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Investor Sophistication

Empirical Analysis of Capital Allocation Decisions of Norwegian Mutual Fund Investors

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Abstract

Whether mutual fund investors act rationally when making capital allocation decision has for long time been one of the key topics in the mutual fund literature. This paper is one of the first attempts to assess investor sophistication in the Norwegian mutual fund market. Using a sample of Norwegian mutual funds in the time period 1996-2018 we find that Norwegian investors do not account for the common risk factors and in fact follow simple signals such as Morningstar ratings when making their investment decisions. We show evidence that Morningstar ratings account only for a very small percentage of funds' volatility and, thus, investments in high-rated funds are unlikely to be motivated by investors' willingness to outsource risk adjustment to Morningstar. Finally, we show that by investing into high-rated funds investors expose themselves to the risk that they are not compensated for. Our findings suggest that Norwegian mutual fund investors are unlikely to be sophisticated.

Keywords: Mutual funds, investor sophistication, Morningstar ratings, fund flows, Norway

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1. Introduction

Whether mutual fund investors act rationally when making capital allocation decisions has for long time been one of the key topics in the mutual fund literature. The two recent papers (Barber, Huang, and Odean (2016) and Berk and van Binsbergen (2016)) try to shed light on the asset pricing models that investors use when evaluating funds. Barber, Huang, and Odean (2016) find that investors account the most for the market risk and, thus, use a model similar to the CAPM when making investment decisions. The fact that they do not account for other risk factors to the same extent is used as evidence that investors are unlikely to be sophisticated. Similarly, Berk and van Binsbergen (2016) conclude that the CAPM is the model that describes investors' decisions (proxied by fund flows) the best. An interesting contribution to the two of the above-mentioned papers is made by Ben-David et al. (2019) who test whether investors also follow simple signals such as Morningstar ratings. When conducting their analysis for the US market, the authors find that Morningstar ratings can explain capital allocation decisions of investors much better than the commonly used asset pricing models.

Building on the methodology from Barber, Huang, and Odean (2016), Berk and van Binsbergen (2016) and Ben-David et al. (2019), in this paper we assess sophistication of Norwegian mutual fund investors (for expositional ease, we define sophisticated investors as investors who account for the common risk factors) by testing whether they follow unadjusted fund returns, Morningstar ratings or alphas. We also explore whether there is any significant effect on the financial wealth of investors who follow these signals.

In order to answer our research question, we go through the following key steps. We first assess whether investors account for alphas or the common return components when making capital allocation decisions (using a sample of Norwegian mutual funds for the time period 1996-2018). For this purpose, we employ the test of Barber, Huang, and Odean (2016), which allows us to model the relationship between fund flows, alphas and the common return components. Further, we compare Morningstar ratings with the common asset pricing models and market-adjusted fund returns in terms of their ability to explain fund flows. We use the approach of Berk and van Binsbergen (2016) and Ben-David et al. (2019) where we measure the frequency with which the signs of alphas or rating-related variables match the signs of fund flows. As our next step, we explore the extent to which the model that explains fund flows the best (from the previous step) can account for funds' risk. Finally, we estimate the effect of following that model on investors' financial wealth (we do so by analyzing total shareholder returns and alphas).

As mentioned before, we start our analysis by conducting the test of Barber, Huang, and Odean (2016) where we analyze, which risk factors investors account for. We find that investors, on aggregate, account the most for alpha and load positively on the momentum and liquidity factors. On the contrary to Barber, Huang, and Odean (2016), we show that there is no discounting of the market factor, which the authors use as evidence that investors utilize the CAPM model when making capital allocation decisions. Using the bootstrapping technique as suggested by Ben-David et al. (2019), we confirm that the coefficients in the panel regression show up mechanically due to the flow-performance sensitivity characteristics and, thus, we cannot reject the hypothesis that investors chase unadjusted fund returns. The findings of the test do not allow us to tell whether Norwegian mutual fund investors are sophisticated or not.

In addition to alphas and the common return components investors might also react to simple signals available in the market. In order to account for this and to overcome the limitations of the Barber, Huang, and Odean (2016) test, which does not allow us to make a conclusion with regards to investor sophistication, we employ the combination of tests of Berk and van Binsbergen (2016) and Ben-David et al. (2019). These tests allow us to look at the direction of fund flows in response to various signals: alphas of the commonly used asset pricing models and Morningstar ratings. We find that the signs of flows are predicted much better by Morningstar ratings compared to the asset pricing models used (the CAPM, the Fama-French three-factor model, the Carhart four-factor model and the five-factor model) or market-adjusted returns. Our results suggest that high-rated funds predict positive flows in the next month in 63.99% of the cases compared to 59.23% for the best-performing asset pricing model (the five-factor model).

As a robustness check we also conduct pairwise comparison between each of the models, which confirms our initial findings: ratings outperform all of the asset pricing models in terms of explanatory power. We also find that the spread between the percentage of positive flows of top- and bottom-ranked funds based on Morningstar ratings is 50.21% compared to 42.20% for the five-factor model (the best performing asset pricing model). Similarly, we find that Morningstar ratings outperform all of the asset pricing models by generating the largest spreads between top- and bottom-ranked funds in terms of average monthly fund flows (as percentage of total net assets) and average monthly fund flows in Norwegian Kroner.

Having found that investors follow Morningstar ratings, we explore whether it is rational for them to do so. One of the potential reasons to follow Morningstar ratings might be risk adjustment. Investors might believe that assessment of mutual funds' risk on their own is costly. Since Morningstar ratings are free, investors might follow them in order to outsource risk adjustment to Morningstar. However, our findings suggest that Morningstar ratings account only for a very small amount of the total variation in fund returns (around 3.6%) and, thus, following them as a means of risk adjustment outsourcing might be inefficient. This also serves as another piece of evidence that Norwegian mutual fund investors are unlikely to be sophisticated on aggregate.

Finally, we explore the effect of following various signals (Morningstar ratings and alphas) on the wealth of Norwegian mutual fund investors. Our analysis suggests that high-rated funds (as classified by Morningstar ratings) generate higher total shareholder returns compared to low-rated ones in the next one, two and three months. However, after accounting for risk (by calculating alphas using various asset pricing models within the groups of high- and low-rated funds), we find evidence of low-rated funds outperforming high-rated ones. We find that the difference in their performance lies in the exposure of these two groups to various risk factors. Low-rated funds load more on smaller stocks compared to high-rated funds. Moreover, they have a negative momentum loading (while the loading of high-rated funds is statistically insignificant).

Overall, our results suggest that Norwegian mutual fund investors are unlikely to be sophisticated on aggregate. When making their capital allocation decisions Norwegian investors seem to follow simple signals such as Morningstar ratings and unadjusted fund returns. At the same time, we could not find any evidence that they account for the common risk factors. Moreover, we find it unlikely that Norwegian mutual fund investors follow Morningstar ratings as a means of delegating risk adjustment to Morningstar as Morningstar ratings account only for a very small percentage of funds' return volatility. We also provide evidence that by following Morningstar ratings, investors are also worse off in terms of risk-adjusted returns.

Our paper contributes to the existing literature in a number of ways. First of all, it is one of the first attempts to assess investor sophistication in the Norwegian mutual fund market. The approach that we employ was previously used for the US market, which has fundamental differences from the Norwegian one. Specifically, the Norwegian mutual fund market is dominated by institutional investors (in 2019 only 21% of the assets of mutual funds belonged to retail investors (VFF, n.d.)) as opposed to the US market, where retail investors hold 89% of the net assets of mutual funds (Investment Company Institute, 2020). A higher share of professional investors in the Norwegian market might be interpreted as evidence of higher investor sophistication on aggregate. Despite the higher share of professional investors represented in the Norwegian mutual fund market, similarly to Ben-David et al. (2019) (who analyzed the US market), we find that simple signals such as Morningstar ratings explain capital allocation decisions of Norwegian mutual fund investors better than the common asset pricing models. We expand the scope of the analysis of Ben-David et al. (2019) by assessing the effect of following Morningstar ratings on investors' financial wealth (proxied by total shareholder returns and alphas), which is another contribution of our paper. Finally, we provide evidence that Morningstar ratings have some predictive power in the short term when it comes to total shareholder returns, which contributes to the academic debate on the ability of simple signals (ratings) to predict funds' future performance.

Our paper is structured in the following way. Section 2 discusses the relevant literature on mutual funds and investor sophistication. In Section 3 we describe our dataset and provide summary statistics. We then present methodology, empirical analysis and results in Section 4. Section 5 summarizes the key findings as well as discusses limitations of the paper and ideas for further research.

2. Literature Review

The global mutual fund industry has seen a dramatic growth since the end of the 20th century. Only in the most recent period (2010-2019) the net assets of global open-ended regulated mutual funds have soared by 89% (from $29.1 trillion up to $54.9 trillion) (Investment Company Institute, 2020). The ever-increasing size of the industry has attracted many researchers to explore the performance of mutual funds and its determinants. Jensen (1968), Elton et al. (1993), Elton et al. (1996), Malkiel (1995) and Gruber (1996) find evidence that mutual funds cannot outperform passive indices. At the same time, Ippolito (1992), Sirri and Tufano (1998), Chevalier and Ellison (1997) show that investors channel their money into funds with positive recent performance and do so faster than they withdraw money from funds with poor recent performance. These findings might suggest that investors do not act rationally as many researchers (Jensen (1969), Malkiel (1995), Jain and Wu (2000)) do not find evidence of funds' performance persistence. The absence of consensus with regards to why this phenomenon is observed in the market led to studies on investor sophistication.

Berk and Green (2004) hypothesize that investors might try to allocate their capital into funds, whose managers possess extraordinary fund picking skills and, thus, would oftentimes invest in funds with high past returns. At the same time, Berk and Green (2004) suggest that investment strategies of mutual funds might be difficult to scale, and, thus, with the growth in the amount of assets under management (AUM), the lack of performance persistence might be observed.

A number of researchers analyze fund flows as a proxy for investors sentiment (for example, Brown et al. (2003) show that mutual fund flows are a good proxy for investor sentiment in the USA and Japan) and try to find what investors base their capital allocation decisions on. One group of studies examine whether investors use one of the common asset pricing models when making investment decisions. Barber, Huang, and Odean (2016) decompose fund returns into components (alpha and factor-related returns) and analyze the extent to which investors account for them (proxied by fund flows). The authors suggest that a lower regression coefficient on a certain return component implies that investors (on aggregate) account for it the most. Using a sample of the US equity mutual funds for the time period 1996-2011, Barber, Huang, and Odean (2016) find that fund flows respond less to the changes in the market component. The authors use this finding as evidence that investors employ the CAPM when evaluating funds. Berk and van Binsbergen (2016) also explore the asset pricing models that the US investors use when making investment decisions, however, they do it in a different way. The authors assess the performance of an asset-pricing model by computing how frequently the signs of its alpha match the signs of flows to mutual funds. The model that explains the flow-alpha relationship most accurately (shows the best match) is considered to be the closest to the true asset pricing model used by investors. Similarly to Barber, Huang, and Odean (2016), Berk and van Binsbergen (2016) conclude that the CAPM is the model that can best describe investors' decisions.

Ben-David et al. (2019) contribute to the two of the abovementioned papers by including simple signals such as Morningstar ratings in the analysis. The authors reevaluate the findings of Barber, Huang, and Odean (2016) and Berk and van Binsbergen (2016) and find that Morningstar ratings outperform all of the commonly used asset pricing models in terms of their ability to predict investors' capital allocation decisions. This result is in line with the findings of Evans and Sun (2018) who show that the average retail investor follows third party ratings (specifically, Morningstar ratings) and not asset pricing models when making investment decisions. Ratings as an important determinant of mutual fund flows have also been examined in earlier studies. For example, Guercio and Tkac (2008) use an event-study approach on more than 10,000 Morningstar rating changes and show that Morningstar ratings have a significant independent effect on mutual fund flows: an increase in ratings leads to abnormal inflows while a decrease in ratings causes abnormal outflows.

Similarly to the studies mentioned above (Guercio and Tkac (2008), Evans and Sun (2018), Ben-David et al. (2019)), in our paper we find that Morningstar ratings explain investment decisions of Norwegian mutual fund investors better than the common asset pricing models.

We then explore whether investors' capital allocation decisions based on Morningstar ratings have any effect on their financial wealth. There are several studies that investigate whether Morningstar star ratings can predict funds' future performance. Morey and Gottesman (2006) using the data for the US mutual funds show that high-rated funds significantly outperform low-rated ones. Similarly, a recent study conducted by Morningstar (Davidson et al., 2016) shows that Morningstar ratings do have "moderate predictive power" in the short term.

In contrast, Philips and Kinniry (2010) find that mutual fund ratings give very little information about future performance. Huebscher (2009) concludes that Morningstar ratings do not have any predictive ability when measured over a full market cycle.

In line with Morey and Gottesman (2006) and Davidson et al. (2016), we find that Morningstar ratings have some predictive ability over the future performance of the Norwegian mutual funds in the short term: high-rated funds outperform low-rated ones in terms of total shareholder returns (unadjusted returns). However, after accounting for risk (by calculating alphas using various asset pricing models within the groups of high- and low-rated funds) we find evidence of low-rated funds outperforming high-rated ones, which is in contrast with the abovementioned studies.

Overall, most of the literature on mutual funds focuses on the US market. Previous research on the Norwegian mutual fund market is, however, sparse. One of the few papers that examine the performance of Norwegian mutual funds is Sørensen (2009). The author studies Norwegian equity mutual funds from 1982 to 2008. While using the risk-adjusted return (alpha) as a performance measure, Sørensen (2009) finds no evidence of abnormal performance or performance persistence. On the other hand, Gallefoss et al. (2015), using daily data of Norwegian mutual funds over the period 2000-2010, finds that mutual funds underperform the benchmark (Oslo Stock Exchange All-Share Index) by about the management fees. On the contrary to Sørensen (2009), the authors show that there exists short-term (up to one year) performance persistence among Norwegian mutual funds. Research on investor sophistication in the Norwegian mutual fund market is limited. To our knowledge, our paper is one of the first attempts to assess whether Norwegian mutual fund investors act rationally when making their capital allocation decisions.

3. Data

3.1 Sample Selection and Variables Description

Our dataset includes fund-month observations on 68 Norwegian mutual funds (84 share classes) over the period January 1996 - December 2018. This time span is chosen due to the availability of data reasons. In our analysis we look at Morningstar ratings, which first became available for Norwegian mutual funds in 2001. In order to estimate alphas for various asset pricing models, we use 60 months of lags, which requires data starting from 1996. At the moment of data collection, the data for the Fama-French three factors, the Carhart Momentum factor, as well as for the liquidity factor, was available up until December 2018. This date, thus, becomes the upper bound for the time span analyzed.

All funds included in our dataset are open-ended equity mutual funds with at least 70% of equity being invested in Norway and which are available for sale in Norway. Moreover, all of them are actively managed Norwegian mutual funds (we do not include index funds, ETFs or balanced funds). We also do not include foreign funds in order to avoid problems with choosing the correct benchmark for performance comparison (not having foreign mutual funds in our dataset allows us to use one benchmark index as a proxy for the Norwegian market). In order to avoid survivorship bias in our dataset, we include all of the funds that existed over the time period analyzed.

We obtain data on funds' monthly returns, monthly Morningstar ratings, net flows (in NOK), inception date, fund net expense ratio, monthly net assets as well as information whether the fund was a no-load fund or not from the Morningstar Direct database.

