, yet these could be unreliable for inferring superior performance, or separating luck from skill (Kosowski et al., 2006). In the following we will employ a bootstrap procedure in an attempt to infer the existence of skill among fund managers in the Norwegian market.

3.4 Luck or skill

Good performance can be a result of both skill and luck. Kosowski et al. (2006) notes at least two issues with using regular t–tests for inferring skill in a sample distribution of alphas: *i)* Simultaneously considering the significance of alpha estimates for a whole sample increases the probability of finding significant results, and the likelihood of incorrectly rejecting the null hypothesis of zero alpha (a type 1 error). This is commonly known as the multiple comparisons problem; *ii)* non–normality in the aggregate distribution of alpha, which can be the result of heterogeneous risk–taking between funds, or the individual alphas themselves not being normally distributed.

In an attempt to alleviate these issues, Kosowski et al. (2006) introduced a bootstrap procedure for testing a sample distribution of alpha. The procedure involves generating simulated distributions of alpha and t–statistics, constructed with an expected alpha of zero. The procedure thereafter compares both tails of the *real* to the tails of *simulated* distributions. If the former has a significantly heavier positive tail, the performance of the top funds can not be the result of luck alone, and vice versa for poor performers. A modified procedure was proposed by Fama and French in 2010, mainly adjusting the sampling method. Instead of independently bootstrapping the residuals of fund returns, they jointly bootstrap fund and risk factor returns. This procedure accounts for the correlation of the alpha estimates, that arises when common variation in fund returns is not captured by the benchmark model. An advantage of Kosowski's method is that the length of the simulated time series match the length of the actual time series. We will use the modified bootstrap procedure of Fama and French to simulate alphas and t–statistics. The procedure is identical for both metrics.

We estimate the three–factor model (Equation 4) for all funds, saving estimated alphas ($\hat{\alpha}_i$) and factor loadings ($\hat{\beta}_{i,MKT}$, $\hat{\beta}_{i,SMB}$, $\hat{\beta}_{i,HML}$), along with vectors of residuals ($\hat{\epsilon}_{i,T}$). A random sample is drawn (with replacement) from the joint distribution of residuals and their corresponding factor returns. This results in a set of vectors with resampled residuals ($\hat{\epsilon}_{i,S}$) and factor returns ($MKT_{i,S}$, $SMB_{i,S}$, $HML_{i,S}$)[18]. Some of the draws will be from points in time without fund returns, for funds with less than a full time series (192 observations). We require at least 36 simulated return observations, else the simulation run is repeated. Pseudo time series of simulated returns are computed from residuals ($\hat{\epsilon}_{i,S}$) and the product of sampled factor returns ($MKT_{i,S}$,

[18] Specified for each fund i, and simulation run S.

$SMB_{i,S}$, $HML_{i,S}$) and fund factor loadings ($\hat{\beta}_{i,MKT}$, $\hat{\beta}_{i,SMB}$, $\hat{\beta}_{i,HML}$):

$$\tilde{r}^{e}_{i,S} = \hat{\beta}_{i,MKT}MKT_{i,S} + \hat{\beta}_{i,SMB}SMB_{i,S} + \hat{\beta}_{i,HML}HML_{i,S} + \hat{\epsilon}_{i,S} \tag{6}$$

Where S denotes the simulation run, and $\tilde{r}^{e}_{i,S}$ is the vector of simulated returns. By not including estimated alpha, these returns correspond to a null hypothesis of zero alpha (no skill). The three-factor model is estimated on the pseudo time series, saving the simulated alpha estimate ($\tilde{\alpha}_{i,S}$). The whole procedure is repeated for all funds in the sample, creating a simulated cross–section of alphas. Repeating this over 10,000 simulations (S) results in a distribution of cross–sections. For each cross–section we compare the actual alpha estimates, with the equivalently ranked simulated alpha[19], and calculate the aggregate percentage of wins. The win–rate is similar to the p-value of a normal t–test. Skill (lack of skill) can be inferred where funds win (lose) more than 95 percent of the time (at a 5 percent significance level). We test for robustness by challenging our choice of factor model, bootstrap method, and benchmark index

Table 6 shows the bootstrap analysis on the alpha and t–statistic, for both the three– and four–factor models (panel A and B, respectively). Panel A indicates negative skill (lack of skill) in the actual alpha distribution, with highly significant alphas in the left tail. The alphas in the right tail are much lower than their simulated counterparts, resulting in no evidence of positive skill. The results on the t–statistics support the findings of significant lack of skill in alpha, but also show indications of positive skill. The single best and worst funds are insignificant, however, indicating that while it is not uncommon to find t–observations far out in both tails, the actual tail observations are far too numerous as a group to be explained by chance alone. Sørensen (2009) finds evidence for lack of skill in the cross–sectional distribution of alphas, but only weak signs of positive skill in the right tail. Gallefoss et al. (2015) examines a daily dataset, finding evidence that alphas in neither tail can be attributed to chance alone, yet their results also reveal stronger evidence for lack of skill.

As evident in panel A in Table 6, and in Figure 4, the actual alpha estimates in the far left tail of the distribution are moderated in the t–distribution. This indicates that they are estimated with considerable uncertainty (high standard errors), possibly due to differences in the variance of the residuals (Fama and French, 2010), or few

[19] In effect, the best fund always competes with the best simulated alpha from each simulation.

Table 6 Bootstrap Results

The table presents estimated actual (Act) and the average of simulated (Sim) alphas and t-statistics, along with the percent of the 10,000 simulation runs producing simulated values lower than the actual (%<Act; also referred to as the "win–rate" of actual over simulated alpha/t–value). High (low) win–rate indicates skill (lack of skill) in the upper (lower) part of the tables. The leftmost column lists the best five funds according to either alpha or t–value, followed by deciles, and the five worst funds at bottom. Panel A shows the bootstrap results using the three–factor model of Fama–French. Panel B show the results using the four–factor model of Carhart. Both use the OSEFX as a benchmark index. The analyses cover 71 funds on net returns. The sample period is 2000–2015.

Panel A: Three-factor model

	Alpha (%)			*t-statistic*		
	Act	Sim	%<Act	Act	Sim	%<Act
Best	4.78	7.95	14.83	2.64	2.41	71.89
2	3.68	5.27	15.90	2.64	2.00	**96.00**
3	2.57	4.18	4.41	2.57	1.78	**99.32**
4	2.50	3.53	10.17	2.28	1.62	**99.32**
5	2.41	3.08	17.76	2.17	1.50	**99.54**
90%	2.30	2.48	40.82	1.69	1.30	**96.28**
80%	1.52	1.39	66.52	1.14	0.85	**95.42**
70%	1.02	0.81	80.08	0.74	0.53	90.76
60%	0.42	0.38	57.95	0.31	0.25	65.43
50%	-0.21	0.00	16.11	-0.13	0.00	19.33
40%	-0.61	-0.37	14.71	-0.31	-0.25	33.98
30%	-1.62	-0.78	**0.13**	-0.81	-0.52	**3.23**
20%	-2.10	-1.30	**0.79**	-1.20	-0.82	**1.62**
10%	-3.57	-2.36	**1.82**	-1.78	-1.23	**0.52**
5	-7.60	-3.19	**0.00**	-2.31	-1.60	**0.46**
4	-11.18	-3.64	**0.00**	-2.60	-1.73	**0.22**
3	-11.57	-4.27	**0.00**	-2.61	-1.90	**1.68**
2	-13.42	-5.33	**0.09**	-2.93	-2.13	**2.28**
Worst	-19.48	-7.81	**0.45**	-3.06	-2.56	15.17

Panel B: Four-factor model

	Alpha (%)			*t-statistic*		
	Act	Sim	%<Act	Act	Sim	%<Act
Best	11.52	8.19	84.27	2.53	2.41	64.08
2	3.50	5.41	10.04	2.35	2.01	84.43
3	3.24	4.29	18.46	2.28	1.78	94.91
4	2.92	3.62	23.14	2.17	1.63	**97.78**
5	2.50	3.16	19.42	2.15	1.50	**99.44**
90%	2.19	2.54	29.57	1.49	1.30	81.36
80%	1.12	1.42	18.72	0.78	0.84	35.56
70%	0.86	0.82	56.80	0.52	0.52	50.87
60%	0.61	0.38	83.96	0.26	0.25	53.80
50%	0.06	-0.01	62.48	0.05	0.00	64.81
40%	-0.64	-0.39	13.98	-0.35	-0.26	26.85
30%	-1.32	-0.81	**2.65**	-0.75	-0.53	8.53
20%	-1.81	-1.35	7.81	-0.98	-0.84	20.37
10%	-3.01	-2.45	13.86	-1.59	-1.25	**4.97**
5	-6.72	-3.33	**0.07**	-2.02	-1.62	6.01
4	-7.86	-3.80	**0.17**	-2.16	-1.75	6.93
3	-8.71	-4.48	**0.58**	-2.45	-1.92	**4.91**
2	-10.57	-5.59	**1.13**	-2.55	-2.16	14.54
Worst	-19.60	-8.05	**0.46**	-2.58	-2.61	46.27

observations. As we have seen previously, poor performers have a tendency to drop out of the sample, resulting in higher standard errors, and lower t–statistics. This has the unfortunate consequence that the left tail of the alpha distribution tends to have lower precision. The t–statistics control for the precision of alpha estimates, and is therefore recommended over alpha in bootstrap analyses by Fama and French (2010) and Busse et al. (2010).

We obtain very similar results when changing to Kososwski's (2006) bootstrap method[20]. Changing benchmark model to the OSEBX yields even stronger evidence of lack of skill, and all indications of positive skill disappear[21] (same as Sørensen's (2009) findings). Changing to Carhart's (1997) four–factor model (panel B in Table 6) has the greatest impact on the conclusions from the original specification. Much of the significance disappears, but there is still evidence of lack of skill in alphas.

Overall, we find evidence for lack of skill in the left tail of the alpha and t–stat distributions, and weak signs of skill in the right tail. This is further supported by our finding in the preceding subsection, that poor performers are more consistent over performance metrics (consistently bad) than high performers. Our results add to the findings of Sørensen (2009) and Gallefoss et al. (2015), in that skill, or lack of skill, is more readily identified among poor performers. The bootstrap evidence provides the basis for the following analysis of investor capital allocation.

[20] Refer to panel A in Table 17, Appendix F

[21] Refer to panel B in Table 17, Appendix F

4 The rational investor — An analysis of capital flows

A fool and his money are soon parted.

Thomas Tusser, 1557

The flows of capital to and from funds represent investor decisions. Investors presumably base these decisions on their belief in the future prospects of the particular funds they invest in, whether those beliefs are rational or not. The net capital flows to funds thus represent aggregate investor beliefs. Marketing and general media visibility no doubt plays a part in forming those beliefs, as evidenced by Sirri and Tufano (1998). Past performance certainly plays a part as well, yet measures of past performance are only useful to the rational investor insofar as they are indicative of expected future outcomes. We will investigate how past performance affects investor capital allocation, as measured by the net flows to funds. Our focus will be on the rationality of investor behavior.

The rational investor will consider both risks and returns for estimating expected performance. By this principle, mean returns alone are insufficient. The simplicity of the performance ratios considered in this paper is both a strength and a weakness. All three adjust returns for a univariate measure of risk, but this might not be a proper reflection of reality. The extensions of the CAPM allow for multivariate risk in computing alpha, attempting to measure abnormal returns beyond what can be gained by exposure to common risk factors. Of the metrics considered in this paper, alpha may be the most sensible estimator of future performance from the perspective of finance theory, a notion supported by, for example, Patel et al. (1996). In spite of this, they find that risk–adjusted measures of performance[22] have no marginal explanatory power, beyond that of simple returns, in accounting for flows to mutual funds.

One component of past performance is chance, and a large one at that. If the rational investor cannot distinguish between randomness and true ability, he could quickly end up choosing the lucky over the skilled. Two common methods for assessing the presence of skill is the bootstrapping procedure from the previous section, and tests for persistence. Evidence from Sørensen (2009) and Gallefoss et al. (2015), using both methods, suggests that the mutual fund industry in aggregate provides little in terms

[22] Patel et al. (1996) use simple returns, the Sharpe ratio, and CAPM alpha in their analysis.

of market beating performance. Furthermore, that past performance is a more reliable predictor of losers (lack of skill) rather than winners. This corresponds with our bootstrap evidence. As it seems that past performance is more accurate at identifying lack of skill, we should expect investors to react more strongly to poor performance.

There is a large body of academic literature investigating the influence of past performance on net flows to mutual funds, yet naught from the Norwegian market that we are aware of. Sirri and Tufano (1998) find a positive but asymmetric relationship; stronger for high performers. Their results indicate that investors invest in past winners, but do not necessarily divest as readily from losers. They investigate the influence of simple and excess returns, along with CAPM alpha, all sorted in quintiles to account for relative performance. Chevalier and Ellison (1997) find a positive relation with active returns, and evidence that older funds experience diminished inflow. Similar results are reported by Bergstresser and Poterba (2000), whose primary focus is to analyze the effects of tax burdens. They employ a range of different performance measures, including CAPM and three–factor alpha. Unlike most studies on the subject, Warther (1995) examines monthly data, but with a different objective from ours. He attempts to explain the effect of net inflow on aggregate security returns, finding a strong correlation between returns and concurrent *unexpected* flows, but not to concurrent expected flows.

Our research differs in some aspects. Previous research is mostly focused on annual data, while ours is monthly. Monthly data holds more information, but also more noise. Our dataset holds reported figures from fund managers, instead of being estimated indirectly[23]. We have used reported net inflow ($Net\ Inflow_{i,t}$) and 1–month lagged assets under management ($Assets_{i,t-1}$) to calculate percentage net inflow ($Flow_{i,t}$).

$$Flow_{i,t} = \frac{Net\ Inflow_{i,t}}{Assets_{i,t-1}} \tag{7}$$

We apply all eight performance metrics from the previous section as measures of past performance in the further analyses. We use rolling windows of three years[24] for all metrics, following Bergstresser and Poterba (2000).

A disproportionate number of flow observations in illiquid funds are zero. Transactions in these funds are likely of a different nature than those of their more liquid

[23] Chevalier and Ellison (1997) estimate percentage net inflow as $Flow_{t+1} = \frac{Assets_{t+1} - Assets_t}{Assets_t} - r_{t+1}$

[24] We also perform analyses with rolling windows of between 1 to 5 years, as a test for robustness.

counterparts. Chevalier and Ellison (1997) alleviate similar issues by excluding funds with high minimum initial purchase and high expense ratios. As we lack the necessary data, we use a different approach. We exclude funds based on their proportion of null–observations of net inflow (zero ratio), and their all–time maximum number of customers. Seven funds in our sample stand out, and are therefore omitted, all with very few customers and high zero ratios. The top seven funds are the same in both categories, reported in Table 7, along with rank number 8 in each category.

Table 7 Illiquid funds omitted from the sample

The table reports the funds with highest zero ratio (percentage of observations with zero net inflow) and fewest customers (maximum number of customers during existence). The leftmost column shows the ranks sorted by zero ratio. The top seven funds are the same in both categories, but in different order. All seven are excluded from the net inflow analysis. The last two funds have the highest zero ratio and fewest customers left in the sample after the exclusion of the former seven. Rank 8 is ordered by zero ratio. Rank 8* is ordered by customers.

Rank		Zero ratio (%)	Customers
1	Fondsfinans Aktiv II	85.5	2
2	ABIF Norge	84.2	3
3	Carnegie Aksje Norge III	75.2	2
4	Storebrand Norge A	66.7	2
5	Nordea Kapital II	54.1	7
6	Nordea Kapital III	53.4	5
7	Storebrand Norge I	45.0	10
8	*Danske Invest NAI II*	**21.1**	76
8*	*Alfred Berg Norge*	12.1	**28**

Institutional flows of capital due to fund mergers and liquidations provide another source of undesirable data points[25], as these transactions do not represent investor decisions. Unfortunately, these events are often hard to identify from our dataset. In examining the data we find asset flows ranging from full liquidation to many fold increase. There is no obvious transition between "normal" flows and those due to mergers and liquidations. We opted for trimming the top and bottom 0.5 percent of observations, resulting in a sample of 64 funds, covering 7422 fund–months, with percentage net inflow ranging between 55 and -38 percent.

4.1 Correlation

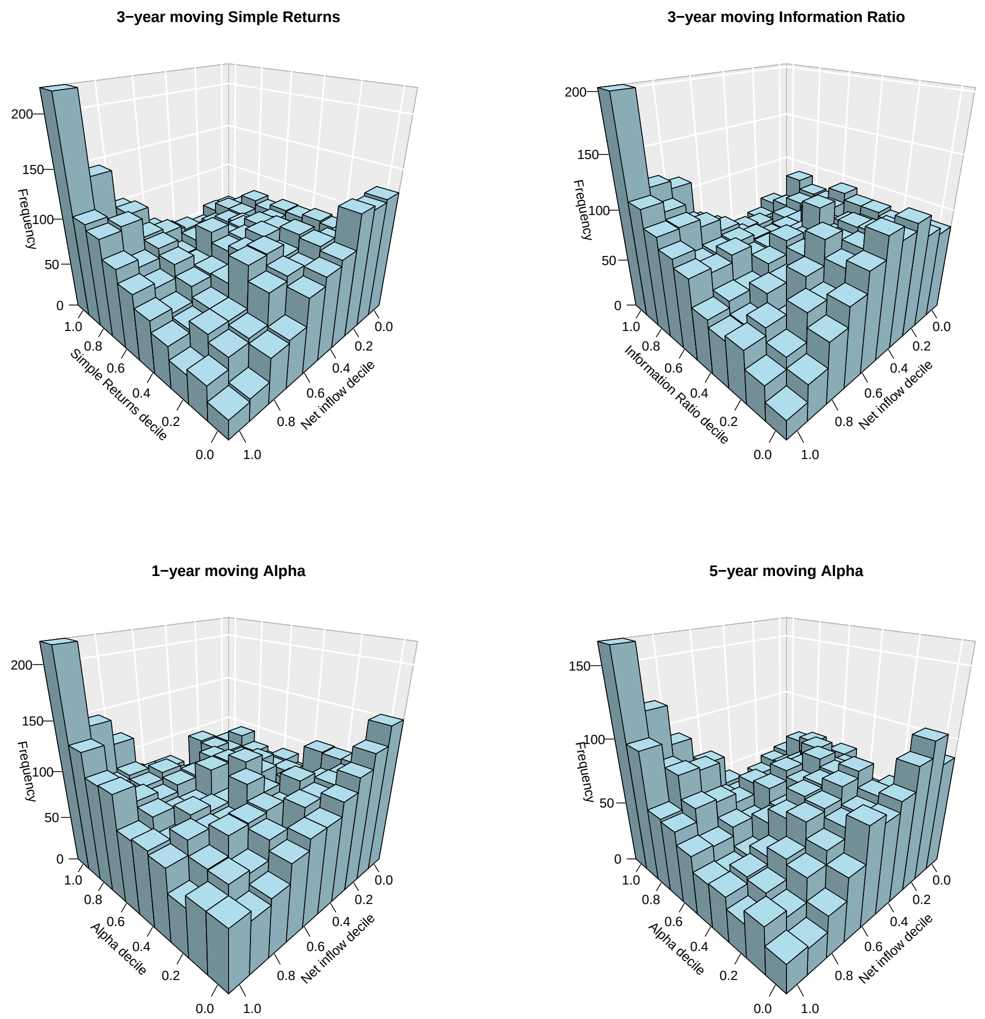
As an initial analysis we construct contingency tables and correlation matrices on net inflow and past performance. The purpose is to illustrate the relationship between

[25]Fund creation is not a problem, as rolling windows of performance metrics remove the 36 leading observations.

measured performance in one month $(t-1)$ to net inflow in the following month (t). For the contingency tables, the cross–section of funds are ranked in deciles each month, on net inflow and performance measures, calculated from rolling windows of between 1 to 5 years. Each fund's rank on net inflow is matched to its corresponding lagged $(t-1)$ performance rank. Correlation matrices are computed on absolute metrics and ranks[26] between net inflow and all performance measures.

Figure 5 Contingency tables of fund ranks on net inflow and performance

The figure illustrates the degree of consistency in fund ranks on net inflow and different performance measures with varying rolling windows (simple mean returns, Sharpe ratio, information ratio, and alpha). The x– and z–axes are labeled from top to bottom decile. The figures illustrate that top and bottom ranking funds on performance are more likely to have a similar rank on net inflow. The results are consistent for all performance measures, and for rolling windows of between 1 to 5 years.



[26] To avoid confusion, and where appropriate, we will use "absolute" and "ranks" to distinguish between variables of absolute values and variables of decile ranks, respectively.

Figure 5 displays three–dimensional histograms of the contingency tables on net inflow and selected performance measures. The results are very robust over rolling time windows of between 1 to 5 years, and between all measures. The plots show a positive relationship between performance and net inflow, with prominent consistency in the top ranks. Top performance is associated with high relative net inflow. The same pattern is present in the lower ranks, but much less pronounced.

In the performance evaluation we noted that there was a clear inconsistency between relative fund ranks on different performance measures. Specifically, the dividing line seemed to be between measures using market–relative[27] and non–market–relative[28] returns. The same division is evidently *not* present in the contingency tables. To the contrary, the association between past performance and net inflow is very consistent over all performance measures.

Table 8 Correlation between net inflow and past performance

The table shows correlation matrices for net inflow and three-year rolling performance measures on: Simple returns ($\bar{r}$), excess returns ($\bar{r}^e$), active returns ($\bar{r}^a$), Sharpe ratio (SR), Treynor ratio (TR), Information ratio (IR), three–factor alpha (α) and t–statistic ($t(\alpha)$). Panel A shows correlation coefficients between absolute values on all variables (including net inflow). Panel B shows the correlation coefficients between ranks on all variables (including net inflow).

Panel A: Correlation — absolute values

		Mean returns			*Ratios*			*Three-factor model*	
	Inflow	Simple	Excess	Active	SR	TR	IR	Alpha	t–stat
$\bar{r}$	−0.050	1	0.998	0.214	0.965	0.991	0.082	0.075	−0.033
$\bar{r}^e$	−0.050	0.998	1	0.203	0.969	0.992	0.072	0.073	−0.036
$\bar{r}^a$	0.185	0.214	0.203	1	0.201	0.215	0.882	0.837	0.769
SR	−0.035	0.965	0.969	0.201	1	0.967	0.090	0.111	0.012
TR	−0.047	0.991	0.992	0.215	0.967	1	0.094	0.121	0.016
IR	0.184	0.082	0.072	0.882	0.090	0.094	1	0.747	0.864
α	0.186	0.075	0.073	0.837	0.111	0.121	0.747	1	0.891
$t(\alpha)$	0.172	−0.033	−0.036	0.769	0.012	0.016	0.864	0.891	1

Panel B: Correlation — ranks

		Mean returns			*Ratios*			*Three-factor model*	
	Inflow	Simple	Excess	Active	SR	TR	IR	Alpha	t–stat
$\bar{r}$	0.254	1	1.000	0.976	0.899	0.910	0.863	0.842	0.792
$\bar{r}^e$	0.254	1.000	1	0.975	0.899	0.909	0.863	0.842	0.792
$\bar{r}^a$	0.241	0.976	0.975	1	0.906	0.916	0.896	0.852	0.811
SR	0.250	0.899	0.899	0.906	1	0.967	0.833	0.903	0.857
TR	0.242	0.910	0.909	0.916	0.967	1	0.851	0.888	0.855
IR	0.204	0.863	0.863	0.896	0.833	0.851	1	0.786	0.864
α	0.226	0.842	0.842	0.852	0.903	0.888	0.786	1	0.917
$t(\alpha)$	0.200	0.792	0.792	0.811	0.857	0.855	0.864	0.917	1

[27] Active returns, IR, alpha, and t–statistic.

[28] Simple and excess returns, SR, and TR.

Table 8 reports correlation coefficients between net inflow and the performance measures. The non–market–relative absolute metrics are negatively correlated with net inflow, as shown in panel A. Ranking funds in deciles each month (panel B) removes the negative coefficients, and increases the correlation between performance measures. Rankings ensure that funds are judged relative to their peers. The market–relative absolute metrics presumably capture this effect by proxy, in that the market is a close approximation to the funds as a group. The combined results suggest that investors use performance measures as ranking criteria. This supports the findings of Patel et al. (1996), that fund flows seem better related to performance ranks than absolute performance metrics.

The results serve as an initial indication that investors could be influenced by past performance, especially in the right tail of the performance distribution (high performers), corresponding to the findings of Sirri and Tufano (1998). Due to the close to perfect correlation between simple and excess returns, the former is omitted from the following analyses.

4.2 Regression analysis

Correlations and contingency tables are suggestive of the association between performance and net inflow. The following regression analysis will attempt to quantify the impact and significance of the relationship. We will estimate a model inspired by the work of Chevalier and Ellison (1997) and Sirri and Tufano (1998). It relates the flow of investments to past performance and other control variables – the primary focus being the effect of past performance.

$$\begin{aligned} Flow_{i,t} = \beta_1 \times Performance^{3-year}_{i,t-1} + \beta_2 \times Industry\ Growth_t \\ + \beta_3 \times Log(Assets_{i,t-1}) + \sum_k \gamma_k \times Age\ k_{i,t} + \sum_l \delta_l \times Month\ l_t + \epsilon_{i,t} \end{aligned} \tag{8}$$

Where the dependent variable is percentage net inflow per month. The main variable of interest, $Performance^{3-year}_{i,t-1}$, is a 1-month lagged performance measure, computed on a three year rolling window. $Industry\ Growth_t$ is the growth in total assets under management by the active equity mutual fund industry (in sample), and $Log(Assets_{i,t-1})$ is the natural logarithm of the specific fund's lagged assets under management. $Age\ k_{i,t}$ and $Month\ l_t$ are dummy variables on fund age and month, for temporal observation t.