<u>Funds' monthly returns</u>

Funds' monthly returns are calculated by Morningstar using the changes in monthly Net Asset Values (NAV) under the assumption that funds reinvest all of their income as well as their capital-gain distributions (Morningstar, 2020). Fund expenses such as management and administrative fees are subtracted from monthly returns, however, sales charges, which are usually more sporadic compared to the abovementioned fees, are not.

Net flows

Net flows are cash flows (represented in Norwegian Kroner) calculated using the changes in net asset values and monthly returns. Following the common practices in literature on fund flows, we also calculate monthly percentage flows using the following formula:

$$F_{p,t} = \frac{TNA_{p,t}}{TNA_{p,t-1}} - (1 + R_{p,t}), \quad (1)$$

where $F_{p,t}$ is the percentage flow of fund p in month t, $TNA_{p,t}$ and $TNA_{p,t-1}$ are total net assets of fund p in month t and month t-1, respectively, $R_{p,t}$ is the monthly return of fund p in month t.

To preclude the influence of outliers that can distort the results of the regressions significantly, we winsorize percentage flows at 0.1 and 99.9 percentiles and also set the upper bound at 100%. The existence of outliers might be explained by the fact that there are some "young" funds in our sample whose percentage flows in the first months of operations might be extremely high.

Morningstar ratings

Morningstar ratings is a rating system that evaluates mutual funds relative to each other (within categories) and assigns them a rating from one to five stars based on their past performance (five stars represent the rating for the best-performing funds). According to Morningstar (2016), ratings are assigned based on funds' Morningstar risk-adjusted return (MRAR), which is calculated in the following way:

$$MRAR\ (\lambda) = \left[\frac{1}{T}\sum_{t=1}^{T}(1 + ER_{p,t})^{-\lambda}\right]^{\frac{-12}{\lambda}} - 1 \quad (2)$$

where $ER_{p,t}$ is the excess return of fund p in month t (calculated using the formula $ER_{p,t} = \frac{1+TR_{p,t}}{1+RF_t} - 1$), $TR_{p,t}$ is the total return for fund p in month t, RF_t – the risk-free rate in month t and λ represents the degree of investors' risk aversion (assumed to be 2 by Morningstar).

The risk aversion coefficient of 2 allows to take into account volatility in returns, however, it is important to note that MRAR does not account for any risk components. Further, MRAR is adjusted for sales charges and redemption fees. Since they can differ even within the same fund, Morningstar ratings are assigned on a share class basis.

Mutual funds are then compared within various categories (for example, international mid-cap growth equities, US small blend equities, etc.) based on their MRAR. Each month the top 10% of funds within each of the Morningstar categories receive a five-star rating, the next 22.5% receive a rating of four stars, subsequent 35%, 22.5% and 10% receive three, two and one stars, respectively. In order to be assigned a rating, a fund should have at least 3 years of return observations. The overall rating is a weighted Morningstar rating calculated using ratings estimated over 3-, 5- and 10-year periods. If a fund has less than 5 years of return observations, its total rating is based on the 3-year rating. For funds that have more than 5 years but less than 10 years of return observations the total rating is calculated using both the 3-year and 5-year ratings (60% weight is assigned to the 5-year rating and 40% weight is assigned to the 3-year rating). Finally, if a fund has more than 10 years of return observations, it receives its total rating based on the 3-, 5- and 10-year ratings (50% weight for the 10-year rating, 30% weight for the 5-year rating and 20% weight for the 3-year rating).

Fund age

For each share class of fund p and each month t, fund age is calculated as the number of months between month t and the share class inception date.

Monthly net assets

Monthly net assets are monthly Net Assets Values (NAV) as calculated by Morningstar. To preclude the influence of outliers, we drop observations of monthly net assets if they are below 1 million NOK.

No-load funds

Our dataset includes a no-load binary variable, which takes a value of 1 if the fund does not charge their investors sales charges or commissions and 0 otherwise.

Net expense ratio

We also obtain data on annual fund net expense ratios, which we divide by 12 to arrive at monthly ones. Barber, Huang, and Odean (2016) – the paper the methodology of which we partly employ in our analysis - use the gross expense ratio. Due to unavailability of the gross expense ratio for Norwegian mutual funds in the Morningstar Direct database, we use the net expense ratio in the analysis. The net expense ratio, as opposed to the gross expense one, is collected after fees reimbursement. In many cases the net expense ratio is equal to the gross expense one as reimbursement of fees does not occur on a regular basis for most of the funds.

Asset pricing factors

In order to estimate the Fama-French three-factor model, the Carhart four-factor model as well as the five-factor model for Norway, we extract the Fama-French, Carhart and liquidity factors from the website of Professor Bernt Arne Ødegaard (Ødegaard, n.d.), who estimated them for the Norwegian market. At the moment of data collection, the data on the factors was available until December 2018, which, as mentioned before, was chosen as the upper bound for the time span of our analysis.

In our analysis, in addition to the Fama-French three-factor (market, size and value factors) and the Carhart four-factor (market, size, value and momentum factors) models we also use the five-factor model, where the liquidity factor is included. Næs, Skjeltorp and Ødegaard (2009) who did an extensive research on stock pricing on the Oslo Stock Exchange, argue that the liquidity component together with the market and size components are the best at explaining the returns of stocks represented there.

Risk-free rate

The risk-free rate for the Norwegian market is extrapolated from the monthly NIBOR rate. NIBOR is the Norwegian Interbank Offered Rate that represents the rate at which Norwegian banks agree to lend to each other in Norwegian Kroner for different maturities (Finans Norge, n.d.). As argued by Ødegaard (2020), the NIBOR rate serves as the best proxy for the risk-free rate in Norway since Norwegian bills and bonds are not very liquid. The monthly risk-free rate is extrapolated using the following formula:

$$r_{f,t} = \left(1 + r_{annual}^{NIBOR,1m}\right)^{1/12} - 1, \tag{3}$$

where $r_{f,t}$ is the monthly risk-free rate at time t and $r_{annual}^{NIBOR,1m}$ is the annualized monthly NIBOR rate at time t.

Market index

In order to calculate market returns and use them in our analysis, we have to select the correct proxy for the Norwegian market. Oftentimes stock indices that represent a large share of the stock market (such as S&P500 for the US market) are used for this purpose. In the case of Norway, the best proxy for the mutual fund market is the OSEFX index (Oslo Stock Exchange Mutual Fund Index). This index includes the majority of Norwegian equity mutual funds and, thus, can serve as a proxy for the market in our analysis.

In our paper we do not aggregate share classes by fund as was done by Barber, Huang, and Odean (2016). The authors argue that various share classes offered by funds are oftentimes exposed to the same exact portfolio of stocks with the only difference between them being fees charged. It is important to note that Barber, Huang, and Odean (2016) perform their analysis for the US market having 3,432 mutual funds in the dataset. Having a small number of funds in our dataset due to the small size of the Norwegian market (84 share classes and 68 funds), it is not feasible to aggregate share classes as doing so would significantly decrease the dataset and the number of observations. Moreover, we believe that doing so would eliminate variance in fund ratings over time. Our dataset shows that in many cases various share classes of the same fund get different Morningstar ratings and, thus, not accounting for this variation would lead to a decrease in explanatory power of variables that we use in our analysis.

3.2 Descriptive Statistics

As was mentioned before, our dataset consists of fund-month observations for 84 Norwegian mutual funds share classes over the period January 1996 - December 2018. Panel A of Table 1 provides summary statistics such as mean, standard deviation, minimum and maximum values for the full sample. The average monthly fund flow is 0.96%. The minimum value of monthly fund flows is negative and equals to -88.10% while the maximum value is 100% (the threshold, at which the variable was winsorized). Monthly fund flows in NOK also vary a lot: from -2.26 billion NOK to 5.4 billion NOK. With regards to fund size, the largest fund in our dataset has net assets of 18.2 billion NOK while the smallest fund has net assets of 1 million NOK (this limit was set during the dataset construction). The average fund size is 1.16 billion NOK and the standard deviation is 1.77 billion NOK. Furthermore, the average fund age exceeds twelve years (143.14 months) and the standard deviation is approximately 8.5 years (102.51 months).

Monthly fund returns vary from -30.06% to 41.77%, with the average of 0.95%. When we adjust monthly returns using the 14-lag decay function (as described in Section 4.1.1), we observe a smaller difference between the minimum and maximum values: weighted past returns vary from -16.99% to 18.36%. As a measure of fund performance, we use exponential-weighted alphas estimated prior to time t using different asset pricing models and adjusted for 14 lags. The average weighted past alphas for three of the four asset pricing models (the Fama-French three-factor, the Carhart four-factor and the five-factor model) are negative (-0.04%, -0.04% and -0.03%, respectively).

Table 1. Descriptive statistics of the Norwegian mutual fund sample

This table provides summary statistics for the sample of Norwegian mutual funds over the period 1996-2018. All variables are measured on a monthly basis. Weighted returns and weighted alphas are estimated using the exponential-decay function (Equation 12) with a decay parameter lambda (0.4329) and 14 lags of returns or alphas, respectively (see Section 4.1.1). For ease of interpretation, returns and alphas are reported in percent. Monthly returns (extracted from the Morningstar database) represent the changes in monthly Net Asset Values (NAV). Percentage fund flow is calculated as the change in total net assets from month t-1 to month t adjusted for fund return in month t. Fund size is measured as the net assets of a mutual fund. Fund age, as mentioned in Section 3.1, is calculated as the number of months a fund share class has been operating since its inception date. Market adjusted return is the difference between the fund's return and the market return in the same month. Panel A presents descriptive statistics across fund-month observations. Panel B provides summary statistics for the Norwegian mutual funds that are grouped based on their Morningstar rating at the beginning of the month.

Panel A: Fund characteristics

	Mean	SD	Min	Max	N
	(1)	(2)	(3)	(4)	(5)
Fund flow (%)	0.96	11.14	-88.10	100.00	7 027
Fund flow (million NOK)	2	127	-2 260	5 400	7 054
Fund size (million NOK)	1 160	1 770	1	18 200	7 320
Monthly return (%)	0.95	6.14	-30.06	41.77	12 208
Weighted past return (%)	0.97	3.27	-16.99	18.36	11 250
Market-adjusted return (%)	0.03	0.93	-4.95	14.97	11 250
Fund age (months)	143.14	102.51	1.00	626.00	13 252
Weighted past CAPM alpha (%)	0.06	0.33	-2.21	2.35	12 149
Weighted past FF three-factor alpha (%)	-0.04	0.41	-8.61	9.07	12 149
Weighted past Carhart four-factor alpha (%)	-0.04	0.36	-5.68	3.15	12 149
Weighted past five-factor alpha (%)	-0.03	0.35	-6.65	4.04	12 149

Panel B. Descriptive statistics of mutual funds, grouped by Morningstar ratings

	1 star	2 stars	3 stars	4 stars	5 stars
	(1)	(2)	(3)	(4)	(5)
Number of fund-month observations	449	1403	2353	2421	653
Average net assets (million NOK)	361	924	1 470	1 470	1 040
Average fund flow (%)	-0.89	-0.46	-0.21	-0.94	3.71
Average fund flow (million NOK)	-2.36	-5.80	-4.52	6.26	19.20
Fraction of positive flows (%)	20.22	26.78	38.19	50.98	70.43
Average monthly return (%)	1.12	0.91	0.95	0.99	1.33
Average weighted past return (%)	1.07	0.88	1.01	1.04	1.30

Panel B presents descriptive statistics for the Norwegian mutual funds that are grouped based on their Morningstar rating at the beginning of each month. Funds rated with one star and two stars have the lowest average net assets: 361 and 924 million NOK, respectively. Funds rated with three and four stars have the highest average net assets: 1.47 billion NOK in both cases. The average fund flow in NOK is the largest for funds rated with four and five stars (6.26 and 19.2 million NOK, respectively), while funds rated with two and three stars receive the lowest average fund flows (-5.8 and -4.52 million NOK, respectively). Furthermore, the fraction of funds with positive flows increases with higher ratings – from 20.22% for the one-star rating to 70.43% for the five-star rating. This might be explained by the fact that Norwegian investors follow Morningstar ratings and allocate their capital to high-rated funds and withdraw their money from low-rated ones. Average weighted past return varies between 0.88% and 1.30%.

4. Empirical Analysis

In this section of the paper we present the methodology and the analysis employed. We start by estimating alphas using the common asset pricing models: the Fama-French three-factor model, the Carhart four-factor model and the five-factor model (Section 4.1). In Section 4.2 we employ the test of Barber, Huang, and Odean (2016) to assess how Norwegian mutual fund investors treat alphas and various fund return components. In the next step of our analysis, we run the test of Berk and van Binsbergen (2016), where we compare Morningstar ratings, asset pricing models and market-adjusted fund returns in terms of their ability to predict fund flows (Section 4.3). In Section 4.4 we look at the ability of Morningstar ratings to account for funds' risk. Finally, in Section 4.5 we estimate the effect of following Morningstar ratings on investors' wealth.

4.1 Alpha Estimation

In order to understand whether Norwegian mutual fund investors are "sophisticated" or not, we explore, which signals they are taking into consideration when making investment decisions. We want to distinguish between the two main signals: signals related to Morningstar ratings and signals related to various asset pricing models. In the previous sections of the paper we have discussed in detail Morningstar ratings, their calculation and meaning. In this section we explore signals related to various asset pricing models. The main signal related to asset pricing models is alpha. According to Jensen (1968), alpha represents outperformance of a certain fund or stock compared to the selected benchmark.

In order to estimate alphas of Norwegian mutual funds using common asset pricing models, we employ the approach used by Barber, Huang, and Odean (2016) and Ben-David et al. (2019). For each fund p in month t we run a time-series regression using 60 lags (from month t-60 to month t-1) of its monthly returns and risk factors (for factor models).

When calculating alphas for the CAPM, we estimate the following regression:

$$R_{p,\tau} - Rf_{\tau} = \alpha_{p,t}^{CAPM} + b_{p,t}(MKT_{\tau} - Rf_{\tau}) + \varepsilon_{p,\tau},$$

$$\tau = t - 60, \dots, t - 1 \qquad (4)$$

where $R_{p,\tau}$ is the monthly return of fund p at time τ, Rf_τ is the monthly risk-free rate at time τ, MKT_τ is the market return at time τ, $MKT_\tau - Rf_\tau$ represents the market risk premium. Alpha is the intercept of the regression.

A positive alpha implies that the fund earns a return higher than what the CAPM says is the correct return given the fund´s systematic risk. A positive alpha means that funds are able to outperform the market, while a negative one implies underperformance.

Although the single-factor model is a very important tool for performance evaluation, there are many studies (for example, Fama and French (1993), Elton et al. (1993), Carhart (1997)) that show that one (single) factor is not enough to explain mutual funds' performance, and, therefore, other factors should also be considered.

One of the several multi-factor models that are used in our analysis is the Fama-French three-factor model, which, in addition to the market risk, also accounts for the two firm characteristics - size and value. When calculating alphas for the Fama-French three-factor model, we run the following regression (similar to Equation 4):

$$R_{p,\tau} - Rf_\tau = \alpha_{p,t}^{FF\ 3F} + b_{p,t}(MKT_\tau - Rf_\tau) + s_{p,t}SMB_\tau + h_{p,t}HML_\tau + \varepsilon_{p,\tau},$$

$$\tau = t - 60, \dots, t - 1 \tag{5}$$

where SMB_τ is the size factor at time τ and HML_τ is the value factor at time τ.