While our model is based on the one suggested by Chevalier and Ellison (1997), there are a few modifications. Their performance variable is active returns, lagged by one, two, and three years. Sirri and Tufano (1998) uses 1-year lagged performance measures (of various kinds), sorting the funds into five performance quintiles. Both papers use annual observations in their regressions. Our method of accounting for past performance is a synthesis of both. We opted for computing the performance metrics on three-year rolling windows of monthly data, thereby always considering the funds' intermediate term track record. A drawback of this is that it does not allow for different effects from recent and longer–term performance. As evident from the correlation matrices, considering the absolute performance metrics directly might be an inappropriate way of accounting for past performance. Our regression analyses includes both absolute metrics and performance ranks. While our focus is on monthly data, we repeat the regressions on annual observations as a test for robustness.

Industry growth ($Industry\ Growth_t$) acts as a trend variable, controlling for sector-level flows and performance. $Log(Assets_{i,t-1})$ is the natural logarithm of fund assets, accounting for size. An equal value flow will have a smaller percentage impact on large funds. Age ($Age\ k_{i,t}$) accounts for differences in maturity , where we expect older funds to experience diminished percentage flows (Chevalier and Ellison, 1997). We use dummy variables to allow for a non–linear relationship. Using monthly data, unlike most similar studies, will potentially introduce seasonality in our data. To control for this effect, we use dummy variables on month of observation ($Month\ l_t$), with January as a base group.

Tests for heteroscedasticity and autocorrelation for all following regressions are in Appendix D. The tests on heteroscedasticity show conflicting evidence. Breuch–Pagan test statistics are highly significant in all regressions, while White statistics are insignificant in most. Durbin–Watson tests all show significant autocorrelation in the residuals. All following regressions use Newey–West heteroscedasticity and autocorrelation consistent standard errors.

Table 9 reports results from regressing net inflow on performance. The regressions in set A use the absolute performance metrics, while Set B uses performance ranks. Both sets use monthly data. Set C is a replica of set B, using annual data. Comparing the first two sets reveal the same pattern observed in the correlation matrices. In and of themselves, the non–market–relative absolute performance metrics are poorly

Table 9 Regressing net inflow on performance

The table reports results from regression analyses of net inflow ($Inflow_t$) on different performance measures: Excess returns ($\bar{r}^e$), active returns ($\bar{r}^a$), Sharpe ratio (SR), Treynor ratio (TR), Information ratio (IR), three–factor alpha (α) and t–statistic ($t(\alpha)$). The control variables are Industry Growth, Log(Assets), and dummy variables on fund age and month of observation. All dummy variables for fund age are included in the regressions, hence the lack of intercepts. Full regression outputs, with dummy variables, are shown in Appendix G. Newey–West heteroscedasticity and autocorrelation consistent standard errors are in parentheses, with stars representing significance levels. Set A shows results from regressing net inflow on absolute performance metrics. Set B shows results from regressing net inflow on performance ranks. Set C is a replica of Set B with annual, instead of monthly, data observations.

Set A: Net inflow on absolute performance metrics

	Mean returns		*Ratios*			*Three-factor model*	
	Excess	Active	SR	TR	IR	Alpha	t–stat
Performance metric	−0.219***	2.888***	−0.998*	−0.219**	5.236***	2.849***	0.762***
	(0.066)	(0.300)	(0.396)	(0.068)	(0.463)	(0.300)	(0.077)
Industry Growth	0.061***	0.068***	0.063***	0.061***	0.068***	0.070***	0.070***
	(0.015)	(0.014)	(0.015)	(0.015)	(0.014)	(0.015)	(0.014)
Log(Assets)	0.233***	0.098	0.228***	0.232***	0.150*	0.095	0.155*
	(0.066)	(0.060)	(0.067)	(0.066)	(0.062)	(0.060)	(0.063)
Age dummies†	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal dummies†	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.035	0.060	0.034	0.035	0.060	0.060	0.056
Observations	7422	7422	7422	7422	7422	7422	7422

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

† *Dummy variables on month and fund age at the time of observation.*

Set B: Net inflow on performance ranks

	Mean returns		*Ratios*			*Three-factor model*	
	Excess	Active	SR	TR	IR	Alpha	t–stat
Performance rank	0.319***	0.299***	0.309***	0.304***	0.247***	0.270***	0.239***
	(0.033)	(0.032)	(0.032)	(0.032)	(0.031)	(0.033)	(0.033)
Industry Growth	0.068***	0.068***	0.068***	0.068***	0.069***	0.068***	0.069***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Log(Assets)	0.091	0.109	0.109	0.114	0.152*	0.138*	0.165*
	(0.063)	(0.063)	(0.063)	(0.064)	(0.065)	(0.064)	(0.065)
Age dummies†	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal dummies†	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.055	0.053	0.054	0.053	0.046	0.049	0.045
Observations	7422	7422	7422	7422	7422	7422	7422

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

† *Dummy variables on month and fund age at the time of observation.*

Set C: Net inflow on performance ranks — annual data

	Mean returns		*Ratios*			*Three-factor model*	
	Excess	Active	SR	TR	IR	Alpha	t–stat
Performance rank	3.007***	4.240***	3.999***	4.167***	3.971***	3.243***	3.725***
	(0.632)	(0.680)	(0.671)	(0.649)	(0.632)	(0.671)	(0.633)
Industry Growth	0.202**	0.201***	0.200***	0.201***	0.202***	0.202**	0.202***
	(0.061)	(0.060)	(0.060)	(0.060)	(0.060)	(0.062)	(0.061)
Log(Assets)	0.034	−0.679	−0.564	−0.357	−0.328	−0.112	−0.224
	(1.367)	(1.331)	(1.349)	(1.336)	(1.334)	(1.373)	(1.343)
Age dummies†	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.182	0.211	0.205	0.209	0.203	0.187	0.198
Observations	612	612	612	612	612	612	612

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

† *Dummy variables on fund age at the time of observation.*

related to net inflow, as evidenced by their negative coefficients in set A. After controlling for the relative rankings of funds (in set B), the coefficients turn positive, and the models explain more of the variation in net inflow. Conversely, ranks reduce the explained variance of the market–relative metrics, both in terms of model R–squared and the coefficients' impact on net inflow. Measuring performance in deciles reduces the variance of the performance variable, and may therefore adversely affect its explanatory power. The regressions in set B all have meaningful results, and use the same unit of measurement (rank). While deciles level the playing field for the performance measures, we cannot be sure that it does not adversely affect some measures more than others. Based on our results, and the previously mentioned findings of Patel et al. (1996), our further analyses will focus on performance ranks. This permits for comparisons between all metrics, along with a standardized unit of measure.

The explained variation is generally low in all regressions in sets A and B, as measured by the R-squared, compared to the studies by Chevalier and Ellison (1997), Sirri and Tufano (1998), and Bergstresser and Poterba (2000). The unfavorable comparison is exacerbated by their use of annual data. As evident from set C, regressions on annual datasets yield far better explanatory power. Monthly data on net inflow is likely to contain a lot more noise, and annual datasets have less overall variation to be explained. All models are significant according to F–tests, monthly and annual data alike[29]. Our choice of a three–year moving performance measure might be an ill fit for explaining monthly variations in net inflow, yet regressions with 1– and 2–year rolling windows prove no better fit. Time intervals shorter than one year are unlikely to be representative of how investors make their decisions.

The performance rank coefficients in sets B and C are all positive and highly significant (on monthly and annual data), supporting that investor capital allocation is affected by past performance. Advancing one rank on *excess returns* in set B is associated with a 0.319 percent increase in monthly net inflow. The same one step increase in performance rank in set C is associated with 3.007 percent increase in annual net inflow. Some performance metrics have higher coefficients and explained variance than others, but the difference between them is generally small. In terms of consistency, active returns, the SR, and the TR seem better at explaining net flows than the IR, alpha, and t–stat (both in terms of coefficient and R–squared). Excess returns is

[29] F–tests are not shown, for brevity.

inconsistent, placing top on monthly data and bottom on annual data (again, both in terms of coefficient and R–squared). Considering the small differences between performance measures, we do not find conclusive evidence for investors favoring one measure over the other.

We would expect fund size to exert a negative influence on percentage net inflow, based on previous studies by Chevalier and Ellison (1997), Sirri and Tufano (1998), and Bergstresser and Poterba (2000). This expectation is not supported by the regressions on monthly data (set B). The coefficients on $Log(Assets_{i,t-1})$ are all positive, and some are significant. The regressions on annual data (set C) show different results: Insignificant coefficients, and negative for all except excess returns. A positive relationship could be explained by the marketing efforts of big funds, or that investors perceive fund size as a signal of reliability (Ippolito, 1992).

The coefficients on industry growth have the expected signs, and are all highly significant. As the industry grows, one would naturally expect this to positively affect funds individually. Coefficients on dummy variables on fund age and month of observation are of varying impact and significance (refer to Appendix G for full regressions). In comparing our results on fund age to those of Chevalier and Ellison (1997) we find the same negative trend as funds mature, but with generally negative signs where theirs are positive. While their results are all highly significant, we only find statistical significance on monthly data. The difference might be an effect of the aggregate net outflow from the Norwegian market in our sample period. All else equal, the mean of the dependent variable (net inflow) will have a positive effect on the age coefficients (which act as intercepts).

Ordinal scales, such as ranks, are not necessarily easy to interpret, as it is not always clear what a one unit increase represents. The funds are not necessarily uniformly distributed over the ranks, yet regressing net inflow on them imposes a discrete, linear effect for each unit increase in rank. Incorporating dummy variables on performance ranks (performance dummies) might therefore be a more sensible approach (Wooldridge, 2009). The contingency tables in Figure 5 suggest a stronger and asymmetric (similar to Sirri and Tufano (1998)) relationship between net flows and past performance in the top and bottom ranks (deciles), implying a non–linear relationship. The same point is argued by Berk and Green (2004), that flows respond more dramatically to extreme performance. To test for this, we construct dummy variables on performance ranks. The base group for the performance dummies is the middle 20 percent of the funds (ranks 5 and 6).

Table 10 reports results from regressing net inflow on performance dummies, on monthly (set D) and annual data (set E). Advancing from the base group to the top rank on *excess returns* in set D is associated with a 2.53 percent increase in net inflow. Similarly, falling into the bottom rank on the same metric is associated with a 1.42 percent decrease in net inflow. The models account for slightly more variation than previous specifications (Table 9), and still show a positive relationship between past performance and net flows. It remains hard to identify substantial differences between performance measures, but the same differences observed in set B and C are present in sets D and E.

The upper (winners) and bottom (losers) ranks have a disproportionate impact on net flows, and are highly significant. Additionally, investors seemingly react more strongly to winners than losers, contrary to what we should expect from bootstrap and persistence evidence, but supporting the results from the contingency tables (Figure 5) and Sirri and Tufano (1998). This could simply be an indication that fund investors are predominantly passive, favoring a buy–and–hold strategy, possibly as a consequence of transaction costs or tax effects. It might also be an indication that investors threat gains and losses differently. Psychological effects have the potential to limit the rationality of investor decisions. With Kahneman and Tversky (1979) came Prospect Theory. The essence of their research is that people have strong preferences for avoiding losses over acquiring gains[30]. Importantly, they find that gains and losses change our risk preferences[31]. We become risk seeking in the face of losses, strongly preferring to take risks that might mitigate the loss. Gains make us risk averse, wanting to protect our achievements. Such psychological effects could manifest themselves in investor hesitation to divest from poor performers.

[30] Most studies suggest that the psychological effect of losses is twice as powerful as that of gains (Tversky and Kahneman, 1992).

[31] Commonly referred to as the reflection effect.

Table 10 Regressing net inflow on performance dummies

This is a continuation of Table 9, with dummy variables on performance ranks (deciles). The table reports results from regression analyses of net inflow ($Inflow_t$) on different performance measures: Excess returns ($\bar{r}^e$), active returns ($\bar{r}^a$), Sharpe ratio (SR), Treynor ratio (TR), Information ratio (IR), three–factor alpha (α) and t–statistic ($t(\alpha)$). The control variables are Industry Growth, Log(Assets), and dummy variables on fund age and month of observation. All dummy variables for fund age are included in the regressions, hence the lack of intercepts. Full regression outputs, with all dummy control variables, are shown in Appendix G. Newey–West heteroscedasticity and autocorrelation consistent standard errors are in parentheses, with stars representing significance levels. Set D shows results from regressing net inflow on performance dummies. Set E is a replica of Set D, with annual, instead of monthly, data observations.