Another multi-factor model is the Carhart four-factor model, which, in addition to all of the factors included in the Fama-French three-factor model, also accounts for the momentum factor. The Carhart four-factor model is estimated in the following way:

$$R_{p,\tau} - Rf_\tau = \alpha_{p,t}^{Carhart\ 4F} + b_{p,t}(MKT_\tau - Rf_\tau) + s_{p,t}SMB_\tau + h_{p,t}HML_\tau + p_{p,t}PR1YR_\tau + \\ + \varepsilon_{p,\tau},$$

$$\tau = t - 60, \dots, t - 1 \tag{6}$$

where $PR1YR_\tau$ is the momentum factor at time τ.

In addition to all of the asset pricing models described above, we also use the five-factor model. The five-factor model uses the liquidity factor in addition to the four risk factors used in the Carhart four-factor model. Næs, Skjeltorp and Ødegaard (2009) analyze the determinants of returns at the Oslo Stock Exchange from 1980 to 2006 and find that the liquidity factor plays a significant role in explaining cross-sectional variation of Norwegian stock returns.

When calculating alphas for the five-factor model, we estimate the following regression:

$$R_{p,\tau} - Rf_{\tau} = \alpha_{p,t}^{5F} + b_{p,t}(MKT_{\tau} - Rf_{\tau}) + s_{p,t}SMB_{\tau} + h_{p,t}HML_{\tau} + p_{p,t}PR1YR_{\tau} + \\ + l_{p,t}LIQ_{\tau} + \varepsilon_{p,\tau},$$

$$\tau = t - 60, \dots, t - 1 \tag{7}$$

where LIQ_{τ} is the liquidity factor at time τ.

Similarly to Barber, Huang, and Odean (2016), we estimate alpha coefficients in the following way:

$$\widehat{\alpha_{p,t}^{5F}} = R_{p,t} - Rf_t - \left[\widehat{b_{p,t}}(MKT_t - Rf_t) + \widehat{s_{p,t}}SMB_t + \widehat{h_{p,t}}HML_t + \widehat{p_{p,t}}PR1YR_t + \widehat{l_{p,t}}LIQ_t\right], \tag{8}$$

where $\widehat{b_{p,t}}$, $\widehat{s_{p,t}}$, $\widehat{h_{p,t}}$, $\widehat{p_{p,t}}$, $\widehat{l_{p,t}}$ are estimated coefficients from the previous regression (Equation 7).

We use the same approach to estimate alphas for the Capital Asset Pricing Model (CAPM), the Fama-French three-factor model and the Carhart four-factor model

In our analysis we also use the market-adjusted return, which is calculated as the difference between the fund's return and the market return in the same month. In this case we treat the abnormal return as a signal (in the absence of alpha):

$$MAR = R_{p,t} - MKT_t \tag{9}$$

4.1.1 Exponential-Decay Adjustment

Coval and Stafford (2007) argue that investors react not only to funds' most recent returns, but also to historical ones. This implies that a model that accounts for historical alphas is needed. We follow the approach of Barber, Huang, and Odean (2016) to determine the number of lags of alphas that Norwegian investors account for. We start by estimating the following regression:

$$F_{p,t} = a + \sum_{s=1}^{14} b_s MAR_{p,t-s} + cX_{p,t} + \mu_t + \varepsilon_{p,t}, \tag{10}$$

where $F_{p,t}$ is the percentage flow of fund p in month t, $MAR_{p,t-s}$ is the market-adjusted return of fund p at time t-s, $X_{p,t}$ is a matrix of control variables and μ_t are time-fixed effects. Control variables $X_{p,t}$ include fund flow from time t-15 (in the case of 14 lags of MAR), lagged net expense ratio, binary variable for no-load funds, standard deviation of fund returns over the past 60 months, the lag of logarithm of fund size, as well as the lag of logarithm of fund age. In order to avoid short-term bias and similarly to Ben-David et al. (2019), we calculate funds' return standard deviation over the past 60 months (contrary to Barber, Huang, and Odean (2016) who use 12 months).

We start by running the above-mentioned regression while changing the number of lags of market-adjusted returns from 1 to 24. We then compare models with different numbers of lags using the Akaike Information Criterion (AIC). AIC is an estimator that allows to compare the quality of various econometric models based on the amount of information lost by each of the models compared. The model with the lowest AIC value is considered to be dominating the other models analyzed. In our case we decide on a model with 14 lags as it is the one that generates the lowest AIC value.

In the next step we analyze the way Norwegian investors treat historical returns of mutual funds. It is unlikely that investors base their investment decisions only on the most recent returns as they are oftentimes noisy and might be outliers compared to the returns that funds generate on a regular basis. A reasonable assumption to make here is that investors assign more value to the most recent returns and treat historical returns as less informative the more in the past they go. Another assumption is that the relationship between the informativeness of returns and the date when they were realized is nonlinear. The closer the returns are to the today's date the more marginally informative they are likely to be. In order to model this relationship, we employ an exponential model.

We estimate a non-linear (exponential) restricted model of the following form using 14 lags of returns:

$$F_{p,t} = a + b \sum_{s=1}^{14} e^{-\lambda(s-1)} MAR_{p,t-s} + cX_{p,t} + \mu_t + \varepsilon_{p,t} \, , \tag{11}$$

By having a restricted non-linear model, we are able to estimate both the b coefficient and the decay parameter λ, which represents the convexity of the decay function that we have. In our case the lambda parameter is estimated to be 0.4329.

Further, in line with Barber, Huang, and Odean (2016), for each month we adjust previously calculated alphas using their 14 lags and the decay parameter λ:

$$ALPHA_{p,t}^{Z} = \frac{\sum_{s=1}^{14} e^{-\lambda(s-1)}\, \widehat{a}_{p,t-s}^{z}}{\sum_{s=1}^{14} e^{-\lambda(s-1)}}, \tag{12}$$

where $\hat{a}_{p,t-s}^{z}$ is the alpha for fund p at time t-s estimated using model z and λ is the decay parameter (0.4329).

Using this formula, we estimate adjusted alphas for the Capital Asset Pricing Model, the Fama-French three-factor model, the Carhart four-factor model and the five-factor model. We also use this formula to adjust for historical market-adjusted returns.

4.2 Panel Regression Analysis

In this subsection we follow the approach of Barber, Huang, and Odean (2016) and test whether Norwegian mutual fund investors account for the common risk factors and alphas when making their capital allocation decisions.

We first split monthly fund returns into the five components: market, size, value, momentum and liquidity. We add the liquidity component, which was not used in the original paper of Barber, Huang, and Odean (2016), as the five-factor model consistently outperforms the four-factor model in our regressions, which is shown in Section 4.3. This is also consistent with the findings of Næs, Skjeltorp and Ødegaard (2009), who show that the liquidity component has a high explanatory power when it comes to predicting Norwegian stock returns. Each component is obtained by multiplying the respective factor loading (which was estimated from month t-60 to month t-1 as shown in Equations 4-7) with the return of this factor in month t. Each of the components is then adjusted using the 14-lag decay function. For example, the liquidity component is adjusted using the following formula:

$$LIQRET_{p,t} = \frac{\sum_{s=1}^{14} e^{-\lambda(s-1)} [\beta_{t-s} LIQ_{t-s}]}{\sum_{s=1}^{14} e^{-\lambda(s-1)}}, \tag{13}$$

Similarly, we estimate the market, size, value and momentum components.

We then run the following panel regression:

$$F_{p,t} = b_0 + \gamma X_{p,t} + b_{alpha} ALPHA_{p,t}^{5F} + b_{MKTRET} MKTRET_{p,t} + b_{SIZRET} SIZRET_{p,t}$$

$$+ b_{VALRET} VALRET_{p,t} + b_{PR1YRRET} PR1YRRET_{p,t} + b_{LIQRET} LIQRET_{p,t} + \mu_t + \varepsilon_{p,t}, \quad (14)$$

where $F_{p,t}$ is the percentage flow of fund p in month t, $X_{p,t}$ is the vector of control variables, $ALPHA_{p,t}^{5F}$ is the adjusted five-factor model alpha for fund p in month t, $MKTRET_{p,t}$ is the market component of fund p in month t, $SIZRET_{p,t}$ is the size component of fund p in month t, $VALRET_{p,t}$ is the value component of fund p in month t, $PR1YRRET_{p,t}$ is the momentum component of fund p in month t and $LIQRET_{p,t}$ is the liquidity component of fund p in month t. Control variables include fund flow from time t-15, lagged net expense ratio, binary variable for no-load funds, standard deviation of funds' returns estimated over the past 60 months, the lag of logarithm of fund size, as well as the lag of logarithm of fund age. We also add time-fixed effects and double-cluster standard errors by fund and month. Clustering by fund helps to deal with the serial correlation in residuals over time for a given fund, while clustering by month helps to deal with cross-sectional correlation in residuals across funds at a given point of time.

When running the panel regression, we would expect sophisticated investors to react more to the alpha component (since alpha represents fund manager's skill) compared to the return components. Sophisticated investors might also positively load on return components as a part of their investment strategy (bet on specific components), however, the reaction of investors on aggregate to these components is likely to be smaller compared to alpha. This is due to the fact that investors are not homogenous and will load differently on the same return components.

The results of the regression (Table 2) show that investors assign different values to return components. The coefficients of the market, size and value components are statistically insignificant, which implies that they are indistinguishable from zero. The coefficient of the alpha, on the other hand, is 4.19 and statistically significant at the 1% threshold. The coefficient is 84% larger than the coefficient of the momentum component (significant at the 5% threshold) and 36.64% larger than the coefficient of the liquidity component (significant at the 10% threshold).

Similarly, Barber, Huang, and Odean (2016) find that the US investors tend to react to alphas more than to other fund return components. The authors show that the reaction to the market return component seems to be the lowest. As mentioned before, Barber, Huang, and Odean (2016) treat a lower coefficient on a return component as a sign that investors are more aware about the risk associated with that specific component and, thus, are more likely to distinguish it from the fund's alpha. In the case of Barber, Huang, and Odean (2016), a much lower coefficient on the market return component serves as an evidence that on aggregate investors seem to account for market risk more than for other return components and, thus, might be using a model similar to the CAPM when evaluating various mutual funds.

Table 2. Response of Norwegian mutual fund flows to return components

This table reports estimates from the panel regressions where we model the relationship between percentage fund flows and different return components - factor-related (market, size, value, momentum and liquidity) and alpha (Equation 14). Each component is obtained by multiplying the respective factor loading (which was estimated from time t-60 to t-1 using the five-factor model, as shown in Equations 4-7 in Section 4.1) by the return of this factor in month t. Each of the components is then adjusted using the 14-lag decay function (Equation 13). Column (1) displays the results from the regression (shown in Equation 14) where the actual fund flows are used. Column (2) and Column (3) report coefficient estimates for Model 1 and Model 2 where the simulated flows (created using the bootstrapping technique) are used. These flows are generated under the assumption that investors treat all of the return components similarly. The simulated flow variable from Model 1 is generated using fund returns and a set of control variables. The simulated flow variable from Model 2 is generated using Morningstar ratings in addition to all of the variables from Model 1. Columns (4) and (5) report the differences between the estimates from the model with the actual fund flows and the estimates from the models with simulated fund flows. Standard errors in the original model are double-clustered by fund and month. The t-statistics (Column (1)), the bootstrapped t-statistics (Columns (2) and (3)) and the Z-statistics (Columns (4) and (5)) are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Using original data	Using simulated flows		Difference between models	
		Model 1	Model 2	Original model vs Model 1	Original model vs Model 2
	(1)	(2)	(3)	(4)	(5)
ALPHA_5F	4.186***	3.834***	3.831***	0.346	0.349
	(4.95)	(7.88)	(7.28)	(0.36)	(0.35)
MKTRET	1.946	1.069*	1.072*	0.877	0.874
	(1.02)	(1.73)	(1.75)	(0.438)	(0.44)
SIZRET	1.070	0.802**	0.799**	0.268	0.271
	(1.14)	(2.04)	(1.97)	(0.26)	(0.26)
VALRET	0.978	-0.842	-0.841	1.820	1.819
	(0.66)	(-1.17)	(-1.19)	(1.10)	(1.11)
MOMRET	2.271**	1.734***	1.734***	0.537	0.537
	(2.47)	(3.21)	(3.24)	(0.50)	(0.50)
LIQRET	3.064*	1.941	1.965***	1.122	1.099
	(2.01)	(2.75)	(2.78)	(0.67)	(0.65)
Month fixed effects	Yes	Yes	Yes	-	-
Controls	Yes	Yes	Yes	-	-
Observations	3484	3370	3370	-	-
Adjusted R-squared	0.064	0.080	0.080	-	-

Barber, Huang, and Odean (2016) assume that sophisticated investors can distinguish between returns related to managers' skills and returns related to the common factors. Sophisticated investors are, thus, expected to be following alphas and do not load positively on the common return components. This assumption allows the authors to distinguish between sophisticated investors (those who follow alphas only) and unsophisticated ones (those who load positively on return components). However, this assumption is unlikely to hold in reality as sophisticated investor might be following specific strategies, where they bet on certain return components. Taking into account this limitation of the approach of Barber, Huang, and Odean (2016), we find that it is unclear whether investors are sophisticated or not. We cannot distinguish whether investors load positively on return components because they mistakenly treat them as alphas or because they bet on specific return components as a part of their investment strategies.

4.2.1 Bootstrapping Analysis

When considering the analysis of Barber, Huang, and Odean (2016) for the US market, it is important to take the approach with a grain of salt, as outlined by Ben-David et al. (2019). The problem with taking the regression results at their face value is the possible downward bias for the coefficients of the return components. As outlined by Franzoni and Schmalz (2017), Starks and Sun (2016) and Harvey and Liu (2019), the flow-performance sensitivity is not constant over time. When the returns of the market are at their extremes (high or low), the sensitivity of flows relative to historical returns is decreased significantly. Franzoni and Schmalz (2017) show that the flow-performance sensitivity is almost two times higher when markets are in their "calm" state compared to the periods when returns are extreme.

Ben-David et al. (2019) show that in the periods of extreme returns the dispersion of market-related returns increases significantly. The authors find a similar pattern for the value factor and a smaller evidence of this pattern for the momentum and size factors.

It is important to note that coefficients in panel regressions are usually influenced the most by volatile periods in the dataset. The flow-performance sensitivity is quite low in volatile periods, as mentioned above, which means that investors attach smaller value to past returns during such periods. This leads to smaller coefficients for the market return component in the regression. Such a result would be persistent no matter whether investors actually care about the market return component or not. We would expect a similar effect for other return components as well.

In order to test if this is true, make the Barber, Huang, and Odean (2016) test more robust and in order to be able to test whether Norwegian mutual fund investors chase unadjusted fund returns, we simulate two flow variables. Both of the simulated flow variables are generated under the assumption that investors treat all of the return components similarly. This allows us to test whether smaller coefficients for the return components are showing up mechanically due to the flow-performance sensitivity characteristics as outlined before.