Set D: Net inflow on performance dummies

	Mean returns		*Ratios*			*Three-factor model*	
	Excess	Active	SR	TR	IR	Alpha	t–stat
Top decile	2.353***	2.451***	2.318***	2.583***	2.335***	2.643***	2.326***
	(0.386)	(0.370)	(0.364)	(0.365)	(0.392)	(0.371)	(0.374)
9th decile	1.138***	1.122***	1.342***	1.529***	0.867**	0.706*	0.752*
	(0.344)	(0.324)	(0.327)	(0.337)	(0.334)	(0.302)	(0.332)
8th decile	0.791*	0.944**	0.603	0.811**	0.705*	1.022**	0.684*
	(0.319)	(0.327)	(0.333)	(0.296)	(0.337)	(0.323)	(0.314)
7th decile	0.340	0.469	−0.079	0.395	0.674*	0.670*	0.597*
	(0.309)	(0.277)	(0.295)	(0.295)	(0.328)	(0.270)	(0.296)
4th decile	−0.196	−0.078	−0.439	−0.049	−0.043	0.166	0.541*
	(0.279)	(0.269)	(0.235)	(0.249)	(0.278)	(0.258)	(0.267)
3rd decile	−0.486	0.136	−0.368	−0.116	0.154	−0.103	0.010
	(0.248)	(0.249)	(0.267)	(0.241)	(0.307)	(0.231)	(0.221)
2nd decile	−0.322	−0.316	−0.580*	−0.277	−0.287	0.066	−0.444
	(0.268)	(0.266)	(0.265)	(0.261)	(0.245)	(0.301)	(0.301)
Bottom decile	−1.423***	−1.258***	−1.157***	−0.947**	−0.731**	−1.062***	−0.705**
	(0.307)	(0.299)	(0.293)	(0.291)	(0.279)	(0.287)	(0.258)
Control variables†	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.058	0.057	0.058	0.058	0.050	0.056	0.050
Observations	7422	7422	7422	7422	7422	7422	7422

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

† *Industry growth, log(assets), and dummy variables on month and fund age at the time of observation.*

Set E: Net inflow on performance dummies — annual data

	Mean returns		*Ratios*			*Three-factor model*	
	Excess	Active	SR	TR	IR	Alpha	t–stat
Top decile	20.872**	32.465***	37.732***	25.707**	30.819***	35.010***	28.849***
	(7.856)	(8.710)	(8.954)	(8.389)	(8.017)	(8.837)	(8.106)
9th decile	10.520	25.439**	23.584**	22.521*	25.778**	13.261	20.536*
	(9.504)	(9.435)	(8.093)	(9.708)	(9.339)	(8.244)	(8.230)
8th decile	14.796*	13.176*	15.400*	9.126	5.029	9.765	11.915
	(6.823)	(6.411)	(6.886)	(5.935)	(6.596)	(7.122)	(6.863)
7th decile	10.071	−0.634	13.929	−4.081	4.689	11.691	5.612
	(6.737)	(5.575)	(7.092)	(7.183)	(6.750)	(6.869)	(6.260)
4th decile	−0.495	2.766	12.736*	−8.634	−2.537	1.584	9.045
	(6.134)	(6.067)	(6.033)	(4.999)	(5.975)	(6.017)	(7.956)
3rd decile	3.530	1.973	8.055	−2.670	3.197	1.422	−10.079
	(6.035)	(5.948)	(5.756)	(7.064)	(6.444)	(5.927)	(5.399)
2nd decile	−8.919	−11.704*	−5.645	−13.577**	−10.223*	−0.909	−3.542
	(4.752)	(5.300)	(4.783)	(5.120)	(5.035)	(6.384)	(5.471)
Bottom decile	−8.240	−10.600*	−7.894	−14.751**	−10.443*	−4.451	−9.739*
	(5.812)	(4.457)	(4.446)	(4.784)	(4.495)	(5.749)	(4.531)
Control variables†	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.187	0.225	0.222	0.219	0.218	0.200	0.209
Observations	612	612	612	612	612	612	612

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

† *Industry growth, log(assets), and dummy variables on fund age at the time of observation.*

5 Conclusion

Using a monthly dataset free of survivorship bias, consisting of 71 active equity mutual funds with a Norwegian mandate, between 2000–2015, we investigate the performance of active equity mutual funds in Norway, and its effect on investor capital allocation. The funds in aggregate have only marginally better net returns than the benchmark portfolio. The aggregate Sharpe and Treynor ratios are slightly higher than the benchmark, while multi–factor alphas are negative but insignificant. The mutual fund index (OSEFX) is the most favorable benchmark for the funds, and thus functions as a minimum requirement. Overall, we do not find conclusive evidence that active equity mutual funds deliver market beating performance in aggregate risk–adjusted net returns.

There are individual funds with superior and inferior performance compared to the market. We attempt to distinguish between luck and skill in the cross–section of three–factor alphas, using the bootstrapping procedure of Fama and French (2010). We find that the abnormal returns in the left tail of the distribution are too extreme to be explained by chance alone, evidencing lack of skill among poor performers. The evidence for skill among high performers is much weaker. This implies that past performance is more sensibly used to avoid losers, rather than chase past winners. Our results are largely in line with those of Sørensen (2009).

For examining how past performance affects investor capital allocation to mutual funds we investigate the association between net capital flows to funds and various measures of past performance, using correlation and regression analysis. We find evidence that investor capital allocation is affected by past performance, but do not find conclusive evidence favoring one measure of performance over another. The extreme tails of the distribution of past performance seem to illicit stronger and more consistent investor reactions. Furthermore, we find that the association is stronger for high than for poor performers, implying that investors more readily invest in winners than they divest from losers. This contrasts the implication of our bootstrap evidence, and previous research by Sørensen (2009) and Gallefoss et al. (2015). The discord could be explained by investor irrationality.

Overall, our results seem to indicate that investors are no worse off investing in a low–cost index fund. The average actively managed mutual fund will not outperform the market in risk–adjusted net returns to investors. If the average fund is able to generate abnormal gross returns, the gains accrue to the fund manager in the form of management fees, and is not reflected in net returns. How reliably investors are able to pick winners with ex ante information remains questionable. In spite of this, there is a strong relationship between past performance and investor capital allocation.

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Appendices

A Data processing and consolidation

The dataset on investor capital allocation from VFF consisted of 192 monthly excel–reports, from January 2000 to December 2015, each divided in sheets for individual fund managers. We extracted all observations for funds with a Norwegian mandate[32]. Due to naming errors, this resulted in 420 different time series. Resolving naming errors reduced the cross–section to 237 different funds. We excluded 36 index, pension, and savings scheme funds. Name changes, mergers and acquisitions have been resolved to the best of our ability. Name changes and acquisitions are pooled in a single time series, keeping the most recent name. Mergers are kept separate until the time of the merger. A total of 88 funds were acquired or had a name change in the period. The resulting intermediate list of 113 funds was used as a basis for gathering returns data from Oslo Stock Exchange[33] and Thompson Reuters Datastream. We were unable to acquire returns data for 11 funds. After combining capital and returns data, 31 more funds were excluded for having less the 3 years (36 months) of observations in either returns or capital. This left us with a total of 71 funds, for which we had in excess of 36 months of data on both capital and returns.

Table 11 presents the 71 funds in our sample, along with 83 of the funds that were pooled due to acquisition or name change. Table 12 presents the 78 excluded funds, the rationale for exclusion, and 5 funds pooled due to acquisitions or name changes.

A few remarks:

- DnB's fund portfolio has been subject to many mergers, acquisitions, and name changes. We were unable to resolve four funds under the DnB umbrella, all of which are excluded for various reasons.
- All three Globus funds had missing returns data for one observation (interruption). We are unaware of the cause. We filled the missing data point with a zero return observation, to avoid losing data when computing performance metrics on rolling windows of 1–5 years.

[32] The VBA code for extraction and consolidation is available upon request.
[33] Provided by Professor Bernt Arne Ødegaard.

Table 11 Resolving name changes and acquisitions

The table presents the resolved name changes, mergers, and acquisitions for the 71 sampled funds. The list is consolidated from 154 individual fund entries in the VFF dataset of investor capital allocation.

No.	Consolidated fund list	Name changes and acquisitions
1	ABIF Norge ++	Industrifinans Aksje Norge Storkunde II; ; ;
2	Alfred Berg Aktiv	ABIF Aktiv; ABN AMRO Aktiv; Industrifinans Aktiv;
3	Alfred Berg Aktiv II	ABIF Kapital; ABN AMRO Kapital; Gambak Kapital;
4	Alfred Berg Gambak	Gambak; ; ;
5	Alfred Berg Humanfond	Banco Humanfond; Humanfond Aksje; ;
6	Alfred Berg Norge +	Industrifinans Aksje Norge Storkunde; ABN AMRO Norge +; ABIF Norge +;
7	Alfred Berg Norge Classic	Industrifinans Aksje Norge; Alfred Berg Norge; ABIF Norge; ABN AMRO Norge
8	Alfred Berg Norge Etisk	Banco Norge; ; ;
9	Atlas Norge	Kaupthing Norge; Tyren Norge; ;
10	Carnegie Aksje Norge	; ; ;
11	Carnegie Aksje Norge III	; ; ;
12	Danske Invest Norge I	Danske Fund Norge I; Firstnordic Norge I; Fokus Norge;
13	Danske Invest Norge II	Danske Fund Norge II; Firstnordic Norge II; Fokus Norge II;
14	Danske Invest Norge Vekst	Danske Fund Norge Vekst; Firstnordic Norge Vekst; Fokus SMB;
15	Danske Invest Norske Aksjer Institusjon I	Danske Fund Norge Aksjer Institusjon I; Firstnordic Norge III; Fokus Norge III;
16	Danske Invest Norske Aksjer Institusjon II	Danske Fund Norske Aksjer Institusjon II; ; ;
17	Delphi Norge	; ; ;
18	Delphi Vekst	; ; ;
19	DnB Norge	Postbanken Aksjespar; Postbanken Norge; ;
20	DnB Norge Avanse I	Avanse; Avanse Norge; Avanse Norge I;
21	DnB Norge Avanse II	Avanse Markedsverdi; Avanse Norge Aktiv; Avanse Norge II;
22	DnB Norge I	DnB NOR Norge; DnB NOR Norge I; DnB Real-Invest;
23	DnB Norge III	DnB NOR Norge III; DnB NOR Norge II; DnB Norge II;
24	DnB Norge IV	DnB NOR Norge IV; ; ;
25	DnB Norge Selektiv I	DnB NOR Norge Selektiv I; DNB Norge Selektiv; DnB 20; DnB NOR 20
26	DnB Norge Selektiv II	DnB NOR Norge Selektiv II; GNKF Norske Aksjer; ;
27	DnB Norge Selektiv III	DnB NOR Norge Selektiv III; Avanse Norge Aktiv II; GJENSIDIGE Kapital;
28	DnB SMB	DnB NOR SMB; ; ;
29	Eika Norge	WarrenWicklund Norge Verdi; Sundal Collier Norge Verdi; WarrenWicklund Norge;
30	Eika SMB	Terra SMB; NB Plussfond; ;
31	Fondsfinans Aktiv II	; ; ;
32	Fondsfinans Norge	Fondsfinans Spar; ; ;
33	Forte Norge	; ; ;
34	Forte Trønder	; ; ;
35	Globus Aktiv	Sundal Collier Aktiv; ; ;
36	Globus Norge	; ; ;
37	Globus Norge II	Sundal Collier Norge; Sundal Collier Spar; ;
38	Handelsbanken Norge	Aksjef. Handelsbanken; ; ;
39	Holberg Norge	; ; ;
40	KLP Aksjeinvest	; ; ;
41	KLP AksjeNorge	; ; ;
42	Landkreditt Norge	; ; ;
43	NB Aksjefond	; ; ;
44	Nordea Avkastning	K-Avkastning; ; ;
45	Nordea Kapital	K-Kapital; ; ;
46	Nordea Kapital II	K-Kapital II; ; ;
47	Nordea Kapital III	K-Kapital III; ; ;
48	Nordea Norge Pluss	; ; ;
49	Nordea Norge Verdi	Nordea Aksjepensjon; ; ;
50	Nordea SMB	K-SMB; ; ;
51	Nordea SMB II	K-SMB II; ; ;
52	Nordea Vekst	K-Vekst; ; ;
53	Odin Norge	; ; ;
54	Omega Investment Fund	Orkla Finans Investment Fund; ; ;
55	Orkla Finans 30	Omega AMS; ; ;
56	Pareto Aksje Norge A	Pareto Aktiv; ; ;
57	Pareto Aksje Norge B	Pareto Verdi; ; ;
58	Pareto Aksje Norge I	Pareto Aksje Norge; ; ;
59	PLUSS Aksje	; ; ;
60	PLUSS Markedsverdi	; ; ;
61	Postbanken Aksjevekst	; ; ;
62	Romsdal Fellesbank Aksjefond	RF Aksjefond; ; ;
63	Storebrand Aksje Innland	; ; ;
64	Storebrand Norge	; ; ;
65	Storebrand Norge A	; ; ;
66	Storebrand Norge I	; ; ;
67	Storebrand Optima Norge A	; ; ;
68	Storebrand Vekst	Storebrand SMB; ; ;
69	Storebrand Verdi	; ; ;
70	Terra Norge	; ; ;
71	WarrenWicklund Alpha	; ; ;

Table 12 Excluded funds

The table presents the 78 excluded funds, and the rational for exclusion. The funds were excluded after attempting to resolve name changes, mergers, and acquisitions. The fund portfolio of DnB has been subject to several acquisitions and both internal and external mergers. We were unable to resolve four funds that were acquired by DnB. Two of them are omitted for having less than 36 observations, while the other two are omitted due to unavailable returns data.