We use two different specifications to generate simulated flows. In the first one we regress fund flows on fund returns and a set of control variables:

$$F_{p,t} = b_0 + \gamma X_{p,t} + b_1 R_{p,t} + e_{p,t}, \tag{15}$$

where $F_{p,t}$ is the percentage flow of fund p in month t, $R_{p,t}$ is the adjusted (using time decay function with 14 lags) return for fund p in month t, $X_{p,t}$ is a set of control variables for fund p in month t. Control variables include net expense ratio, no-load binary variable, standard deviation of fund's return measured over the past 60 months, the 1 month-lagged logarithm of fund's net assets, the logarithm of fund's age, as well as the fund's percentage flow from month t-15.

In the second specification we add Morningstar ratings to the regression:

$$F_{p,t} = b_0 + \gamma X_{p,t} + \sum_{k=1}^{5} \gamma_{p,t}^{k} I_{(star=k)} + b_1 R_{p,t} + e_{p,t}, \tag{16}$$

where $I_{(star=k)}$ represents Morningstar rating indicator variables, which are binary variables for every single rating category (from 1 to 5). Other variables are the same as in the first specification. In contrast to the analysis of Ben-David et al. (2019), we include the intercept in the second specification due to the fact that some of the Norwegian funds in the sample had missing observations for ratings, which was not the case for the US funds that were analyzed in the paper by Ben-David et al. (2019).

In order to generate simulated fund flows, we employ the bootstrapping technique, where we bootstrap residuals with replacement. We run the two abovementioned OLS regressions (Equations 16 and 17) and save the regression coefficients, predicted fitted values, as well as residuals. This leaves us with a time-series of predicted flow values as well as residuals for each fund.

For each fund p = [1, 2, …, 84] we then randomly draw a sample of residuals (with replacement) from the time-series of its residuals. This way, for every single bootstrap simulation we generate a new time series of fund residuals. We then add these resampled residuals to the predicted values of fund flows in each month to generate a new "simulated" flow variable. We run 1000 simulations in order to generate a distribution of funds' flows.

We use the two simulated flow variables to run the panel regression in Equation 14. The coefficients on the components from the regressions with the simulated flow variables are the average coefficients obtained over 1000 simulations in each case. Standard errors are standard deviations of each of the coefficients over 1000 simulations.

The results of the regressions with simulated flows show a similar pattern as the original regression (Table 2). We see that investors focus more on alpha compared to other components: the alpha coefficient is 3.834 in the first specification, 3.831 in the second specification (both significant at the 0.1% threshold). In line with Barber, Huang, and Odean (2016) and Ben-David et al. (2019), we find evidence that investors' focus on the market component is much smaller than their focus on alpha (1.069 in the first specification, 1.072 in the second specification (both significant at the 10% threshold)). Similarly, we find evidence of lower than alpha coefficients on the size (0.802 in the first specification, 0.799 in the second specification (both significant at the 5% threshold)), momentum (1.734 in the first specification, 1.734 in the second specification (both significant at the 1% threshold)) and liquidity (1.941 in the first specification, 1.965 in the second specification (both significant at the 1% threshold)) components. The only insignificant coefficient we obtain is for the value component.

In order to test whether the results of the original regression and the two regressions with simulated flows are statistically different, we perform a Z-test. We employ the approach suggested by Clogg et al. (1995):

$$Z = \frac{\beta_x - \beta_y}{\sqrt{(SE_{\beta_x})^2 + (SE_{\beta_y})^2}}, \tag{17}$$

where β_x and β_y are the tested coefficients from the regression in Equation 14 and SE_{β_x} and SE_{β_y} - standard errors of the tested coefficients in the regression in Equation 14.

Columns (4) and (5) in Table 2 suggest that we cannot reject the hypothesis that the there is no statistically significant difference between the estimates from the regression with the simulated flow variables and the original one. This supports the evidence of Ben-David et al. (2019) that lower coefficients on some of the return components are likely to be showing up mechanically. As a result, we cannot make an inference that investors account for certain risk components more. These results imply that we also cannot reject the hypothesis that Norwegian mutual fund investors simply chase unadjusted fund returns. The reason for this is the possible downward bias for some of the coefficients due to the flow-performance sensitivity characteristics in volatile periods.

Overall, in this section we looked at how Norwegian mutual fund investors account for various risk factors. Our original regression showed that investors accounted for alpha the most. We then proceeded with the bootstrapping analysis, which suggested that even in the world where investors are not sophisticated (where they do not distinguish between various return components), regression results would still show that they are (Columns (2) and (3)). This implies that the findings from the original regression (Column (1)) do not serve as evidence that investors are sophisticated since the regression results show up mechanically. These findings do not allow us to answer our research question whether Norwegian mutual fund investors are sophisticated or not and that is why we proceed with further analysis in the subsequent sections of this paper.

4.3 Analysis of Fund Flows' Determinants

Analysis conducted in the previous subsection does not allow us to make a conclusion whether Norwegian mutual fund investors are sophisticated or not, specifically, whether they use one of the common asset pricing models when making their capital allocation decisions. To be able to answer our research question, in this subsection we apply the methods of Berk and van Binsbergen (2016) and Ben-David et al. (2019). Using their methods, we explore whether asset pricing models can explain capital allocation decisions of Norwegian mutual fund investors better than simple signals such as Morningstar ratings.

4.3.1 Sign Test

The primary objective of the approach of Berk and van Binsbergen (2016) is to assess the performance of an asset-pricing model by computing how frequently the signs of alphas match the signs of flows to mutual funds. The model that explains the flow-alpha relationship most accurately (shows the best match) is considered to be the closest to the true asset pricing model used by investors. The underlying idea is that investors allocate their capital to funds with positive NPV opportunities, and in the context of a specific asset pricing model, these are the funds with positive alphas. Therefore, positive alphas will attract significant inflows while negative alphas – significant outflows. The evidence from the past academic research supports this argument. Ippolito (1992), Chevalier and Ellison (1997), Sirri and Tufano (1998) show that investors reward superior past performance (alpha) with positive flows while bad past performance is punished with negative flows.

We begin by examining the relationship between the signs of flows and the signs of alphas of different asset pricing models – the Capital Asset Pricing Model (CAPM), the Fama-French three-factor model, the Carhart four-factor model and the five-factor model. We also analyze market-adjusted returns and how the signs of market-adjusted returns explain the signs of mutual funds' flows. We follow the methodology of Berk and van Binsbergen (2016) with the exception that we use the exponential-weighted alpha estimated prior to month t (Equation 12) instead of the contemporaneous alpha (to avoid the look-ahead bias). For each model we then estimate the following regression:

$$sign\left(F_{p,t}\right) = \beta_0^{\mu} + \beta_1^{\mu} sign(ALPHA_{p,t}^{\mu}) + \epsilon_{p,t}, \tag{18}$$

where:

- $sign()$ is a simple function that returns the sign of a real number, taking a value of 1 for a positive number and -1 for a negative number. This function makes the approach of Berk and van Binsbergen (2016) robust to nonlinearities in the flow-performance relationship;
- $ALPHA_{p,t}^{\mu}$ is the exponential-weighted alpha estimated for fund p prior to month t using the asset pricing model μ;
- standard errors are double-clustered by fund and month: the first helps to deal with the serial correlation in residuals over time for a given fund, the second helps to deal with cross-sectional correlation in residuals across funds at a given point of time.

We use the regression coefficient β_1^{μ} to compute the frequency with which the signs of alphas match the signs of flows:

$$\frac{\beta_1^{\mu}+1}{2} = \frac{Pr\,(sign(F_{p,t}) = 1 \mid sign\left(ALPHA_{p,t}^{\mu}\right)=1)}{2} + \frac{Pr\,(sign(F_{p,t}) = -1 \mid sign\left(ALPHA_{p,t}^{\mu}\right)=-1)}{2} \tag{19}$$

The formula above comes from the Lemma 2 in Berk and van Binsbergen (2016) where the authors show that a linear transformation of β_1^{μ} represents the average probability that conditional on alpha being positive (negative), the sign of the fund flow is positive (negative). For example, if the alpha of a certain asset pricing model predicts the direction of fund flows correctly in all of the cases, then $(\beta_1^{\mu} + 1)/2$ = 1 and $\beta_1^{\mu} = 1$. If the alpha and flows are totally unrelated, then $(\beta_1^{\mu} + 1)/2$ = ½ and $\beta_1^{\mu} = 0$.

Further, we assess the performance of rating-based models. Since Berk and van Binsbergen (2016) do not account for them in their analysis, we follow Ben-David et al. (2019) and include Morningstar ratings. The main argument for including ratings is that, as shown in Table 1, Morningstar ratings have a big impact on the flows to Norwegian mutual funds: the fraction of funds with positive flows increases with higher ratings – from 20.22% for the one-star rating to 70.43% for the five-star rating.

The core idea of a rating-based model is that funds with ratings equal to or greater than a certain threshold k receive significant inflows while the funds with ratings lower than k experience significant outflows. Similar to Ben-David et al (2019), we use three thresholds (k=3, 4 and 5) to divide funds into groups. For each rating group (Rating>=3, Rating>=4, Rating=5) we create variables (sign_Rating3, sign_Rating4 and sign_Rating5) that take on a value of 1 if the fund was in the respective rating group in the previous month and -1 otherwise. For example, for the group Rating>=3, the variable sign_Rating3 takes on a value of 1 if the rating at the end of the previous month was 3, 4 or 5, and -1 otherwise. The similar logic applies to the variables sign_Rating4 and sign_Rating5. We estimate the following regression for each of the rating-based models:

$$sign(F_{p,t}) = \beta_0^{Rat\_k} + \beta_1^{Rat\_k} sign\_RatingK_{p,t} + \epsilon_{p,t}, \qquad (20)$$

where:

- Rat_k indicates the rating-based model estimated;
- $sign\_RatingK_{p,t}$, as was explained above, is a binary variable that takes on a value of 1 if the fund had a rating >=k in the previous month, or -1 otherwise.

Finally, we compute the frequency with which the signs of the rating-related variables match the signs of flows:

$$\frac{\beta_1^{Rat\_k}+1}{2}=\frac{Pr\ (sign(F_{p,t})=1\mid sign\_Rating_{p,t}^{Rat\_k}=1)}{2}+\frac{Pr\ (sign(F_{p,t})=-1\mid sign\_Rating_{p,t}^{Rat\_k}=-1)}{2} \quad (21)$$

The results for both asset pricing models and rating-based models are reported in Table 3. Column (2) presents the frequency (in percent) with which the signs of flows match the signs of alphas (for asset pricing models) or the signs of the rating-related variables (for rating-based models).

Table 3. Pairwise comparison of the predictive ability of asset pricing and rating-based models

This table compares the ability of asset pricing and rating-based models to predict the signs of fund flows (Berk and van Binsbergen (2016) test). Column (1) displays coefficient estimates from the regression of the signs of fund flows on the signs of alphas (Equation 18) or rating-related variables (Equation 20). These estimates are then linearly transformed and presented in Column (2) as the frequency (%) with which the signs of alphas match the signs of flows. Models are presented in decreasing order of the frequency estimate. Columns (3) - (9) report the results of pairwise tests (Equation 22). Each t-statistic in these columns (reported in parentheses) refers to the null hypothesis that the model in a certain row is better in explaining the signs of fund flows than the model in the respective column. Univariate t-statistics are reported in parentheses in Column (1). Standard errors are double-clustered by fund and month. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Model	β_1^{μ}	% of flow explained $(\beta_1^{\mu}+1)/2$	Rating >=3	Rating >= 4	Five-factor model	CAPM	FF three-factor	Carhart four-factor	Market-adjusted (MAR)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rating =5	0.280***	63.99	0.023	0.028	0.042**	0.045***	0.046***	0.048***	0.053***
	(6.26)		(1.21)	(1.52)	(2.52)	(2.92)	(2.86)	(3.04)	(3.50)
Rating >=3	0.222***	61.09	-	-0.002	0.043**	0.058**	0.055**	0.058**	0.061***
	(6.43)		-	(-0.07)	(2.17)	(2.64)	(2.27)	(2.64)	(3.29)
Rating >=4	0.212***	60.61	-	-	0.055**	0.074***	0.077***	0.074***	0.071***
	(6.26)		-	-	(2.30)	(2.90)	(2.67)	(2.86)	(3.47)
Five-factor	0.185***	59.23	-	-	-	0.009	0.028	0.107**	0.028
	(5.36)		-	-	-	(0.30)	(0.80)	(2.18)	(1.43)
CAPM	0.184***	59.21	-	-	-	-	0.025	0.035	0.025
	(5.76)						(0.58)	(1.26)	(1.37)
FF three-factor	0.163***	58.15	-	-	-	-	-	0.028	0.018
	(5.08)		-	-	-	-	-	(1.02)	(0.96)
Carhart four-factor	0.154***	57.69	-	-	-	-	-	-	0.008
	(4.96)		-	-	-	-	-	-	(0.47)
Market-adjusted (MAR)	0.137***	56.83	-	-	-	-	-	-	-
	(6.26)								

As we can see from the table, the five-factor model and the CAPM are the two best performing models among the asset pricing models: they explain 59.23% and 59.21% of the flow signs, respectively. The difference between the performance of these two models is almost indistinguishable: only 0.02 percentage points. The Fama-French three-factor model explains 58.15% of the flow signs while the Fama-French four-factor model - 57.69%. The worst performing model is the MAR, which gets the sign of flows right in 56.83% of the cases. All of the estimates are significant at the 0.1% threshold.

Although the CAPM and the five-factor model (the best performing among asset pricing models) explain a relatively large percentage of fund flows, the rating-based ones significantly outperform them. The best-performing model among rating-based models is "Rating=5" (the first row of Table 3), which indicates funds that had a five-star rating in the previous month. The model explains fund flow signs in 63.99% of the cases, which is 4.76 percentage points higher than the best performing asset pricing model (the five-factor model). Since all of the values of t-statistics in Column (2) are higher than 1.96, the results presented in the first column are statistically significant at the 5% significance level. Our findings are in line with those of Del Guercio and Tkac (2008) and Ben-David et al. (2019): there exists a strong positive relationship between Morningstar ratings and fund flows.

At the same time, the estimates in Table 3 show that the "Rating>=3" model gets the sign of flows right in 61.09% of the cases while the "Rating>=4" model - in 60.61% of the cases. We would expect higher ratings to have higher explanatory power. It might be the case that the outperformance of the "Rating>=3" is statistically unmeaningful, and, thus, further comparison of the two models is needed.

4.3.2 Pairwise Comparison

To check whether the difference between the two models is significantly different from zero (whether one model does outperform the second one), we follow the approach of Berk and van Binsbergen (2016) and conduct pairwise model comparison:

$$sign\left(F_{p,t}\right) = \gamma_0 + \gamma_1 \left(\frac{sign\left(ALPHA_{p,t}^{\mu 1}\right)}{var\left(sign\left(ALPHA_{p,t}^{\mu 1}\right)\right)} - \frac{sign\left(ALPHA_{p,t}^{\mu 2}\right)}{var\left(sign\left(ALPHA_{p,t}^{\mu 2}\right)\right)} \right) + \varepsilon_{p,t}, \tag{22}$$

where $\mu 1$ and $\mu 2$ indicate the models that we compare, $var\left(sign\left(ALPHA_{p,t}^{\mu 1}\right)\right)$ and $var\left(sign\left(ALPHA_{p,t}^{\mu 2}\right)\right)$ represent variances of the sign variables of the two models.

Note: When we use rating-based models, we replace $sign\left(ALPHA_{p,t}^{\mu 1}\right)$ by $sign\_RatingK_{p,t}$.

The coefficient of interest in our regression is γ_1. The expression in parentheses shows the difference between the risk-adjusted performance of the models under consideration. If γ_1>0 we would expect model $\mu 1$ to dominate model $\mu 2$ in terms of explanatory power. The t-statistics of the pairwise test coefficient γ_1 is presented in the remaining columns of Table 3. The null hypothesis is that the beta coefficient of the model represented in a certain row is higher than the beta coefficient of the model represented in the respective column. As we can see from the reported results, each of the rating-based models outperform all of the asset pricing models (t-statistic is higher than 1.96). For example, the "Rating=5" model significantly outperforms the five-factor model (t-statistic of 2.52), the CAPM (t-statistic of 2.92), the Fama-French three-factor (t-statistic of 2.86), the Carhart four-factor (t-statistic of 3.04) and the market-adjusted model (t-statistic of 3.5). At the same time, there is no significant difference between any two rating-based models. The difference between the performance of the "Rating=5" model and the "Rating>=3" or "Rating>=4" models is insignificant: t-statistic equals 1.21 and 1.52, respectively. The same is relevant for the pair "Rating>=3" and "Rating>=4" for which t-statistic equals to -0.07. Furthermore, there is no difference between any two asset pricing models, except the five-factor model that outperforms the Carhart four-factor model with a t-statistic of 2.18.

The reported results confirm that the rating-based models (the first three rows of Table 3) do outperform the asset pricing models and the market-adjusted model. This serves as evidence that Norwegian investors use Morningstar ratings and not common asset pricing models when making capital allocation decisions.

4.3.3 Top- and Bottom-Ranked Funds Comparison

One of the main limitations of the test of Berk and van Binsbergen (2016) is that it considers only the signs of alphas and flows, but not their magnitudes. Trying to overcome this limitation, we follow Ben-David et al. (2019) and examine the difference in fund flows between top-ranked and bottom-ranked funds that are classified using different asset pricing models and Morningstar ratings. First of all, we calculate the number of five-star and one-star funds for each month and denote these numbers as *k* and *m,* respectively. We also split funds in each month into two groups based on their alphas: top-ranked (with the highest alphas) and bottom-ranked (with the lowest alphas). The number of top-ranked funds is limited by k – the number of five-star funds for that month, the number of bottom-ranked funds is limited by m - the number of one-star funds for that month. For example, if there were 25 funds with a one-star rating, then the 25 funds with the lowest five-factor model alpha are defined as bottom-ranked by the five-factor model. If there were 50 funds with a five-star rating, then the 50 funds with the highest five-factor model alpha are defined as top-ranked by the five-factor model.

Finally, we calculate the fraction of positive flows, flows as percentage of total net assets and flows measured in NOK of top- and bottom-ranked funds. The results are presented in Table 4. When we use Morningstar ratings to classify funds, we find that 70.43% of top-ranked funds (Column (1)) receive positive flows compared to 20.22% of bottom-ranked ones (Column (2)), leading to a spread of 50.21% (Column (3)). At the same time, when we use the asset pricing models (the CAPM, the Fama-French three-factor, the Carhart four-factor and the five-factor model) or market-adjusted returns, the spreads between the fraction of top- and bottom-ranked funds that receive positive flows lie in the range of 37.62% - 42.20%. Similarly, high-ranked funds (classified by Morningstar ratings) show the highest monthly fund flows as percentage of total net assets (Column (4)) - 2.56%, as well as the highest spread between the high- and bottom-ranked funds (Column (6)) - 5.20%. This is significantly higher than the spread of the market-adjusted model (3.77%), which is the second-best model. In general, the spread of fund flows (as percentage of total net assets) between the top- and bottom-ranked funds (as measured by asset pricing models and market-adjusted returns) is in the range 1.87% - 3.77% (Column (6)). The economic significance of the results is also noteworthy. The difference in average monthly fund flows (in NOK) between top- and bottom-ranked funds (Column (9)) is much higher when we use Morningstar ratings for classification (21.56 million NOK) than when we use the asset pricing models. For instance, the next biggest difference between top-ranked and bottom-ranked funds is 20.44 million NOK (when we use the Fama-French three-factor model for classification). Overall, the spread in average fund flows (in NOK) between top- and bottom-ranked funds is in the range between -0.9 million NOK and 20.44 million NOK for the asset pricing models and market-adjusted returns. As we see, Morningstar ratings produce the biggest spreads among all of the models under consideration, which is in line with the findings of Ben-David et al. (2019) for the US market.

Table 4. Difference between flows to top- and bottom-ranked Norwegian mutual funds

This table compares flows to top- and bottom-ranked funds that are classified using different asset pricing models and Morningstar ratings. Each month the funds are ranked by alpha into two groups: funds with the highest alpha (top-ranked) and funds with the lowest alpha (bottom-ranked). The number of top-ranked funds is limited by the number of five-star funds in that month while the number of bottom-ranked – by the number of one-star funds in that month. Columns (1) - (3) represent the fraction of funds with positive flows in top-ranked and bottom-ranked funds, and the spread between them. Columns (4) - (6) display the average monthly fund flows as a fraction of total net assets (in percent) while Columns (7) - (9) show the average flows in million NOK.

Model	Positive flow (%)			Fund flow (%)			Fund flow (million NOK)		
	Top-ranked	Bottom-ranked	Spread	Top-ranked	Bottom-ranked	Spread	Top-ranked	Bottom-ranked	Spread
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Morningstar ratings	70.43	20.22	50.21	2.56	-2.64	5.20	19.20	-2.36	21.56
Five-factor	70.77	28.57	42.20	1.83	-0.50	2.33	13.30	14.20	-0.90
Carhart four-factor	71.92	31.88	40.04	2.39	-0.13	2.52	17.00	-2.35	19.35
FF three-factor	69.96	28.12	41.84	2.06	-0.60	2.66	17.30	-3.14	20.44
CAPM	69.05	31.43	37.62	1.74	-0.13	1.87	18.40	13.60	4.80
Market-adjusted	63.60	25.00	38.60	2.40	-1.37	3.77	9.45	-6.91	16.36

To conclude, the test of Berk and van Binsbergen (2016) for the Norwegian mutual fund data shows that the rating-based models explain the signs of mutual fund flows significantly better than the asset pricing models do (the degree of outperformance in terms of explanatory power is 4.76 percentage points). The additional test based on nominal magnitudes and spreads between the top- and bottom-ranked funds in terms of positive flows (in percent), fund flows as percentage of total net assets and fund flows (in NOK) strengthens the conclusion above and, furthermore, shows that the outperformance of Morningstar ratings is economically meaningful. This implies that Norwegian investors follow simple signals - Morningstar ratings - and not common asset pricing models when making their capital allocation decisions. This could imply that Norwegian mutual fund investors are unsophisticated on aggregate as they seem to ignore the common risk factors.

4.4 Morningstar Ratings as a Risk Adjustment Mechanism

In this subsection we want to discover whether there are cases when it might be rational for investors to follow Morningstar ratings. As shown by Clifford et al. (2013), funds with high volatility usually receive smaller flows. In our analysis we want to explore whether investors might be chasing Morningstar ratings as a means of outsourcing risk analysis to Morningstar.

As we know, Morningstar ratings account for funds' volatility of returns and punish highly volatile funds with low ratings. Outsourcing risk assessment to Morningstar might be an easier and cheaper alternative for investors to account for risk than to calculate and adjust for risk on their own (since Morningstar ratings are free).

First of all, we want to test whether volatility can explain fund flows in excess of what is already explained by Morningstar ratings. For this purpose, we run a regression of fund flows on volatility, ratings and a set of control variables:

$$F_{p,t} = b_0 + b_1 Ratings_{p,t} + b_2 Vol^5_{p,t} + b_3 Y_{p,t} + v_t + \varepsilon_{p,t}, \tag{23}$$

where $F_{p,t}$ is the percentage flow of fund p in month t, $Ratings_{p,t}$ is the Morningstar rating of fund p in month t, $Vol^5_{p,t}$ is the volatility of monthly fund returns of fund p at time t calculated using the last five years of returns (standard deviation), $Y_{p,t}$ is a set of control variables for fund p at time t. The set of control variables includes the same variables as in the previous regressions: net expense ratio, the 1-month lagged logarithm of fund's size (net assets), the logarithm of fund's age, lagged percentage flows from month t-15 and a binary variable for no-load funds. In this regression we also account for time-fixed effects in our dataset and double-cluster errors by fund and date. As a robustness check we run the same regression replacing five-year volatility with a volatility measured over the prior one year.

The results of the regressions both with five- and one-year volatility variables show similar results (Table 5). We observe a highly significant effect of ratings on flows. In the case of five-year volatility, an increase in fund's Morningstar rating of one star (for example, from a rating of two stars to a rating of five stars) leads to an increase in flows by 1 percentage point. In the case of one-year volatility the increase is also around 1 percentage point. At the same time, the coefficients on volatility measures are insignificant in both cases. This implies that Norwegian investors do not account for any additional volatility, which is not already accounted for by Morningstar ratings.

Further, we want to explore the extent to which Morningstar ratings explain variation in funds' monthly returns and, thus, whether by chasing Morningstar ratings investors can account for most of the risk associated with fund returns.

Here, we regress five-year volatility on Morningstar ratings:

$$Vol_{p,t}^{5} = b_0 + b_1 Ratings_{p,t} + \varepsilon_{p,t}, \qquad (24)$$

where $Vol_{p,t}^{5}$ is the five-year volatility of fund p in month t and $Ratings_{p,t}$ is the Morningstar rating of fund p in month t.

Column (4) of Table 5 shows that a higher Morningstar rating is associated with a lower five-year volatility, which is consistent with the way Morningstar accounts for volatility when calculating its ratings. A one star increase in Morningstar ratings leads to a 0.3 percentage point decrease in five-year volatility. The coefficient is significant at the 1% threshold. Worth noting here is the adjusted R-square of the regression, which shows how much of the total variation in five-year volatility is explained by Morningstar ratings. As we see only 3.62% of it is explained by Morningstar ratings, which implies that relying on Morningstar ratings to account for funds' volatility does not seem to be a rational thing to do.

As a robustness check, we run a similar regression with one-year volatility variable, which produces similar results as in the previous regression. As shown in Column (3) of Table 5, a one star increase in Morningstar ratings is associated with a decrease of 0.3 percentage points in one-year volatility. This coefficient is significant even at the 0.1% threshold. The adjusted R-square of the regression is 1.52%, which implies that in the case of one-year volatility, Morningstar ratings account for even less volatility compared to the previous regression.

Finally, in order to conclude whether outsourcing risk adjustment to Morningstar is rational or not, we perform the following analysis: for each of the two above mentioned regressions (for five- and one-year volatility) we predict the volatility variable and estimate its residual. Then we estimate the following regression:

$$F_{p,t} = b_0 + b_1 Vol_{predicted,p,t}^{5} + b_2 Vol_{residual,p,t}^{5} + b_3 Y_{p,t} + v_t + \varepsilon_{p,t}, \qquad (25)$$

where $F_{p,t}$ is the percentage flow of fund p in month t, $Vol_{predicted,p,t}^{5}$ is the predicted five-year volatility of fund p in month t (estimated from the regression in Equation 24), $Vol_{residual,p,t}^{5}$ is the estimated residual for fund p at time t, $Y_{p,t}$ is a set of control variables for fund p at time t (the same as in Equation 23), v_t is the time fixed effects variable. Standard errors are double-clustered by fund and month.

For robustness, we also estimate the same regression for one-year predicted volatility and its residual. In both cases the coefficients on the predicted volatility variables are highly significant (at the 0.1% threshold). As shown in the last columns of Table 5, a 1 percentage point increase in the predicted five-year volatility variable leads to a decrease of 3.30 percentage points in fund flows. Similarly, a 1 percentage point increase in the predicted one-year volatility variable leads to a decrease of 3.44 percentage points in fund flows. The coefficients on the residual variables are insignificant in both cases. This means that only the 3.62% (1.52% in the case of one-year volatility) of volatility explained by Morningstar ratings can predict percentage fund flows with a high level of significance. All the residual volatility, which is 96.38% (98.48% in the case of one-year volatility), is not a good predictor of fund flows.

Table 5. The effect of Morningstar ratings on risk-adjustment of Norwegian mutual fund investors

This table reports estimates from the panel regressions of percentage fund flows on one- and five-year return volatility, Morningstar ratings and control variables. Column (1) and Column (2) provide the results from the model where the percentage flow is the dependent variable and Morningstar ratings and volatility are independent variables (Equation 23). Column (3) and Column (4) display coefficient estimates from the regressions of one- and five-year volatility on Morningstar ratings (Equation 24). These two regressions are used to predict volatility variables and estimate residual variables. Column (5) and (6) represent the effect of the predicted one- and five-year volatilities and their residuals, respectively, on the percentage flow variable. Monthly fixed effects and control variables are used in all columns, except Column (3) and Column (4). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The t-statistics are reported in parentheses. Standard errors are double-clustered by fund and month.

	Flow	Flow	Volatility 1 year	Volatility 5 year	Flow	Flow
	(1)	(2)	(3)	(4)	(5)	(6)
Volatility 1year	-0.191					
	(-0.56)					
Volatility 1y_pred						-3.435***
						(-4.48)
Volatility 1y_res						-0.191
						(-0.56)
Volatility 5years		-0.275				
		(-0.71)				
Volatility 5y_pred					-3.295***	
					(-4.72)	
Volatility 5y_res					-0.275	
					(-0.71)	
Morningstar ratings	0.010***	0.010***	-0.003**	-0.003***		
	(5.14)	(5.12)	(-10.45)	(-16.24)		
Month fixed effects	Yes	Yes	No	No	Yes	Yes
Controls	Yes	Yes	No	No	Yes	Yes
Adjusted R-squared	0.059	0.059	0.015	0.036	0.059	0.059

Our results in this section suggest that Morningstar ratings explain only a small amount of the total funds' return volatility (3.62%), while the residual volatility is not accounted for. This implies that following Morningstar ratings as a means of risk adjustment outsourcing does not seem to be a rational thing to do. Thus, it is unlikely to be the reason why Norwegian mutual fund investors chase Morningstar ratings.

4.5 Performance of High- and Low-Rated Mutual Funds

The analysis conducted in the previous parts of our paper shows that Norwegian mutual fund investors follow Morningstar ratings when making capital allocation decisions. In this section we investigate whether such behavior is optimal.

The object of our analysis is the future performance of high-rated and low-rated mutual funds and its effect on investors' wealth. As a measure of funds' future performance we use total shareholder return (TSR) that represents all the benefits created for shareholders. We also use alphas of funds that belong to each of the groups of funds analyzed in order to account for the common risk factors. In each month we group funds based on their Morningstar ratings into high-rated (those that have four- or five-star ratings) and bottom-rated (those that have one- or two-star ratings) funds. Then within each of these rating groups we split funds into terciles based on their alphas: tercile 1 – the bottom-performing funds (low alpha), tercile 2 – the medium-performing funds (medium alpha), tercile 3 – the top-performing funds (high alpha). In our analysis we focus on the two main groups (high-rated and low-rated funds) and four smaller subgroups (high-rated high alpha funds, high-rated low alpha funds, low-rated high alpha funds and low-rated low alpha funds). Each of the groups is treated as an equally weighted portfolio. We then calculate one-, two- and three-month returns for the created portfolios. For two- and three-month periods we rebalance our portfolios each second and third month, respectively.