No.	Excluded funds	Rationale	Comment
1	ABIF Indeks	Index fund	
2	ABIF Indeks +	Index fund	
3	ABIF OBX	Index fund	
4	ABN AMRO Indeks	Index fund	
5	ABN AMRO Indeks +	Index fund	
6	Alfred Berg Indeks	Index fund	
7	Alfred Berg Indeks Classic	Index fund	
8	Alfred Berg OBX	Index fund	
9	Avanse OBX Indeks	Index fund	
10	AvanseOBX Indeks	Index fund	
11	Carnegie Norge Indeks	Index fund	
12	Carnegie OBX	Index fund	
13	DnB NOR Norge Indeks	Index fund	
14	DnB NOR OBX	Index fund	
15	DNB Norge Indeks	Index fund	
16	DNB OBX	Index fund	
17	F-OBX	Index fund	
18	GJENSIDIGE OBX Indeks	Index fund	
19	KLP AksjeNorge Indeks	Index fund	
20	KLP AksjeNorge Indeks II	Index fund	
21	PLUSS Indeks	Index fund	
22	PLUSS OBX-Indeks	Index fund	
23	Skandia Indeks Norge	Index fund	
24	Storebrand Indeks - Norge	Index fund	
25	Sundal Collier Indeks +	Index fund	
26	Vesta Indeks Norge	Index fund	
27	WarrenWicklund Indeks +	Index fund	
28	XACT OBX	Index fund	
29	Alfred Berg Norge Inst	Less than 36 observations	
30	Alfred Berg Vekst	Less than 36 observations	
31	Danske Invest Aktiv Formuesforvaltning Aksjer	Less than 36 observations	Incl. Danske Fund Aktiv Formuesforvaltning Aksjer
32	DnB Real-Vekst	Less than 36 observations	
33	First Generator	Less than 36 observations	
34	Gambak Oppkjøp	Less than 36 observations	
35	GJENSIDIGE Invest	Less than 36 observations	
36	K-IPA Aksjefond	Less than 36 observations	
37	Landkreditt Utbytte	Less than 36 observations	
38	Nordea PBPM Norsk Aksje Portefølje	Less than 36 observations	
39	ODIN Norge A	Less than 36 observations	
40	ODIN Norge B	Less than 36 observations	
41	ODIN Norge C	Less than 36 observations	
42	ODIN Norge D	Less than 36 observations	
43	Odin Norge II	Less than 36 observations	
44	Pareto Aksje Norge C	Less than 36 observations	
45	Pareto Aksje Norge D	Less than 36 observations	
46	Pareto Investment Fund A	Less than 36 observations	
47	Pareto Investment Fund B	Less than 36 observations	
48	Pareto Investment Fund C	Less than 36 observations	
49	Pareto Sicav - Pareto Equity Norway A	Less than 36 observations	
50	Pareto Sicav - Pareto Equity Norway B	Less than 36 observations	
51	Pareto Sicav - Pareto Equity Norway C	Less than 36 observations	
52	Pareto Sicav - Pareto Equity Norway D	Less than 36 observations	
53	Skandia Horisont	Less than 36 observations	Incl. Vesta Horisont; Unable to resolve later DnB merger
54	Skandia SMB Norge	Less than 36 observations	Incl. Skandia AMS & Vesta AMS; Unable to resolve later DnB merger
55	Storebrand Aksjespar	Less than 36 observations	
56	Storebrand Norge H	Less than 36 observations	
57	Swedbank Generator	Less than 36 observations	
58	Terra Vekst	Less than 36 observations	
59	VÅR Aksjefond	Less than 36 observations	
60	Banco Norge +	NA returns	
61	Carnegie Aksje Norge II	NA returns	
62	Carnegie Aksje Norge IV	NA returns	
63	Carnegie Aksje Norge V	NA returns	
64	Diversifiserte Norske Aksjer	NA returns	Incl. Navigator Aksje Norge
65	ESG Norske Aksjer	NA returns	
66	Nordea Norwegian Equity Market	NA returns	
67	Romsdal Fellesbank Plussfond	NA returns	
68	Skandia Norge	NA returns	Unable to resolve later DnB merger
69	Skandia Norge II	NA returns	Unable to resolve later DnB merger
70	Storebrand Norge Institusjon	NA returns	
71	DnB Aksje Pensjon	Pension fund	
72	DnB AksjePensjon	Pension fund	
73	DnB NOR Norge Pensjon	Pension fund	
74	DnB Norge Pensjon	Pension fund	
75	K-Aksjepensjon	Pension fund	
76	Fokus Barnespar	Savings scheme	
77	K-Barnespar	Savings scheme	
78	Nordea Barnespar	Savings scheme	

B Sampled funds, with summary statistics

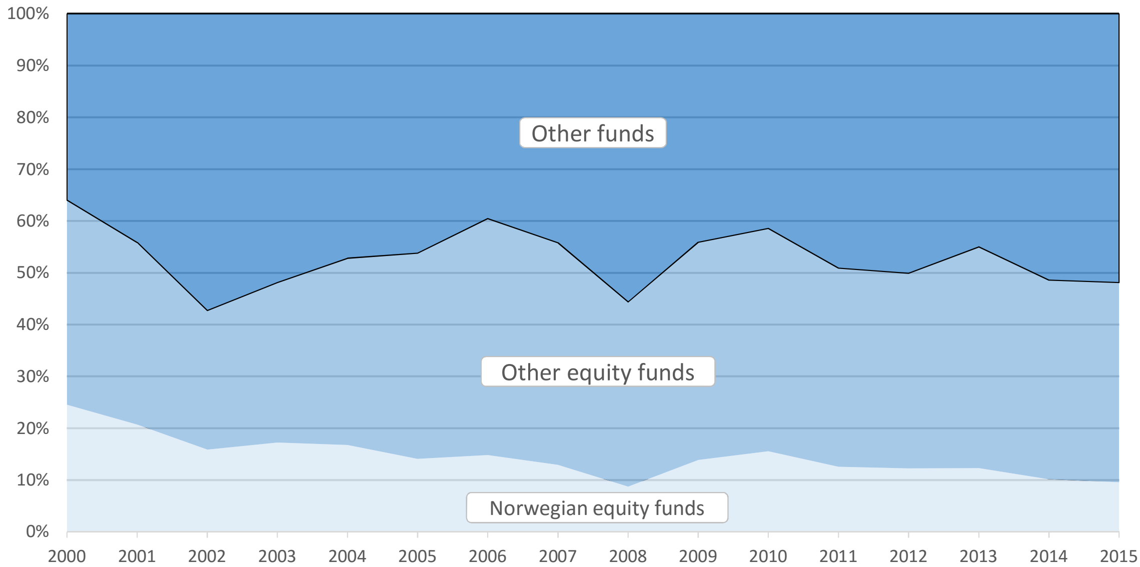
Table 13 List of funds in sample, with summary statistics

The table presents a list of sampled funds, along with descriptive statistics. The third and fourth columns show number of observations, and last month in sample. Column five shows the average Assets Under Management (AUM). The last three columns show mean simple and active returns, along with three–factor alpha (with the OSEFX as benchmark index).

					Performance (%)		
No.	Fund	# Obs	End Date	AUM (MNOK)	Simple returns	Active returns	3–factor alpha
1	ABIF Norge ++	56	2004:11	182	5.43	0.93	1.32
2	Alfred Berg Aktiv	192	2015:12	411	8.51	0.91	-0.35
3	Alfred Berg Aktiv II	154	2012:10	66	7.92	1.23	-0.17
4	Alfred Berg Gambak	192	2015:12	719	11.07	3.50	0.42
5	Alfred Berg Humanfond	192	2015:12	69	7.89	0.28	0.36
6	Alfred Berg Norge +	172	2014:04	756	9.26	1.41	1.17
7	Alfred Berg Norge Classic	192	2015:12	659	9.53	1.90	1.71
8	Alfred Berg Norge Etisk	145	2014:04	68	9.04	-0.81	-0.89
9	Atlas Norge	192	2015:12	24	5.88	-1.39	-2.10
10	Carnegie Aksje Norge	192	2015:12	461	9.16	1.52	2.02
11	Carnegie Aksje Norge III	164	2015:12	569	12.02	1.93	2.30
12	Danske Invest Norge I	192	2015:12	389	8.79	0.97	1.28
13	Danske Invest Norge II	192	2015:12	284	9.80	1.88	2.22
14	Danske Invest Norge Vekst	192	2015:12	461	7.38	-0.65	-1.91
15	Danske Invest Norske Aksjer Institusjon I	188	2015:12	1,016	10.45	2.04	2.57
16	Danske Invest Norske Aksjer Institusjon II	109	2015:12	2,078	7.99	3.32	3.68
17	Delphi Norge	192	2015:12	609	9.50	2.11	-0.30
18	Delphi Vekst	166	2013:10	168	6.31	-1.29	-3.57
19	DnB Norge	192	2015:12	2,776	6.45	-1.10	-0.50
20	DnB Norge Avanse I	171	2014:03	2,262	5.98	-1.52	-1.28
21	DnB Norge Avanse II	178	2014:10	168	5.41	-2.04	-1.78
22	DnB Norge I	171	2014:03	2,395	7.32	-0.46	-0.03
23	DnB Norge III	192	2015:12	173	7.67	0.05	0.49
24	DnB Norge IV	157	2015:12	354	13.38	0.23	1.17
25	DnB Norge Selektiv I	192	2015:12	674	7.59	0.14	0.20
26	DnB Norge Selektiv II	168	2015:12	168	10.73	0.67	1.52
27	DnB Norge Selektiv III	192	2015:12	797	7.76	0.11	0.40
28	DnB SMB	177	2015:12	640	10.72	2.15	-0.84
29	Eika Norge	147	2015:12	445	16.00	2.77	2.34
30	Eika SMB	166	2013:10	42	6.07	-1.85	-2.99
31	Fondsfinans Aktiv II	47	2004:08	156	-2.52	-1.36	-1.62
32	Fondsfinans Norge	156	2015:12	790	16.46	2.01	2.04
33	Forte Norge	57	2015:12	20	3.04	-3.71	-2.90
34	Forte Trønder	36	2015:12	10	13.24	0.88	4.78
35	Globus Aktiv	76	2006:04	94	1.93	-8.28	-11.18
36	Globus Norge	83	2006:11	43	1.62	-8.38	-11.57
37	Globus Norge II	83	2006:11	35	-0.77	-10.46	-13.42
38	Handelsbanken Norge	192	2015:12	984	8.70	1.30	0.95
39	Holberg Norge	180	2015:12	867	8.34	-0.11	-0.93
40	KLP Aksjeinvest	44	2003:08	60	-5.06	1.07	0.93
41	KLP AksjeNorge	192	2015:12	2,123	8.41	0.81	0.81
42	Landkreditt Norge	114	2015:12	86	5.07	-0.75	-0.28
43	NB Aksjefond	166	2013:10	155	6.16	-1.54	-1.96
44	Nordea Avkastning	192	2015:12	1,824	6.59	-0.80	-0.85
45	Nordea Kapital	192	2015:12	1,354	7.51	0.03	-0.04
46	Nordea Kapital II	71	2005:11	103	6.27	-2.20	-2.36
47	Nordea Kapital III	69	2006:04	289	10.24	-1.95	-1.83
48	Nordea Norge Pluss	56	2015:12	411	6.73	-0.28	-0.76
49	Nordea Norge Verdi	192	2015:12	691	8.11	-0.07	-0.43
50	Nordea SMB	181	2015:01	267	2.76	-5.17	-7.60
51	Nordea SMB II	39	2003:03	38	-27.76	-12.25	-19.48
52	Nordea Vekst	181	2015:01	972	5.49	-2.04	-2.18
53	Odin Norge	192	2015:12	4,274	7.97	-0.14	-1.93
54	Omega Investment Fund	192	2015:12	498	10.24	2.68	2.41
55	Orkla Finans 30	78	2006:06	228	11.88	0.56	1.02
56	Pareto Aksje Norge A	62	2015:12	2,239	2.22	-5.89	-5.86
57	Pareto Aksje Norge B	120	2015:12	736	3.60	-3.35	-2.88
58	Pareto Aksje Norge I	171	2015:12	3,550	12.64	0.98	1.46
59	PLUSS Aksje	192	2015:12	170	8.11	0.21	1.15
60	PLUSS Markedsverdi	192	2015:12	115	9.07	1.22	2.28
61	Postbanken Aksjevekst	63	2005:03	489	0.28	-5.00	-4.44
62	Romsdal Fellesbank Aksjefond	87	2007:03	58	10.93	-2.20	-1.81
63	Storebrand Aksje Innland	192	2015:12	890	8.12	0.45	0.85
64	Storebrand Norge	192	2015:12	320	7.33	-0.03	-0.21
65	Storebrand Norge A	42	2005:12	373	26.40	-0.33	-0.61
66	Storebrand Norge I	188	2015:12	1,095	8.61	0.62	0.62
67	Storebrand Optima Norge A	180	2015:12	193	9.71	1.72	1.68
68	Storebrand Vekst	192	2015:12	263	8.17	0.54	-0.39
69	Storebrand Verdi	192	2015:12	809	9.38	1.34	2.50
70	Terra Norge	166	2013:10	398	6.05	-1.36	-2.10
71	WarrenWicklund Alpha	55	2007:01	65	29.11	0.44	-2.65