We begin our analysis by comparing average future TSRs for high-rated and low-rated funds over one-, two- and three-month periods. Table 6 shows that by investing in funds with high ratings, investors get significantly higher total shareholder returns. The average TSR for high-rated funds is 0.99% compared to 0.95% for low-rated funds (for a 1-month period). High-rated funds also outperform low-rated ones over two- and three-month holding periods: 1.02% and 1.05% average monthly TSR for high-rated funds when the portfolio is rebalanced every two and three months, respectively (0.99% and 1.03% average monthly TSR for low-rated funds when the portfolio is rebalanced every two and three months, respectively). Blake and Morey (2000) examine the ability of Morningstar ratings to predict the performance of the US mutual funds and find that low Morningstar ratings indicate poor future performance. At the same time, their results suggest that there is no clear evidence of high ratings indicating superior future performance, and, therefore, investors should be cautious when they make their decisions simply based on ratings.

Table 6. Average total shareholder return of high-rated and low-rated funds

This table reports average monthly total shareholder returns (TSR) over one, two- and three-month holding periods for two groups of funds: high-rated funds (those that have four- or five-star Morningstar ratings) and low-rated funds (those that have one- or two-star ratings). Each of these groups is treated as an equally weighted portfolio. For two- and three- month periods the portfolios are rebalanced every second and third month, respectively. The last column represents p-values of the t-statistics under the null hypothesis that average total shareholder return of high-rated funds is lower than that of low-rated funds. Average TSRs are reported in percent.

Average TSR, %	High-rated funds (HR)	Low-rated funds (LR)	p-value (HR<LR)
1-month TSR	0.990	0.945	0.000
2-month TSR	1.015	0.987	0.001
3-month TSR	1.048	1.025	0.003

As mentioned before, Gallefoss et al. (2015) find evidence of performance persistence in the Norwegian market over short periods of time. If performance persistence exists, we would expect funds that were performing well/poorly in the past to perform well/poorly in the next period as well (consistent with Jensen (1969), Malkiel (1995), Jain and Wu (2000)). Since Morningstar ratings are based on past performance, investors might expect that funds with high ratings are those that will perform well in the future. However, as mentioned earlier (see Section 3.1), Morningstar ratings do not account for the common risk factors and, thus, might not be a good indicator of funds' future risk-adjusted performance. By following Morningstar ratings investors might not get enough compensation for the risk that they are taking (some of the funds that have high Morningstar ratings might have low alphas). Investors who simply rely on Morningstar ratings can, thus, make two potential mistakes that might have a negative effect on their financial wealth in the future.

The first potential mistake (mistake 1) is that investors might allocate capital to funds with high ratings expecting them to perform best. In reality, they may end up with funds that do have high ratings, but have low alphas based on the common asset pricing models (we call this group high-rated low alpha funds). To check whether Norwegian investors get "punished" by investing in high-rated funds, we conduct the following analysis. Firstly, we compare the average TSR for the portfolio of high-rated high alpha funds with the portfolio of high-rated low alpha funds. The results are reported in Table 7. We can see that funds with high ratings and low alpha generate higher total shareholder returns over the periods of one, two and three months. As shown in Column (9), the average monthly TSRs for high-rated low alpha funds are 1.016%, 1.028%, and 1.065% when the portfolio of funds is rebalanced every one, two and three months, respectively (0.938%, 0.963% and 0.999% for high-rated high alpha funds). This might imply that investors do not make mistake 1 when buying high-rated funds.

Table 7. Average total shareholder return of high-rated high alpha funds and high-rated low alpha funds

This table compares average monthly total shareholder returns (TSR) for two subgroups of high-rated funds: low alpha funds and high alpha funds. Each month funds with high ratings are divided into terciles based on their past alphas: tercile 1 – the bottom-performing funds (low alpha), tercile 2 – the medium-performing funds (medium alpha), tercile 3 – the top-performing funds (high alpha). Medium alpha funds are not included in further analysis. Since alphas are estimated using four different asset pricing models (see Section 4.1), funds can be divided into low and high alpha groups in four different ways: by CAPM alpha, by Fama-French three-factor alpha, by Carhart four-factor alpha and by five-factor alpha. Each of the subgroups formed (each column) is treated as an equally weighted portfolio. For two- and three- month periods the portfolios are rebalanced each second and third month, respectively. P-values are generated under the null hypothesis that high-rated high alpha funds generate higher total shareholder returns than high-rated low alpha funds. Average monthly TSRs are reported in percent.

	High-rated funds									
	CAPM-sorted		FF three-factor sorted		Carhart four-factor sorted		Five-factor model sorted		Mean	
	Low Alpha	High Alpha	Low Alpha	High Alpha	Low Alpha	High Alpha	Low Alpha	High Alpha	Low Alpha	High Alpha
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1-month TSR	0.998	0.871	1.025	0.925	0.994	0.995	1.046	0.961	1.016	0.938
p-value (high alpha - low alpha > 0)	*0.000*		*0.000*		*0.555*		*0.000*		-	-
2-month TSR	1.019	0.894	1.035	0.964	1.012	1.009	1.046	0.987	1.028	0.963
p-value (high alpha - low alpha > 0)	*0.000*		*0.000*		*0.348*		*0.000*		-	-
3-month TSR	1.067	0.925	1.088	0.987	1.028	1.045	1.076	1.041	1.065	0.999
p-value (high alpha - low alpha > 0)	*0.000*		*0.000*		*0.983*		*0.000*		-	-

However, since TSR represents unadjusted fund returns, it does not account for the common risk factors. The reason for the outperformance of high-rated low alpha funds might be the higher risk these funds are exposed to. If we believe that high-rated low alpha funds would outperform high-rated high alpha ones (after the risk has been accounted for), then we would expect that a strategy where we buy an equally weighted portfolio of high-rated high alpha funds and sell an equally weighted portfolio of high-rated low alpha ones would generate negative alphas based on the common asset pricing models. The results in Table 8 confirm our hypothesis. We see that no matter, which sort we use to divide funds into high and low alpha groups (we use sorts based on the CAPM, the Fama-French three-factor, the Carhart four-factor and the five-factor models) and which asset pricing model we use to estimate alphas of the strategy, the results remain the same: alpha is negative and statistically significant in all of the cases (at the 5% threshold). This supports the finding that Norwegian mutual fund investors do not make mistake 1 when investing in high-rated funds.

Table 8. Risk-adjusted performance of Strategy 1 (buy high-rated high alpha funds, sell high-rated low alpha funds)

This table reports monthly alphas for a strategy where investors buy an equally weighted portfolio of high-rated high alpha funds and sell an equally weighted portfolio of high-rated low alpha funds. For a 1-month holding period, each portfolio is formed based on whether the fund was in the high-rated high alpha group or high-rated low-alpha group, respectively, in the previous month. For 2- and 3-month holding periods we look whether the fund was in the high-rated high alpha group or high-rated low-alpha group two and three months ago, respectively. Alphas are estimated based on four different asset-pricing models: the CAPM, the Fama-French three-factor, the Carhart four-factor and the five-factor model. ***, **, and * indicate significance at the 1%, 5%, and 10% threshold, respectively. The t-statistics are reported in parentheses.

	Strategy 1: Buy high-rated high alpha funds Sell high-rated low alpha funds											
	CAPM-sorted			FF three-factor sorted			Carhart four-factor sorted			Five-factor model sorted		
	1m	2m	3m	1m	2m	3m	1m	2m	3m	1m	2m	3m
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CAPM alpha	-0.0036***	-0.0036***	-0.0038***	-0.0034***	-0.0031***	-0.0035***	-0.0024***	-0.0024***	-0.0023***	-0.0033***	-0.0030***	-0.0027***
	(-4.19)	(-4.15)	(-4.39)	(-4.60)	(-4.17)	(-4.58)	(-3.03)	(-3.09)	(2.96)	(-4.22)	(-3.80)	(-3.50)
FF three-factor alpha	-0.0041***	-0.0042***	-0.0043***	-0.0035***	-0.0032***	-0.0036***	-0.0026***	-0.0027***	-0.0025***	-0.0035***	-0.0032***	-0.0029***
	(-4.70)	(-4.82)	(-4.89)	(-4.54)	(-4.17)	(-4.49)	(-3.17)	(-3.28)	(-3.10)	(-4.35)	(-3.98)	(-3.60)
Carhart four-factor alpha	-0.0039***	-0.0038***	-0.0041***	-0.0033***	-0.0029***	-0.0034***	-0.0022**	-0.0021**	-0.0023***	-0.0031***	-0.0028***	-0.0026***
	(-4.32)	(-4.27)	(-4.51)	(-4.17)	(-3.65)	(-4.12)	(-2.56)	(-2.54)	(-2.73)	(-3.79)	(-3.35)	(-3.15)
Five-factor model alpha	-0.0039***	-0.0038***	-0.0041***	-0.0033***	-0.0029***	-0.0034***	-0.0022**	-0.0021**	-0.0023***	-0.0031***	-0.0028***	-0.0026***
	(-4.32)	(-4.26)	(-4.51)	(-4.16)	(-3.63)	(-4.13)	(-2.57)	(-2.54)	(-2.76)	(-3.78)	(-3.34)	(-3.15)

The second potential mistake (mistake 2) that investors can make is to follow high-rated funds and by doing so ignore low-rated funds with high alpha. To assess the effect of such behavior, we calculate the average TSR for low-rated funds with low alpha and with high alpha. Our results (Table 9) suggest that high alpha funds seem to outperform low alpha ones in terms of total shareholder returns. The average monthly TSR for low-rated high alpha funds are 1.01%, 1.041% and 1.014% when the portfolio is rebalanced every one, two and three months, respectively (0.854%, 0.936% and 0.966% for low-rated low alpha funds). We find that low-rated high alpha funds outperform high-rated high alpha funds not only over one month, but also over two and three months. This might suggest that investors do make mistake 2 by not investing in low-rated funds.

Table 9. Average total shareholder return of low-rated high alpha funds and low-rated low alpha funds

This table shows average monthly total shareholder returns (TSR) for two subgroups of low-rated funds: low alpha funds and high alpha funds. Each month funds with low ratings are divided into terciles based on their past alphas: tercile 1 – the bottom-performing funds (low alpha), tercile 2 – the medium-performing funds (medium alpha), tercile 3 – the top-performing funds (high alpha). Medium alpha funds are not included in further analysis. Since alphas are estimated using four different asset pricing models (see Section 4.1), funds can be divided into low and high alpha groups in four different ways: by CAPM alpha, by Fama-French three-factor alpha, by Carhart four-factor alpha and by five-factor alpha. Each of the subgroups formed (each column) is treated as an equally weighted portfolio. For two- and three- month periods the portfolios are rebalanced each second and third month, respectively. P-values are generated under the null hypothesis that low-rated high alpha funds generate higher total shareholder returns than low-rated low alpha funds. Average monthly TSRs are reported in percent.

	Low-rated funds									
	CAPM-sorted		FF three-factor sorted		Carhart four-factor sorted		Five-factor model sorted		Mean	
	Low Alpha	High Alpha	Low Alpha	High Alpha	Low Alpha	High Alpha	Low Alpha	High Alpha	Low Alpha	High Alpha
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1-month TSR	0.938	0.997	0.797	1.013	0.828	1.030	0.853	1.030	0.854	1.010
p-value (high alpha - low alpha > 0)	*1.000*		*1.000*		*1.000*		*1.000*		-	-
2-month TSR	0.998	1.055	0.863	1.038	0.989	1.019	0.892	1.019	0.936	1.041
p-value (high alpha - low alpha > 0)	*1.000*		*1.000*		*1.000*		*1.000*		-	-
3-month TSR	1.020	1.010	0.924	1.011	0.952	1.040	0.966	1.040	0.966	1.014
p-value (high alpha - low alpha > 0)	*1.000*		*1.000*		*1.000*		*1.000*		-	-

Similarly to the previous case, we also estimate alphas using the common asset pricing models (to adjust for risk). We generate a strategy where we buy an equally weighted portfolio of low-rated high alpha funds and sell an equally weighted portfolio of low-rated low alpha funds. We would expect the alpha of this strategy to be positive if we believe that the high alpha funds outperform the low alpha ones (after the risk has been accounted for). The results of the regressions (Table 10) show that no significant outperformance can be found. None of the alphas estimated for the strategy are significant at the 5% threshold.

Table 10. Risk-adjusted performance of Strategy 2 (buy low-rated high alpha funds, sell low-rated low alpha funds)

This table provides monthly alphas for a strategy where investors buy an equally weighted portfolio of low-rated high alpha funds and sell an equally weighted portfolio of low-rated low alpha funds. For a 1-month holding period, each portfolio is formed based on whether the fund was in the low-rated high alpha group or low-rated low-alpha group, respectively, in the previous month. For 2- and 3-month holding periods we look whether the fund was in the low-rated high alpha group or low-rated low-alpha group two and three months ago, respectively. Alphas are estimated based on four different asset-pricing models: the CAPM, the Fama-French three-factor, the Carhart four-factor and the five-factor model. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The t-statistics are reported in parentheses.

Strategy 2: Buy low-rated high alpha funds Sell low-rated low alpha funds												
	CAPM-sorted			FF three-factor sorted			Carhart four-factor sorted			Five-factor model sorted		
	1m	2m	3m	1m	2m	3m	1m	2m	3m	1m	2m	3m
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CAPM alpha	-0.0011	-0.0015	-0.0019*	0.0005	-0.0001	-0.0008	0.0003	-0.0018*	-0.0007	-0.0001	-0.0002	-0.0013
	(-1.01)	(-1.28)	(-1.68)	(0.48)	(-0.14)	(-0.67)	(0.30)	(-1.93)	(-0.62)	(-0.09)	(-0.17)	(-1.08)
FF three-factor alpha	-0.0011	-0.0017	-0.0020*	0.0012	0.0007	0.0000	0.0007	-0.0018*	-0.0004	0.0003	0.0002	-0.0009
	(-1.00)	(-1.39)	(-1.73)	(1.17)	(0.62)	(0.04)	(0.65)	(-1.96)	(-0.32)	(0.29)	(0.18)	(-0.76)
Carhart four-factor alpha	-0.0015	-0.0017	-0.0020*	0.0005	0.0000	-0.0009	0.0002	-0.0016	-0.0011	-0.0003	-0.0003	-0.0016
	(-1.22)	(-1.36)	(-1.68)	(0.45)	(-0.03)	(-0.78)	(0.15)	(-1.63)	(-0.89)	(-0.26)	(-0.25)	(-1.27)
Five-factor model alpha	-0.0015	-0.0017	-0.0021*	0.0005	0.0000	-0.0009	0.0002	-0.0016	-0.0011	-0.0003	-0.0003	-0.0016
	(-1.23)	(-1.38)	(-1.69)	(0.45)	(-0.04)	(-0.77)	(0.15)	(-1.63)	(-0.87)	(-0.25)	(-0.24)	(-1.26)

We then compare the performance of high-rated low alpha funds (the best performing group among high-rated funds) with the performance of low-rated high alpha funds (the best performing group among low-rated funds). We create a strategy where we buy an equally weighted portfolio of high-rated low alpha funds and sell an equally weighted portfolio of low-rated high alpha funds. If we believe that investors make mistake 2 by not investing in low-rated funds, we would expect the alpha of the strategy to be negative. The results reported in Table 11 show that by buying high-rated low alpha funds and selling low-rated high alpha funds investors actually lose money and, thus, make mistake 2. In the majority of cases alpha of the strategy is negative and statistically significant at the 5% threshold.

Table 11. Risk-adjusted performance of Strategy 3 (buy high-rated low alpha funds, sell low-rated high alpha funds)

This table presents monthly alphas for a strategy where investors buy an equally weighted portfolio of high-rated low alpha funds and sell an equally weighted portfolio of low-rated high alpha funds. For a 1-month holding period, each portfolio is formed based on whether the fund was in the high-rated low alpha group or low-rated high alpha group in the previous month. For 2- and 3-month holding periods we look whether the fund was in the high-rated low alpha group or low-rated high alpha group two and three months ago, respectively. Alphas are estimated based on four different asset-pricing models: the CAPM, the Fama-French three-factor, the Carhart four-factor and the five-factor model. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The t-statistics are reported in parentheses.

	Strategy 3: Buy high-rated low alpha funds Sell low-rated high alpha funds											
	CAPM-sorted			FF three-factor sorted			Carhart four-factor sorted			Five-factor model sorted		
	1m	2m	3m	1m	2m	3m	1m	2m	3m	1m	2m	3m
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CAPM alpha	-0.0026**	-0.0027**	-0.0019*	-0.0025***	-0.0024**	-0.0016*	-0.0029***	-0.0024**	-0.0026**	-0.0022**	-0.0024**	-0.0017
	(-2.31)	(-2.25)	(-1.67)	(-2.63)	(-2.39)	(-1.70)	(-2.74)	(-2.55)	(-2.29)	(-2.05)	(-2.17)	(-1.52)
FF three-factor alpha	-0.0018	-0.0016	-0.0009	-0.0022**	-0.0021**	-0.0014	-0.0023**	-0.0021**	-0.0019*	-0.0016	-0.0018	-0.0011
	(-1.59)	(-1.39)	(-0.84)	(-2.25)	(-2.05)	(-1.38)	(-2.16)	(-2.15)	(-1.70)	(-1.48)	(-1.59)	(-0.93)
Carhart four-factor alpha	-0.0029**	-0.0029**	-0.0022*	-0.0033***	-0.0033***	-0.0023**	-0.0037***	-0.0032***	-0.0031***	-0.0028***	-0.0031***	-0.0022*
	(-2.50)	(-2.50)	(-1.94)	(-3.41)	(-3.27)	(-2.29)	(-3.46)	(-3.41)	(-2.68)	(-2.63)	(-2.80)	(-1.96)
Five-factor model alpha	-0.0028**	-0.0029**	-0.0022*	-0.0033***	-0.0033***	-0.0023**	-0.0036***	-0.0033***	-0.0030***	-0.0028***	-0.0031***	-0.0022*
	(-2.49)	(-2.49)	(-1.93)	(-3.41)	(-3.26)	(-2.28)	(-3.46)	(-3.39)	(-2.67)	(-2.62)	(-2.78)	(-1.96)

Overall, after accounting for various risk factors, we find that high-rated low alpha funds outperform high-rated high alpha funds. At the same time, we find that low-rated high alpha funds outperform high-rated low alpha funds. We do not find evidence of outperformance of any alpha group within low-rated funds. Following transitivity rules, we would expect that low-rated funds would dominate high-rated ones in terms of performance (after the risk factors have been accounted for). To test this empirically, we also generate a strategy where we buy high-rated funds and sell low-rated ones. Consistent with our findings, we would expect a negative alpha resulting from this strategy. As can be seen from Table 12, by investing in high-rated funds and selling low-rated ones, investors do lose money: the results show that most of the alphas of the strategy are negative (significant at the 5% threshold).

Table 12. Risk-adjusted performance of Strategy 4 (buy high-rated funds, sell low-rated funds)

This table reports monthly alphas for a strategy where investors buy an equally weighted portfolio of high-rated funds and sell an equally weighted portfolio of low-rated funds. For a 1-month holding period, each portfolio is formed based on whether the fund had a high or low rating in the previous month. For 2- and 3-month holding periods we look whether the fund had a high or low rating two and three months ago, respectively. Alphas are estimated based on four different asset-pricing models: the CAPM, the Fama-French three-factor, the Carhart four-factor and the five-factor model. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The t-statistics are reported in parentheses.

Strategy 4: Buy high-rated funds Sell low-rated funds												
	CAPM-sorted			FF three-factor sorted			Carhart four-factor sorted			Five-factor model sorted		
	1m	2m	3m	1m	2m	3m	1m	2m	3m	1m	2m	3m
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CAPM alpha	-0.0029***	-0.0031***	-0.0027***	-0.0017*	-0.0018*	-0.0017*	-0.0018**	-0.0020**	-0.0020**	-0.0017*	-0.0018**	-0.0017*
	(-3.38)	(-3.45)	(-3.00)	(-1.87)	(-1.95)	(-1.89)	(-1.99)	(-2.24)	(-2.19)	(-1.90)	(-2.01)	(-1.90)
FF three-factor alpha	-0.0022***	-0.0024***	-0.0019**	-0.0009	-0.0010	-0.0009	-0.0010	-0.0012	-0.0012	-0.00084	-0.0010	-0.0008
	(-2.59)	(-2.67)	(-2.15)	(-1.02)	(-1.13)	(-1.01)	(-1.09)	(-1.39)	(-1.28)	(-0.98)	(-1.13)	(-0.95)
Carhart four-factor alpha	-0.0032***	-0.0035***	-0.0029***	-0.0022**	-0.0024***	-0.0021**	-0.0022***	-0.0026***	-0.0024***	-0.0021**	-0.0024***	-0.0021**
	(-3.72)	(-3.85)	(-3.30)	(-2.49)	(-2.71)	(-2.39)	(-2.59)	(-2.99)	(-2.72)	(-2.46)	(-2.76)	(-2.43)
Five-factor model alpha	-0.0031***	-0.0035***	-0.0029***	-0.0021**	-0.0024***	-0.0021**	-0.0022***	-0.0026***	-0.0024***	-0.0020**	-0.0023***	-0.0021**
	(-3.72)	(-3.84)	(-3.28)	(-2.48)	(-2.70)	(-2.37)	(-2.59)	(-2.98)	(-2.70)	(-2.46)	(-2.75)	(-2.41)

So far, our analysis has shown that high-rated funds generate higher unadjusted returns compared to low-rated ones. However, after accounting for the common risk factors no evidence of this outperformance can be found. Moreover, if we account for the common risk factors, low-rated funds actually outperform high-rated ones. To find where this outperformance comes from, we look at the exposure of high-rated and low-rated funds to various risk factors.

Using the five-factor model we estimate loadings on each of the risk components (market, size, value, momentum and liquidity). The results in Table 13 show that the size and momentum loadings are statistically different for high- and low-rated funds suggesting that these two risk components might be the drivers of outperformance of low-rated funds.

We find that low-rated funds are more exposed to the size factor: the average loading on the size component is 0.23 for low-rated funds and 0.10 for high-rated ones. This implies that low-rated funds focus more on smaller stocks in their portfolios compared to high-rated ones (see Table 14). Moreover, low-rated funds have a negative exposure to the momentum component

(-0.08). We find no statistically significant evidence of exposure of high-rated funds to this component.

Table 13. Difference in factor loadings of high-rated and low-rated funds

This table shows p-values generated under the null hypothesis that there is no difference between estimated common risk factor loadings of high-rated and low-rated funds. P-values lower than 0.01, 0.05 or 0.1 indicate that the estimates of risk factors of high-rated funds are statistically different from the estimates of risk factors of low-rated funds at the 1%, 5% or 10% significance level, respectively. The chi-square statistic is reported in parentheses.

Difference in factor loadings between high-rated and low-rated funds (p-values)												
Common risk factors	CAPM-sorted			FF three-factor sorted			Carhart four-factor sorted			Five-factor sorted		
	1m	2m	3m	1m	2m	3m	1m	2m	3m	1m	2m	3m
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
rmrf	0.840	0.866	0.608	0.983	0.731	0.221	0.8340	0.732	0.355	0.754	0.766	0.320
	(0.04)	(0.03)	(0.26)	(0.00)	(0.12)	(1.50)	(0.04)	(0.12)	(0.86)	(0.10)	(0.09)	(0.99)
smb	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(18.75)	(18.07)	(17.66)	(22.84)	(22.11)	(19.10)	(24.65)	(23.29)	(21.11)	(27.09)	(26.99)	(24.93)
hml	0.198	0.236	0.466	0.515	0.447	0.824	0.543	0.389	0.706	0.268	0.191	0.648
	(1.65)	(1.41)	(0.53)	(0.42)	(0.58)	(0.05)	(0.37)	(0.74)	(0.14)	(1.23)	(1.71)	(0.21)
pr1yr	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(21.04)	(21.85)	(20.22)	(30.45)	(37.61)	(26.52)	(32.63)	(42.57)	(30.30)	(29.02)	(41.63)	(31.00)
liq	0.102	0.109	0.109	0.047	0.113	0.169	0.032	0.065	0.122	0.040	0.042	0.156
	(2.67)	(2.57)	(2.57)	(3.94)	(2.51)	(1.89)	(4.60)	(3.42)	(2.40)	(4.22)	(4.13)	(2.01)

To conclude, by blindly following Morningstar ratings Norwegian investors might make two mistakes: they might invest in funds with high ratings but low alpha and ignore funds with low ratings but high alpha. The results suggest that mistake 2 is more prevalent among Norwegian mutual funds investors (we do not find evidence of investors making mistake 1).

We find that despite the fact that high-rated funds generate higher total shareholder returns, low-rated funds dominate them in terms of performance when we adjust for risk. This suggests that investors are not compensated enough for the risk that they are exposed to when they blindly follow Morningstar ratings and invest in high-rated funds. We also find that the difference in the performance of high- and low-rated funds lies in the different exposure of these two groups to the common risk factors. Low-rated funds invest more in smaller stocks (higher load on the size factor) and load negatively on the momentum factor (we do not find any statistically significant loading for high-rated funds).

Overall, our results suggest that the behavior of the Norwegian mutual fund investors is suboptimal and serves as another piece of evidence that they are unlikely to be sophisticated.

Table 14. Factor loadings of high-rated and low-rated funds

This table reports exposure of high-rated and low-rated funds to the common risk factors. Panel A shows estimates of factor loadings for high-rated funds. For a 1-month holding period, a portfolio of high-rated funds is formed from funds that had a high Morningstar rating (four or five stars) in the previous month. For 2- and 3-month holding periods, portfolios are formed from funds that had a high rating two and three months ago, respectively. Panel B presents estimates of risk factors for low-rated funds. For a 1-month holding period, a portfolio of low-rated funds is formed from funds that had a low Morningstar rating (one or two stars) in the previous month. For 2- and 3-month holding periods, portfolios are formed from funds that had a low rating two and three months ago, respectively. Factor loadings are obtained using the five-factor model (see Appendix C for estimates of factor loadings obtained using other common asset pricing models). ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The t-statistics are reported in parentheses.

Panel A: High-rated funds												
	CAPM-sorted			FF three-factor sorted			Carhart four-factor sorted			Five-factor model sorted		
	1m	2m	3m	1m	2m	3m	1m	2m	3m	1m	2m	3m
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
rmrf	0.932***	0.923***	0.926***	0.938***	0.937***	0.928***	0.935***	0.932***	0.934***	0.932***	0.931***	0.928***
	(50.16)	(48.49)	(47.42)	(52.07)	(50.75)	(49.71)	(52.95)	(51.17)	(50.27)	(52.73)	(51.25)	(50.97)
smb	0.105***	0.104***	0.106***	0.108***	0.109***	0.107***	0.103***	0.104***	0.101***	0.103***	0.098***	0.098***
	(4.81)	(4.64)	(4.65)	(5.11)	(4.99)	(4.86)	(4.99)	(4.81)	(4.63)	(4.95)	(4.58)	(4.55)
hml	-0.019	-0.026	-0.017	-0.018	-0.022	-0.024	-0.022	-0.026	-0.025	-0.021	-0.027	-0.025
	(-1.13)	(-1.48)	(-0.99)	(-1.13)	(-1.29)	(-1.44)	(-1.44)	(-1.58)	(-1.53)	(-1.34)	(-1.60)	(-1.54)
pr1yr	0.009	0.005	0.003	0.019	0.017	0.009	0.017	0.011	0.012	0.015	0.013	0.011
	(0.58)	(0.30)	(0.18)	(1.31)	(1.09)	(0.61)	(1.18)	(0.74)	(0.77)	(1.08)	(0.83)	(0.72)
liq	-0.095***	-0.102***	-0.091***	-0.084	-0.087***	-0.091***	-0.081***	-0.087***	-0.076***	-0.087	-0.090***	-0.085***
	(-3.63)	(-3.79)	(-3.32)	(-3.29)	(-3.33)	(-3.46)	(-3.24)	(-3.35)	(-2.91)	(-3.49)	(3.49)	(-3.29)

Panel B: Low-rated funds												
	CAPM-sorted			FF three-factor sorted			Carhart four-factor sorted			Five-factor model sorted		
	1m	2m	3m	1m	2m	3m	1m	2m	3m	1m	2m	3m
rmrf	0.928***	0.920***	0.938***	0.939***	0.945***	0.954***	0.939***	0.939***	0.955***	0.938***	0.937***	0.950***
	(36.97)	(36.04)	(36.89)	(35.72)	(35.95)	(36.41)	(35.56)	(35.84)	(36.52)	(35.93)	(36.06)	(37.15)
smb	0.216***	0.224***	0.221***	0.229***	0.231***	0.222***	0.233***	0.229***	0.222***	0.233***	0.229***	0.222***
	(7.33)	(7.44)	(7.37)	(7.44)	(7.42)	(7.18)	(7.52)	(7.39)	(7.20)	(7.61)	(7.46)	(7.36)
hml	-0.044**	-0.052**	-0.033	-0.032	-0.038	-0.029	-0.036	-0.045*	-0.034	-0.044*	-0.054**	-0.035
	(-1.98)	(-2.24)	(-1.46)	(-1.36)	(-1.59)	(-1.24)	(-1.52)	(-1.88)	(-1.45)	(-1.90)	(-2.27)	(-1.53)
pr1yr	-0.067***	-0.079***	-0.075***	-0.080***	-0.091***	-0.083***	-0.083***	-0.095***	-0.084***	-0.081***	-0.094***	-0.085***
	(-3.30)	(-3.74)	(-3.65)	(-3.81)	(-4.19)	(-3.92)	(-3.90)	(-4.38)	(-3.96)	(-3.87)	(-4.37)	(-4.12)
liq	-0.150***	-0.158***	-0.146***	-0.149***	-0.141***	-0.137***	-0.152***	-0.148***	-0.131***	-0.154***	-0.155***	-0.133***
	(-4.22)	(-4.37)	(-4.07)	(-4.02)	(-3.78)	(-3.70)	(-4.08)	(-3.99)	(-3.54)	(-4.17)	(-4.20)	(-3.69)

5. Conclusion

In this paper we analyze sophistication of Norwegian mutual fund investors. Specifically, we investigate how Norwegian mutual fund investors make their capital allocation decisions by exploring the signals that they follow.