Figure 6 Distribution of mutual fund assets under management in Norway

The chart shows the distribution of assets under management in mutual funds in Norway (that are members of Verdipapirfondenes Forening, VFF). Norwegian funds are funds with a Norwegian mandate, at least 80 percent invested in the Norwegian stock market. "Other equity funds" include funds with an international or mixed mandate. "Other funds" are bond funds, money market funds, combination funds, and other.



C Performance ratios

Sharpe Ratio (SR) First derived by William Sharpe in 1966 and later modified in 1994, the SR measures excess return over the risk free rate per unit of total (absolute) risk, consisting of both systematic and idiosyncratic risk. The interpretation of the ratio requires the total investor portfolio. The relative ranking of portfolios necessitates that the investor carries the total risk inherent in the investment options. Combining portfolios based on the SR is difficult due to covariance between assets, which is the mechanism that enables benefits of diversification.

$$SR(r_i) = \frac{E(r_i^e)}{\sigma(r_i^e)} \tag{9}$$

Where $E(r_i^e)$ is expected excess return over the risk free rate, and $\sigma(r_i^e)$ is the volatility of excess portfolio returns, as measured by its standard deviation.

Treynor Ratio (TR) The TR was developed by Jack L. Treynor in 1965, and was the first composite risk–adjusted measure of portfolio performance. Where the SR accounts for total portfolio risk, the TR adjusts excess returns for systematic risk—the portfolio beta. The intuition of the ratio is that idiosyncratic risk is ameliorated by diversification, and is thus not a priced risk factor in the market. The TR assumes a well diversified investor, able to ignore idiosyncratic risk. Whereas the volatility in the SR complicates portfolio consolidation, the betas of individual portfolios enable simple combination to form the total investor portfolio.

$$TR(r_i) = \frac{E(r_i^e)}{\beta_i} \tag{10}$$

Where $E(r_i^e)$ is expected excess return over the risk free rate, and β_i is the portfolio CAPM beta.

Information Ratio (IR) Based on alpha intuition[34] and the SR, the IR accounts for returns in excess of a reference index, or *active returns*, adjusted for the total risk of the differential, or *active risk* (Eckbo and Ødegaard, 2015). The market index is a better representative than the risk free rate at measuring what the active mutual fund manager is trying to beat. It is likely a better reflection of business cycles and shifting market conditions faced by the manager. A crucial input to the IR is the reference index; the choice of which opens up the possibility for manipulation and unfair comparison. Like the SR, its interpretation requires the total investor portfolio.

$$IR(r_i) = \frac{E(r_i^a)}{\sigma(r_i^a)} \tag{11}$$

Where $E(r_i^a)$ is expected active return over the market index, and $\sigma(r_i^a)$ is the volatility of the returns differential—often referred to as the "tracking error" or active risk.

[34] Alpha will be considered in the following

D Testing OLS variance assumptions

Table 14 Testing pricing models

The table reports test results for the three different picing models, the CAPM, the Fama–French three–factor model, and Carhart's four–factor model, estimated on the equal and value weighted aggregate fund portfolios. subsection 3.3. Tests include Breuch–Pagan (BP) and White tests for heteroscedasticity, and Durbin–Watson (DW) test for autocorrelation. The p–values from the BP and White tests imply a rejection of the null hypothesis of no heteroscedasticity. The p–values from the DW test implies that we cannot reject the null hypothesis of no autocorrelation.

	Equally Weighted			*Value Weighted*		
	CAPM	3–factor	4–factor	CAPM	3–factor	4–factor
BP (p–value)	0.009	0.020	0.040	0.001	0.002	0.005
White (p–value)	0.001	0.000	0.000	0.000	0.000	0.000
DW–statistic	1.987	2.196	2.191	1.866	2.053	2.064
DW (p–value)	0.459	0.911	0.903	0.171	0.635	0.662

Table 15 Testing net inflow regressions

The table reports test results for all five models from section 4 (set A to E presented in Table 9 and Table 10), and tested on all the performance metrics: Simple returns ($\bar{r}$), excess returns ($\bar{r}^e$), active returns ($\bar{r}^a$), Sharpe ratio (SR), Treynor ratio (TR), Information ratio (IR), three–factor alpha (α) and t–statistic ($t(\alpha)$). Tests include the Breuch–Pagan (BP) and White tests for heteroscedasticity, and the Durbin–Watson (DW) test for autocorrelation. Whereas the BP test provides evidence for heteroscedasticity, the White test adds mixed results. The p–values from the DW test implies a rejection of the null hypothesis, evidence that the errors follow a first order auto–regressive process.

Panel A: Breuch–Pagan test for heteroscedasticity

	Mean returns		*Ratios*			*Three-factor model*	
(p–values)	Excess	Active	SR	TR	IR	Alpha	t–stat
All sets	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Panel B: White test for heteroscedasticity

	Mean returns		*Ratios*			*Three-factor model*	
(p–values)	Excess	Active	SR	TR	IR	Alpha	t–stat
Set A	0.139	0.163	0.125	0.140	0.393	0.260	0.489
Set B	0.470	0.415	0.384	0.303	0.365	0.189	0.209
Set C	0.020	0.374	0.525	0.030	0.053	0.154	0.119
Set D	0.347	0.234	0.282	0.247	0.268	0.171	0.244
Set E	0.176	0.060	0.547	0.068	0.385	0.023	0.635

Panel C: Durbin–Watson test for autocorrelation

	Mean returns		*Ratios*			*Three-factor model*	
	Excess	Active	SR	TR	IR	Alpha	t–stat
Set A	1.672	1.713	1.669	1.671	1.715	1.712	1.708
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Set B	1.702	1.700	1.704	1.701	1.689	1.695	1.688
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Set C	1.533	1.589	1.569	1.568	1.565	1.550	1.556
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Set D	1.710	1.710	1.712	1.709	1.695	1.705	1.697
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Set E	1.543	1.621	1.591	1.596	1.589	1.580	1.576
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000

E Performance metric consistency

Table 16 Rank consistency between performance metrics

The table reports consistency in top (panel A) and bottom (panel B) ten ranks between the performance metrics: Simple returns ($\bar{r}$), excess returns ($\bar{r}^e$), active returns ($\bar{r}^a$), Sharpe ratio (SR), Treynor ratio (TR), Information ratio (IR), three–factor alpha (α) and t–statistic ($t(\alpha)$). The tables compare the consistency between pairs of metrics, in terms of how many of their individual top and bottom ten ranked funds are present in both metrics, but not necessarily in the same order. A value of 10 means that all the same funds are present in both metrics' top or bottom ten.

Panel A: Top ten ranks

	$\bar{r}$	$\bar{r}^e$	$\bar{r}^a$	SR	TR	IR	α	$t(\alpha)$
$\bar{r}$	-	9	4	9	9	3	4	2
$\bar{r}^e$	9	-	4	9	9	3	4	2
$\bar{r}^a$	4	4	-	3	5	7	6	6
SR	9	9	3	-	8	2	4	2
TR	9	9	5	8	-	3	4	2
IR	3	3	7	2	3	-	7	8
α	4	4	6	4	4	7	-	8
$t(\alpha)$	2	2	6	2	2	8	8	-

Panel B: Bottom ten ranks

	$\bar{r}$	$\bar{r}^e$	$\bar{r}^a$	SR	TR	IR	α	$t(\alpha)$
$\bar{r}$	-	9	8	9	10	6	8	7
$\bar{r}^e$	9	-	7	10	9	6	7	7
$\bar{r}^a$	8	7	-	7	8	6	8	7
SR	9	10	7	-	9	6	7	7
TR	10	9	8	9	-	6	8	7
IR	6	6	6	6	6	-	6	8
α	8	7	8	7	8	6	-	7
$t(\alpha)$	7	7	7	7	7	8	7	-

F Sensitivity of bootstrap results

Table 17 Sensitivity of the bootstrap results

The table presents estimated actual (Act) and average of simulated (Sim) alphas and t-statistics, along with the percent of the 10,000 simulation runs producing simulated values lower than the actual (%<Act; also referred to as the "win–rate" of actual over simulated alpha/t–value). High (low) win–rate indicates skill (lack of skill) in the upper (lower) part of the tables. The leftmost column lists the best five funds according to either alpha or t–value, followed by deciles, and the five worst funds at the bottom. Panel A shows the results using Kosowski's bootstrap procedure with the Fama–French three–factor model. Panel B shows the bootstrap results using the three–factor model of Fama–French with the OSEBX as benchmark index. The analyses cover 71 funds on net returns. The sample period is 2000–2015.

Panel A: Kosowski et al. (2006) bootstrap procedure

	Alpha (%)			*t-statistic*		
	Act	Sim	%<Act	Act	Sim	%<Act
Best	4.78	8.13	13.63	2.64	2.44	70.29
2	3.68	5.40	13.92	2.64	2.04	**95.07**
3	2.57	4.27	3.76	2.57	1.82	**99.11**
4	2.50	3.60	8.85	2.28	1.66	**98.78**
5	2.41	3.15	16.20	2.17	1.54	**99.30**
90%	2.30	2.52	38.28	1.69	1.34	**95.31**
80%	1.52	1.41	64.14	1.14	0.88	92.81
70%	1.02	0.84	78.15	0.74	0.56	87.45
60%	0.42	0.41	52.22	0.31	0.29	56.47
50%	-0.21	0.05	11.09	-0.13	0.04	13.29
40%	-0.61	-0.31	8.84	-0.31	-0.21	26.14
30%	-1.62	-0.70	**0.05**	-0.81	-0.48	**2.04**
20%	-2.10	-1.21	**0.38**	-1.20	-0.78	**0.71**
10%	-3.57	-2.24	**1.32**	-1.78	-1.18	**0.15**
5	-7.60	-3.06	**0.01**	-2.31	-1.54	**0.18**
4	-11.18	-3.50	**0.00**	-2.60	-1.67	**0.10**
3	-11.57	-4.12	**0.02**	-2.61	-1.83	**0.86**
2	-13.42	-5.14	**0.08**	-2.93	-2.05	**1.09**
Worst	-19.48	-7.57	**0.46**	-3.06	-2.46	11.08

Panel B: Fama and French (2010) bootstrap procedure with OSEBX

	Alpha (%)			*t-statistic*		
	Act	Sim	%<Act	Act	Sim	%<Act
Best	5.67	8.38	23.85	1.90	2.41	12.40
2	3.27	5.58	5.37	1.88	2.01	36.79
3	2.28	4.41	0.84	1.88	1.79	64.11
4	2.13	3.73	1.46	1.68	1.63	58.85
5	1.96	3.27	2.07	1.54	1.51	57.65
90%	1.91	2.64	8.83	1.33	1.31	54.53
80%	1.34	1.50	34.41	0.84	0.85	46.09
70%	0.63	0.87	19.83	0.47	0.53	35.77
60%	-0.03	0.40	**3.40**	-0.02	0.26	2.83
50%	-0.55	0.01	**0.72**	-0.27	0.01	**2.82**
40%	-1.00	-0.38	**0.53**	-0.43	-0.24	11.00
30%	-1.75	-0.81	**0.10**	-1.06	-0.51	**0.02**
20%	-2.35	-1.38	**0.43**	-1.36	-0.82	**0.04**
10%	-4.14	-2.51	**0.42**	-1.83	-1.22	**0.28**
5	-8.07	-3.37	**0.00**	-2.24	-1.59	**0.66**
4	-11.41	-3.83	**0.00**	-2.39	-1.72	**1.01**
3	-11.45	-4.49	**0.03**	-2.51	-1.88	**2.14**
2	-13.26	-5.60	**0.16**	-2.82	-2.11	**3.28**
Worst	-19.16	-8.14	**0.54**	-3.06	-2.53	14.27

G Full net inflow regressions

Table 18 Set A: Net inflow on absolute performance metrics

The table reports full regression output for Set A in Table 9, regression analyses of net inflow ($Inflow_t$) on different absolute performance metrics: Excess returns ($\bar{r}^e$), active returns ($\bar{r}^a$), Sharpe ratio (SR), Treynor ratio (TR), Information ratio (IR), three–factor alpha (α) and t–statistic ($t(\alpha)$). The control variables are Industry Growth, Log(Assets), and dummy variables on fund age and month of observation. All dummy variables for fund age are included, hence the lack of an intercept. Newey–West heteroscedasticity and autocorrelation consistent standard errors are in parentheses, with stars representing significance levels.

	Mean returns		*Ratios*			*Three-factor model*	
	Excess	Active	SR	TR	IR	Alpha	t–stat
Performance metric	−0.219***	2.888***	−0.998*	−0.219**	5.236***	2.849***	0.762***
	(0.066)	(0.300)	(0.396)	(0.068)	(0.463)	(0.300)	(0.077)
Industry Growth	0.061***	0.068***	0.063***	0.061***	0.068***	0.070***	0.070***
	(0.015)	(0.014)	(0.015)	(0.015)	(0.014)	(0.015)	(0.014)
Log(Assets)	0.233***	0.098	0.228***	0.232***	0.150*	0.095	0.155*
	(0.066)	(0.060)	(0.067)	(0.066)	(0.062)	(0.060)	(0.063)
Age 3 years	0.164	0.970	0.238	0.234	0.463	1.199	0.580
	(1.234)	(1.143)	(1.239)	(1.234)	(1.136)	(1.147)	(1.150)
Age 4 years	0.185	1.259	0.283	0.274	0.554	1.338	0.619
	(1.087)	(1.042)	(1.089)	(1.088)	(1.055)	(1.033)	(1.059)
Age 5 years	−1.845	−0.401	−1.717	−1.774	−1.273	−0.084	−1.006
	(1.042)	(0.966)	(1.042)	(1.043)	(0.989)	(0.959)	(0.989)
Age 6 years	−2.897**	−1.266	−2.777*	−2.824*	−2.104*	−0.938	−1.929
	(1.123)	(1.020)	(1.125)	(1.122)	(1.057)	(0.991)	(1.042)
Age 7 years	−3.588***	−1.849*	−3.483***	−3.518***	−2.587**	−1.480	−2.417**
	(0.993)	(0.901)	(0.998)	(0.993)	(0.935)	(0.884)	(0.923)
Age 8 years	−2.861**	−1.312	−2.768**	−2.796**	−1.944*	−0.977	−1.771
	(0.979)	(0.914)	(0.981)	(0.979)	(0.933)	(0.909)	(0.935)
Age 9 years	−3.668***	−2.019*	−3.579***	−3.603***	−2.623**	−1.728*	−2.492**
	(0.889)	(0.829)	(0.892)	(0.889)	(0.851)	(0.826)	(0.852)
Age 10+ years	−3.297***	−1.616	−3.185***	−3.225***	−2.308**	−1.447	−2.248*
	(0.913)	(0.849)	(0.915)	(0.913)	(0.872)	(0.847)	(0.876)
February	−0.340	−0.312	−0.349	−0.338	−0.325	−0.360	−0.374
	(0.302)	(0.302)	(0.303)	(0.302)	(0.302)	(0.302)	(0.302)
March	−0.573	−0.530	−0.581	−0.572	−0.534	−0.574	−0.585
	(0.303)	(0.303)	(0.303)	(0.303)	(0.303)	(0.302)	(0.303)
April	−0.424	−0.397	−0.434	−0.425	−0.407	−0.431	−0.452
	(0.331)	(0.329)	(0.331)	(0.331)	(0.330)	(0.329)	(0.330)
May	−0.884**	−0.848**	−0.881**	−0.884**	−0.871**	−0.898**	−0.907**
	(0.327)	(0.325)	(0.327)	(0.327)	(0.324)	(0.325)	(0.325)
June	−0.211	−0.202	−0.197	−0.207	−0.228	−0.266	−0.279
	(0.335)	(0.331)	(0.335)	(0.335)	(0.331)	(0.332)	(0.332)
July	−0.300	−0.295	−0.296	−0.298	−0.317	−0.353	−0.370
	(0.299)	(0.295)	(0.300)	(0.299)	(0.296)	(0.296)	(0.297)
August	0.097	0.156	0.102	0.099	0.130	0.097	0.085
	(0.319)	(0.317)	(0.319)	(0.319)	(0.318)	(0.318)	(0.318)
September	−0.214	−0.176	−0.212	−0.213	−0.198	−0.210	−0.219
	(0.316)	(0.315)	(0.316)	(0.316)	(0.315)	(0.314)	(0.314)
October	0.608	0.609	0.605	0.608	0.606	0.584	0.584
	(0.360)	(0.357)	(0.361)	(0.361)	(0.357)	(0.357)	(0.357)
November	−0.271	−0.280	−0.277	−0.272	−0.302	−0.287	−0.308
	(0.335)	(0.334)	(0.336)	(0.335)	(0.334)	(0.333)	(0.333)
December	1.043**	1.015**	1.032**	1.043**	1.017**	0.963*	0.963*
	(0.383)	(0.382)	(0.384)	(0.384)	(0.382)	(0.382)	(0.382)
R-squared	0.035	0.060	0.034	0.035	0.060	0.060	0.056
Observations	7422	7422	7422	7422	7422	7422	7422

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 19 Set B: Net inflow on performance ranks

The table reports full regression output for Set B in Table 9, regression analyses of net inflow ($Inflow_t$) on different performance ranks: Excess returns ($\bar{r}^e$), active returns ($\bar{r}^a$), Sharpe ratio (SR), Treynor ratio (TR), Information ratio (IR), three–factor alpha (α) and t–statistic ($t(\alpha)$). The control variables are Industry Growth, Log(Assets), and dummy variables on fund age and month of observation. All dummy variables for fund age are included, hence the lack of an intercept. Newey–West heteroscedasticity and autocorrelation consistent standard errors are in parentheses, with stars representing significance levels.

	Mean returns		*Ratios*			*Three-factor model*	
	Excess	Active	SR	TR	IR	Alpha	t–stat
Performance rank	0.319***	0.299***	0.309***	0.304***	0.247***	0.270***	0.239***
	(0.033)	(0.032)	(0.032)	(0.032)	(0.031)	(0.033)	(0.033)
Industry Growth	0.068***	0.068***	0.068***	0.068***	0.069***	0.068***	0.069***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Log(Assets)	0.091	0.109	0.109	0.114	0.152*	0.138*	0.165*
	(0.063)	(0.063)	(0.063)	(0.064)	(0.065)	(0.064)	(0.065)
Age 3 years	−0.857	−0.866	−0.879	−0.895	−0.920	−0.997	−1.061
	(1.182)	(1.190)	(1.194)	(1.199)	(1.206)	(1.224)	(1.233)
Age 4 years	−0.496	−0.523	−0.690	−0.728	−0.725	−0.778	−0.914
	(1.078)	(1.080)	(1.060)	(1.066)	(1.082)	(1.092)	(1.094)
Age 5 years	−2.199*	−2.310*	−2.494*	−2.466*	−2.591*	−2.479*	−2.666**
	(1.007)	(1.012)	(1.001)	(1.004)	(1.029)	(1.024)	(1.035)
Age 6 years	−3.036**	−3.128**	−3.235**	−3.283**	−3.485**	−3.384**	−3.592***
	(1.049)	(1.058)	(1.044)	(1.050)	(1.095)	(1.065)	(1.087)
Age 7 years	−3.627***	−3.729***	−3.787***	−3.816***	−4.039***	−3.943***	−4.135***
	(0.938)	(0.944)	(0.937)	(0.943)	(0.973)	(0.959)	(0.975)
Age 8 years	−3.036**	−3.119***	−3.071**	−3.138***	−3.318***	−3.257***	−3.407***
	(0.938)	(0.942)	(0.937)	(0.943)	(0.961)	(0.956)	(0.971)
Age 9 years	−3.683***	−3.790***	−3.756***	−3.828***	−3.996***	−4.008***	−4.144***
	(0.854)	(0.860)	(0.854)	(0.859)	(0.877)	(0.874)	(0.885)
Age 10+ years	−3.204***	−3.350***	−3.396***	−3.435***	−3.629***	−3.575***	−3.757***
	(0.872)	(0.879)	(0.875)	(0.880)	(0.901)	(0.895)	(0.907)
February	−0.348	−0.348	−0.349	−0.349	−0.349	−0.349	−0.349
	(0.302)	(0.302)	(0.302)	(0.302)	(0.302)	(0.302)	(0.302)
March	−0.588	−0.587	−0.588	−0.588	−0.586	−0.587	−0.587
	(0.302)	(0.302)	(0.303)	(0.302)	(0.303)	(0.302)	(0.302)
April	−0.449	−0.448	−0.449	−0.449	−0.449	−0.449	−0.449
	(0.329)	(0.330)	(0.330)	(0.330)	(0.330)	(0.330)	(0.330)
May	−0.897**	−0.895**	−0.897**	−0.897**	−0.894**	−0.897**	−0.897**
	(0.324)	(0.325)	(0.326)	(0.325)	(0.325)	(0.326)	(0.327)
June	−0.224	−0.223	−0.225	−0.224	−0.221	−0.223	−0.224
	(0.332)	(0.332)	(0.332)	(0.332)	(0.333)	(0.333)	(0.334)
July	−0.328	−0.327	−0.329	−0.329	−0.329	−0.328	−0.329
	(0.296)	(0.296)	(0.296)	(0.296)	(0.297)	(0.297)	(0.297)
August	0.092	0.092	0.090	0.091	0.090	0.091	0.089
	(0.318)	(0.318)	(0.318)	(0.318)	(0.318)	(0.319)	(0.319)
September	−0.220	−0.219	−0.221	−0.220	−0.220	−0.219	−0.220
	(0.314)	(0.315)	(0.315)	(0.315)	(0.315)	(0.315)	(0.316)
October	0.561	0.563	0.560	0.561	0.562	0.562	0.562
	(0.358)	(0.358)	(0.358)	(0.358)	(0.359)	(0.358)	(0.359)
November	−0.319	−0.318	−0.320	−0.319	−0.319	−0.318	−0.319
	(0.333)	(0.334)	(0.333)	(0.333)	(0.334)	(0.334)	(0.334)
December	0.957*	0.960*	0.957*	0.958*	0.958*	0.959*	0.958*
	(0.382)	(0.382)	(0.382)	(0.382)	(0.382)	(0.382)	(0.382)
R-squared	0.055	0.053	0.054	0.053	0.046	0.049	0.045
Observations	7422	7422	7422	7422	7422	7422	7422

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 20 Set C: Net inflow on performance ranks —annual data

The table reports full regression output for Set C in Table 9, regression analyses of net inflow ($Inflow_t$) on different performance ranks with annual data: Excess returns ($\bar{r}^e$), active returns ($\bar{r}^a$), Sharpe ratio (SR), Treynor ratio (TR), Information ratio (IR), three–factor alpha (α) and t–statistic ($t(\alpha)$). The control variables are Industry Growth, Log(Assets), and dummy variables on fund age and month of observation. All dummy variables for fund age are included, hence the lack of an intercept. Newey–West heteroscedasticity and autocorrelation consistent standard errors are in parentheses, with stars representing significance levels.

	Mean returns		*Ratios*			*Three-factor model*	
	Excess	Active	SR	TR	IR	Alpha	t–stat
Performance decile	3.007***	4.240***	3.999***	4.167***	3.971***	3.243***	3.725***
	(0.632)	(0.680)	(0.671)	(0.649)	(0.632)	(0.671)	(0.633)
Industry Growth	0.202**	0.201***	0.200***	0.201***	0.202***	0.202**	0.202***
	(0.061)	(0.060)	(0.060)	(0.060)	(0.060)	(0.062)	(0.061)
Log(Assets)	0.034	−0.679	−0.564	−0.357	−0.328	−0.112	−0.224
	(1.367)	(1.331)	(1.349)	(1.336)	(1.334)	(1.373)	(1.343)
Age 3 years	10.779	7.912	8.460	4.421	5.591	9.749	7.066
	(33.533)	(32.975)	(33.218)	(32.825)	(32.989)	(33.245)	(33.302)
Age 4 years	67.364	67.234	68.559	64.321	63.622	68.514	64.110
	(36.196)	(35.313)	(35.312)	(35.555)	(36.019)	(35.665)	(36.110)
Age 5 years	12.780	14.835	14.126	9.078	11.305	12.081	12.060
	(21.245)	(21.214)	(21.344)	(20.803)	(20.861)	(21.166)	(21.298)
Age 6 years	−17.168	−13.474	−13.217	−18.448	−17.769	−17.136	−17.402
	(17.891)	(17.665)	(17.725)	(17.605)	(17.550)	(18.135)	(17.616)
Age 7 years	−29.134	−26.927	−27.056	−30.305	−29.423	−29.075	−29.393
	(18.024)	(17.739)	(18.009)	(17.754)	(17.720)	(18.492)	(17.744)
Age 8 years	−21.957	−22.332	−21.612	−23.610	−23.096	−22.100	−23.302
	(18.979)	(18.752)	(18.982)	(18.626)	(18.622)	(19.210)	(18.713)
Age 9 years	−20.118	−18.513	−18.508	−21.083	−21.038	−19.152	−21.617
	(17.317)	(16.837)	(17.031)	(16.718)	(16.698)	(17.500)	(16.995)
Age 10+ years	−20.391	−17.552	−17.872	−21.517	−20.771	−19.643	−20.782
	(18.207)	(17.823)	(18.071)	(17.894)	(17.850)	(18.407)	(17.958)
R-squared	0.182	0.211	0.205	0.209	0.203	0.187	0.198
Observations	612	612	612	612	612	612	612

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 21 Set D: Net inflow on performance dummies

The table reports full regression output for Set D in Table 10, regression analyses of net inflow ($Inflow_t$) on different performance dummies: Excess returns ($\bar{r}^e$), active returns ($\bar{r}^a$), Sharpe ratio (SR), Treynor ratio (TR), Information ratio (IR), three–factor alpha (α) and t–statistic ($t(\alpha)$). The control variables are Industry Growth, Log(Assets), and dummy variables on fund age and month of observation. All dummy variables for fund age are included, hence the lack of an intercept. Newey–West heteroscedasticity and autocorrelation consistent standard errors are in parentheses, with stars representing significance levels.

	Mean returns		*Ratios*			*Three-factor model*	
	Excess	Active	SR	TR	IR	Alpha	t–stat
Top decile	2.353***	2.451***	2.318***	2.583***	2.335***	2.643***	2.326***
	(0.386)	(0.370)	(0.364)	(0.365)	(0.392)	(0.371)	(0.374)
9th decile	1.138***	1.122***	1.342***	1.529***	0.867**	0.706*	0.752*
	(0.344)	(0.324)	(0.327)	(0.337)	(0.334)	(0.302)	(0.332)
8th decile	0.791*	0.944**	0.603	0.811**	0.705*	1.022**	0.684*
	(0.319)	(0.327)	(0.333)	(0.296)	(0.337)	(0.323)	(0.314)
7th decile	0.340	0.469	−0.079	0.395	0.674*	0.670*	0.597*
	(0.309)	(0.277)	(0.295)	(0.295)	(0.328)	(0.270)	(0.296)
4th decile	−0.196	−0.078	−0.439	−0.049	−0.043	0.166	0.541*
	(0.279)	(0.269)	(0.235)	(0.249)	(0.278)	(0.258)	(0.267)
3rd decile	−0.486	0.136	−0.368	−0.116	0.154	−0.103	0.010
	(0.248)	(0.249)	(0.267)	(0.241)	(0.307)	(0.231)	(0.221)
2nd decile	−0.322	−0.316	−0.580*	−0.277	−0.287	0.066	−0.444
	(0.268)	(0.266)	(0.265)	(0.261)	(0.245)	(0.301)	(0.301)
Bottom decile	−1.423***	−1.258***	−1.157***	−0.947**	−0.731**	−1.062***	−0.705**
	(0.307)	(0.299)	(0.293)	(0.291)	(0.279)	(0.287)	(0.258)
Industry Growth	0.069***	0.068***	0.069***	0.069***	0.069***	0.069***	0.069***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Total Capital	0.083	0.088	0.096	0.096	0.137*	0.128*	0.160*
	(0.062)	(0.062)	(0.063)	(0.063)	(0.065)	(0.063)	(0.064)
Age 3 years	0.617	0.501	0.624	0.381	0.116	−0.098	−0.225
	(1.169)	(1.158)	(1.170)	(1.160)	(1.177)	(1.176)	(1.196)
Age 4 years	1.034	0.905	0.773	0.539	0.277	0.158	−0.116
	(1.061)	(1.062)	(1.075)	(1.066)	(1.089)	(1.075)	(1.089)
Age 5 years	−0.689	−0.917	−0.829	−1.019	−1.512	−1.343	−1.647
	(0.983)	(0.988)	(1.005)	(1.000)	(1.024)	(1.003)	(1.030)
Age 6 years	−1.495	−1.645	−1.705	−1.926	−2.400*	−2.199*	−2.635*
	(1.044)	(1.052)	(1.047)	(1.037)	(1.095)	(1.042)	(1.061)
Age 7 years	−1.966*	−2.135*	−2.126*	−2.312*	−2.749**	−2.766**	−3.113**
	(0.930)	(0.927)	(0.940)	(0.932)	(0.965)	(0.935)	(0.953)
Age 8 years	−1.395	−1.554	−1.380	−1.627	−2.151*	−2.136*	−2.409*
	(0.929)	(0.925)	(0.949)	(0.940)	(0.955)	(0.942)	(0.954)
Age 9 years	−2.037*	−2.215**	−2.054*	−2.301**	−2.823**	−2.825**	−3.145***
	(0.857)	(0.855)	(0.873)	(0.867)	(0.884)	(0.870)	(0.883)
Age 10+ years	−1.547	−1.764*	−1.680	−1.907*	−2.426**	−2.322**	−2.732**
	(0.875)	(0.874)	(0.894)	(0.888)	(0.905)	(0.892)	(0.905)
February	−0.348	−0.349	−0.352	−0.349	−0.348	−0.348	−0.347
	(0.301)	(0.302)	(0.302)	(0.302)	(0.302)	(0.302)	(0.303)
March	−0.592	−0.592	−0.596*	−0.593	−0.589	−0.592*	−0.587
	(0.303)	(0.303)	(0.303)	(0.303)	(0.302)	(0.302)	(0.302)
April	−0.453	−0.452	−0.455	−0.454	−0.452	−0.454	−0.451
	(0.329)	(0.329)	(0.331)	(0.330)	(0.329)	(0.331)	(0.331)
May	−0.900**	−0.899**	−0.901**	−0.899**	−0.894**	−0.900**	−0.895**
	(0.325)	(0.325)	(0.326)	(0.325)	(0.325)	(0.325)	(0.327)
June	−0.228	−0.227	−0.230	−0.228	−0.222	−0.227	−0.224
	(0.331)	(0.332)	(0.332)	(0.331)	(0.332)	(0.331)	(0.332)
July	−0.332	−0.331	−0.335	−0.332	−0.331	−0.332	−0.329
	(0.295)	(0.295)	(0.296)	(0.296)	(0.296)	(0.296)	(0.297)
August	0.091	0.092	0.089	0.092	0.092	0.091	0.092
	(0.318)	(0.317)	(0.318)	(0.318)	(0.317)	(0.319)	(0.319)
September	−0.223	−0.223	−0.226	−0.223	−0.221	−0.224	−0.220
	(0.314)	(0.315)	(0.315)	(0.315)	(0.315)	(0.315)	(0.316)
October	0.557	0.556	0.554	0.556	0.559	0.555	0.560
	(0.358)	(0.357)	(0.359)	(0.359)	(0.358)	(0.359)	(0.360)
November	−0.323	−0.324	−0.326	−0.323	−0.321	−0.324	−0.319
	(0.334)	(0.334)	(0.334)	(0.334)	(0.334)	(0.334)	(0.334)
December	0.951*	0.952*	0.950*	0.951*	0.952*	0.947*	0.952*
	(0.382)	(0.384)	(0.383)	(0.383)	(0.383)	(0.382)	(0.383)
R-squared	0.058	0.057	0.058	0.058	0.050	0.056	0.050
Observations	7422	7422	7422	7422	7422	7422	7422

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 22 Set E: Net inflow on performance dummies —annual data

The table reports full regression output for Set E in Table 10, regression analyses of net inflow ($Inflow_t$) on different performance dummies: Excess returns ($\bar{r}^e$), active returns ($\bar{r}^a$), Sharpe ratio (SR), Treynor ratio (TR), Information ratio (IR), three–factor alpha (α) and t–statistic ($t(\alpha)$). The control variables are Industry Growth, Log(Assets), and dummy variables on fund age and month of observation. All dummy variables for fund age are included, hence the lack of an intercept. Newey–West heteroscedasticity and autocorrelation consistent standard errors are in parentheses, with stars representing significance levels.

	Mean returns		*Ratios*			*Three-factor model*	
	Excess	Active	SR	TR	IR	Alpha	t–stat
Top decile	20.872**	32.465***	37.732***	25.707**	30.819***	35.010***	28.849***
	(7.856)	(8.710)	(8.954)	(8.389)	(8.017)	(8.837)	(8.106)
9th decile	10.520	25.439**	23.584**	22.521*	25.778**	13.261	20.536*
	(9.504)	(9.435)	(8.093)	(9.708)	(9.339)	(8.244)	(8.230)
8th decile	14.796*	13.176*	15.400*	9.126	5.029	9.765	11.915
	(6.823)	(6.411)	(6.886)	(5.935)	(6.596)	(7.122)	(6.863)
7th decile	10.071	−0.634	13.929	−4.081	4.689	11.691	5.612
	(6.737)	(5.575)	(7.092)	(7.183)	(6.750)	(6.869)	(6.260)
4th decile	−0.495	2.766	12.736*	−8.634	−2.537	1.584	9.045
	(6.134)	(6.067)	(6.033)	(4.999)	(5.975)	(6.017)	(7.956)
3rd decile	3.530	1.973	8.055	−2.670	3.197	1.422	−10.079
	(6.035)	(5.948)	(5.756)	(7.064)	(6.444)	(5.927)	(5.399)
2nd decile	−8.919	−11.704*	−5.645	−13.577**	−10.223*	−0.909	−3.542
	(4.752)	(5.300)	(4.783)	(5.120)	(5.035)	(6.384)	(5.471)
Bottom decile	−8.240	−10.600*	−7.894	−14.751**	−10.443*	−4.451	−9.739*
	(5.812)	(4.457)	(4.446)	(4.784)	(4.495)	(5.749)	(4.531)
Industry Growth	0.201**	0.202***	0.200***	0.204***	0.205***	0.203**	0.206***
	(0.062)	(0.059)	(0.060)	(0.061)	(0.060)	(0.062)	(0.061)
Total Capital	−0.009	−0.709	−0.927	−0.369	−0.368	−0.257	0.159
	(1.373)	(1.394)	(1.357)	(1.342)	(1.368)	(1.353)	(1.384)
Age 3 years	24.693	22.697	19.781	24.665	19.336	16.608	15.283
	(34.165)	(33.013)	(32.330)	(33.544)	(33.290)	(32.914)	(34.385)
Age 4 years	81.395*	84.149*	83.621*	83.710*	80.101*	79.643*	72.379*
	(36.498)	(35.291)	(34.925)	(35.719)	(36.144)	(36.181)	(36.482)
Age 5 years	26.816	32.470	29.812	31.226	30.362	25.028	23.093
	(21.516)	(21.439)	(21.051)	(21.252)	(21.538)	(20.941)	(22.835)
Age 6 years	−4.641	4.316	1.767	−0.180	−2.860	−7.215	−7.414
	(18.366)	(18.647)	(17.868)	(18.957)	(19.148)	(18.036)	(19.031)
Age 7 years	−16.205	−8.725	−11.778	−9.216	−13.162	−14.858	−19.330
	(18.396)	(18.359)	(18.214)	(18.810)	(19.051)	(18.560)	(19.239)
Age 8 years	−9.285	−3.395	−2.903	−2.208	−5.077	−9.294	−13.309
	(19.418)	(19.261)	(19.025)	(19.656)	(19.637)	(18.963)	(20.089)
Age 9 years	−9.029	0.442	−1.338	1.281	−2.857	−6.005	−11.932
	(17.613)	(17.871)	(17.443)	(17.704)	(17.777)	(17.365)	(18.355)
Age 10+ years	−7.521	0.819	−0.881	0.395	−2.970	−6.639	−10.448
	(18.778)	(18.830)	(18.222)	(19.046)	(19.165)	(18.274)	(19.611)
R-squared	0.187	0.225	0.222	0.219	0.218	0.200	0.209
Observations	612	612	612	612	612	612	612

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$