In the first step of our analysis, we test whether Norwegian mutual fund investors follow simple signals such as unadjusted fund returns when deciding, in which funds to invest. Our test consists of modeling the relationship between fund flows, alphas and the common return components (market, size, value, momentum and liquidity), which allows us to see whether investors account for the common risk factors. Using the bootstrapping approach of Ben-David et al. (2019), we cannot reject the hypothesis that Norwegian investors chase unadjusted fund returns.

In the second step of our analysis, we look into the allocation decisions of Norwegian mutual fund investors. We assess the magnitude of reaction of Norwegian investors to various signals: alphas of various asset pricing models, market-adjusted returns, as well as Morningstar ratings. By looking at the relationship between signs of alphas (positive/negative sign if alpha was above/below zero in the past month) or Morningstar ratings (positive sign if the fund was high-rated by Morningstar in the past month) and signs of fund flows, we assess the frequency with which the asset pricing models and Morningstar ratings predict fund flows. The results show that Morningstar ratings outperform all of the asset pricing models and market-adjusted returns when predicting the direction of fund flows (Morningstar ratings predict them correctly in 63.99% of the cases compared to 59.23% in the case of the best performing asset pricing model (the five-factor model)). In order to test the significance of this outperformance, we conduct pairwise comparison of various models, which confirms that Morningstar ratings dominate all of the asset pricing models in terms of the ability to predict the direction of fund flows.

Having found that Norwegian mutual fund investors follow simple signals, specifically Morningstar ratings, we look into possible explanations of such behavior. We explore whether investors follow Morningstar ratings as a means of outsourcing risk adjustment to Morningstar. The evidence we find suggests that Norwegian mutual fund investors do not account for any extra risk, which is not already accounted for by Morningstar ratings. Our next regressions show that Morningstar ratings account only for 3.62% of the total volatility in fund returns, which implies that outsourcing risk adjustment to Morningstar ratings would be an irrational thing to do.

Finally, after having found multiple pieces of evidence suggesting that Norwegian mutual fund investors are unlikely to be sophisticated on aggregate, we explore whether their capital allocation decisions based on Morningstar ratings have any significant effect on their financial wealth. We analyze total shareholder returns, as well as alphas calculated using various asset pricing models for portfolios of high-rated and low-rated funds. Our tests show that high-rated funds outperform low-rated ones in terms of total shareholder returns (unadjusted returns), however, when risk is accounted for, the opposite evidence is found. This tells us that Norwegian mutual fund investors are not compensated enough for the risk they are exposing themselves to when investing into high-rated funds. This also means that Norwegian mutual fund investors focus on unadjusted returns and do not account for the common risk factors.

Overall, our paper presents evidence that Norwegian mutual fund investors are unlikely to be sophisticated. Despite the percentage of retail investors represented in the market being much smaller compared to the USA, Norwegian mutual fund investors (on aggregate) still seem to be following simple signals such as Morningstar ratings and, by doing so, they expose themselves to extra risk that they are not compensated for. It seems unlikely that they follow Morningstar ratings as a means of outsourcing risk adjustment to Morningstar, as this would be irrational to do due to the small percentage of the total volatility accounted for by Morningstar ratings.

A potential limitation to our analysis might be the short holding period (one, two and three months) analyzed for the four strategies that we tested. To some extent this was dictated by a small population of Norwegian mutual funds: longer holding periods would mean that observations in the last periods of our dataset would not be accounted for. In reality, Norwegian investors might have longer holding periods, which would imply different risk-adjusted returns observed over those time horizons. Related to the previous point, another limitation is data quality. Compared to the US mutual funds, the Norwegian ones oftentimes have missing observations in the Morningstar Direct database (especially, for Morningstar ratings) making the dataset on them unbalanced.

An idea for further research might be to look into the various groups of Norwegian mutual fund investors separately. By splitting investors into institutional and retail investors, local and foreign investors, it would be possible to assess, which groups contribute the most to the low aggregate investor sophistication in the market. Currently the Norwegian Fund and Asset Management Association provides the data on these groups on an annual basis. The availability of monthly data would allow to enhance our analysis with more details and allow to see the bigger picture of investor sophistication in Norway.

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Appendices

Appendix A

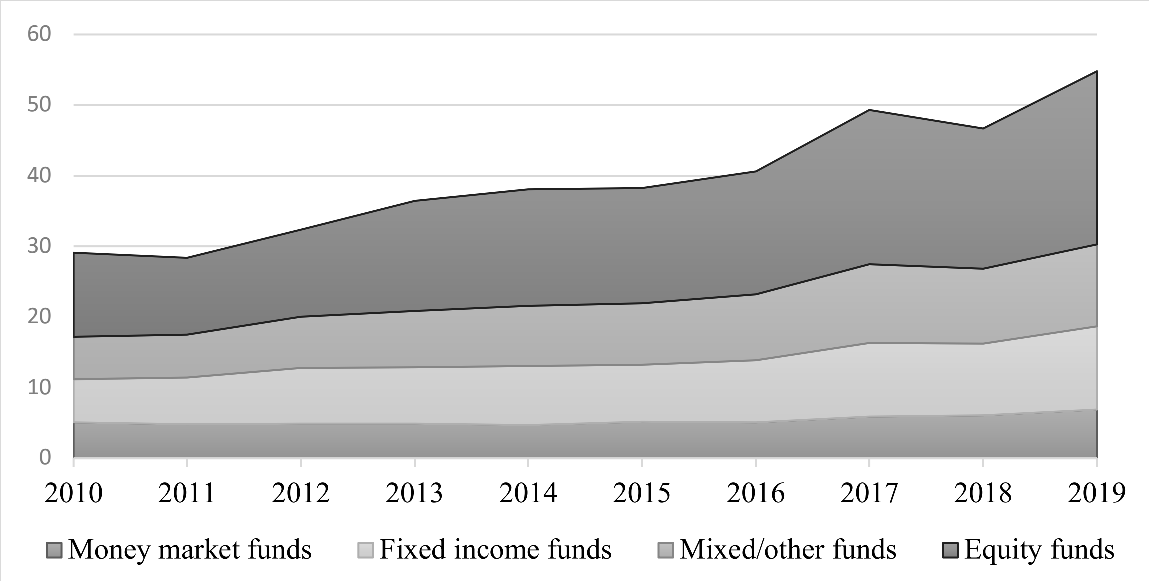

Figure A.1. The total amount of net assets under management by mutual funds globally in trillions of US dollars (USD). The y axis represents the amount of net assets. Net assets are further split between various types of funds that manage them.

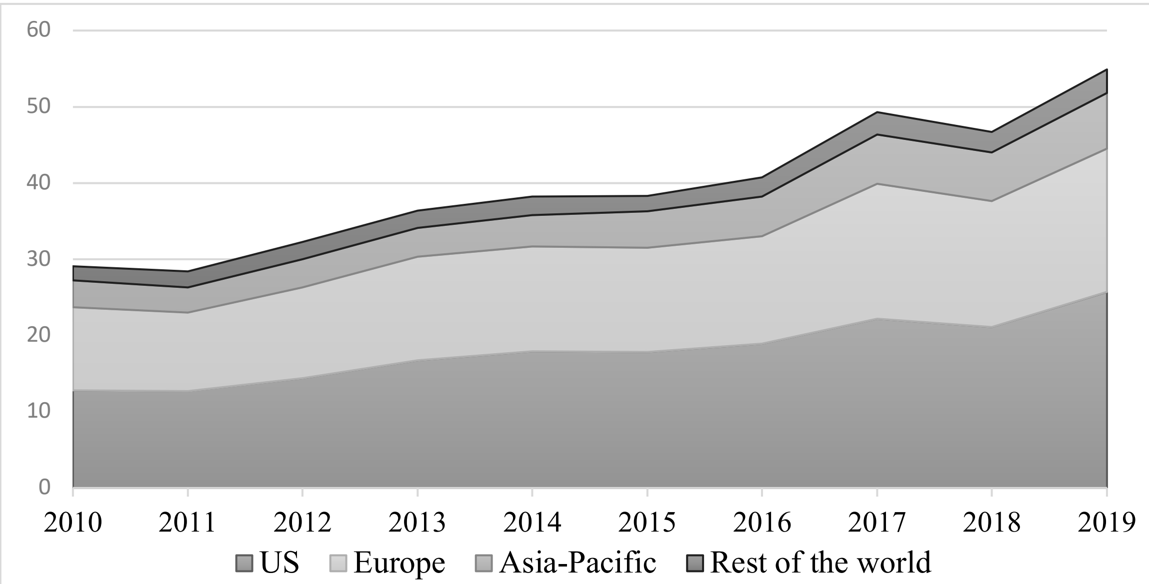

Figure A.2. The total amount of net assets under management by mutual funds globally in trillions of US dollars (USD). The y axis represents the amount of net assets. Net assets are further split between geographies where the funds managing them are located.

Appendix B

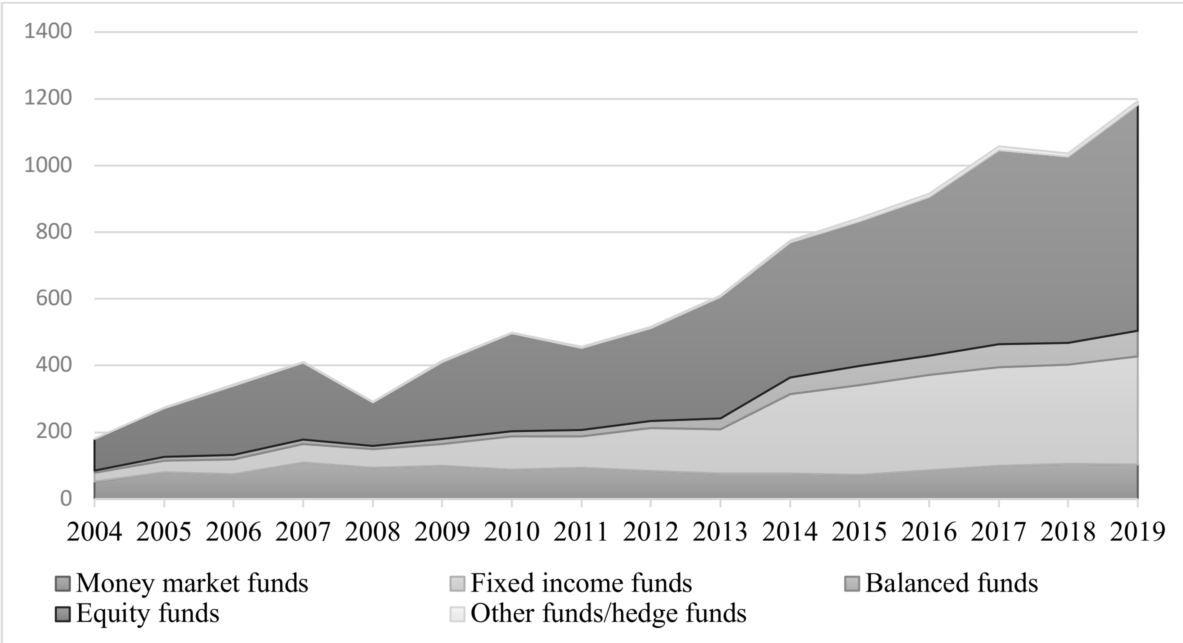

Figure B.1. The total amount of assets under management by mutual funds in Norway in billions of Norwegian Kroner (NOK). The y axis represents the amount of assets. Assets are further split between various types of funds that manage them.

Appendix C

Table C.1. Factor loadings of high-rated funds

This table reports exposure of high-rated funds to the common risk factors. For a 1-month holding period, a portfolio of high-rated funds is formed from funds that had a high Morningstar rating (four or five starts) in the previous month. For 2- and 3-month holding periods, portfolios are formed from funds that had a high rating two and three months ago, respectively. Factor loadings are obtained using the four different asset-pricing models: the CAPM, the Fama-French three-factor, the Fama-French four-factor and the five-factor model. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The t-statistics are reported in parentheses.

	High-rated funds											
	CAPM-sorted			FF three-factor sorted			Carhart four-factor sorted			Five-factor model sorted		
	1m	2m	3m	1m	2m	3m	1m	2m	3m	1m	2m	3m
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CAPM												
rmrf	0.948***	0.944***	0.939***	0.945***	0.946***	0.941***	0.943***	0.943***	0.940***	0.944***	0.946***	0.941***
	(85.01)	(82.10)	(81.05)	(86.94)	(84.54)	(83.67)	(88.68)	(85.79)	(84.78)	(88.58)	(86.40)	(86.31)
FF three-factor												
rmrf	0.977***	0.972***	0.969***	0.975***	0.976***	0.970***	0.971***	0.972***	0.968***	0.972***	0.972***	0.967***
	(73.58)	(70.71)	(69.91)	(75.88)	(73.54)	(72.48)	(77.22)	(74.35)	(73.26)	(76.91)	(74.36)	(74.21)
smb	0.088***	0.087***	0.090***	0.093***	0.093***	0.091***	0.089***	0.088***	0.087***	0.087***	0.083***	0.082***
	(4.02)	(3.81)	(3.95)	(4.37)	(4.26)	(4.10)	(4.26)	(4.09)	(4.01)	(4.16)	(3.82)	(3.83)
hml	-0.020	-0.027	-0.018	-0.019	-0.023	-0.025	-0.024	-0.028	-0.026	-0.022	-0.028	-0.026
	(-1.18)	(-1.50)	(-1.02)	(-1.16)	(-1.34)	(-1.46)	(-1.47)	(-1.62)	(-1.55)	(-1.38)	(-1.64)	(-1.56)
Carhart four-factor												
rmrf	0.979***	0.974***	0.970***	0.980***	0.980***	0.973***	0.975***	0.974***	0.971***	0.976***	0.975***	0.970***
	(71.79)	(69.08)	(67.93)	(74.48)	(72.25)	(70.62)	(75.69)	(72.82)	(71.45)	(75.33)	(72.90)	(72.36)
smb	0.089***	0.087***	0.091***	0.094***	0.094***	0.091***	0.090***	0.089***	0.088***	0.088***	0.083***	0.083***
	(4.05)	(3.82)	(3.96)	(4.44)	(4.29)	(4.13)	(4.33)	(4.11)	(4.05)	(4.22)	(3.84)	(3.87)
hml	-0.020	-0.027	-0.018	-0.020	-0.023	-0.025	-0.024	-0.027	-0.026	-0.023	-0.027	-0.026
	(-1.19)	(-1.48)	(-1.03)	(-1.19)	(-1.30)	(-1.47)	(-1.49)	(-1.59)	(-1.56)	(-1.40)	(-1.60)	(-1.57)
pr1yr	0.012	0.009	0.006	0.022	0.020	0.012	0.020	0.014	0.014	0.019	0.016	0.014
	(0.78)	(0.53)	(0.37)	(1.48)	(1.28)	(0.80)	(1.35)	(0.94)	(0.93)	(1.27)	(1.04)	(0.90)
Five-factor model												
rmrf	0.932***	0.923***	0.926***	0.938***	0.937***	0.928***	0.935***	0.932***	0.934***	0.932***	0.931***	0.928***
	(50.16)	(48.49)	(47.42)	(52.07)	(50.75)	(49.71)	(52.95)	(51.17)	(50.27)	(52.73)	(51.25)	(50.97)
smb	0.105***	0.104***	0.106***	0.108***	0.109***	0.107***	0.103***	0.104***	0.101***	0.103***	0.098***	0.098***
	(4.81)	(4.64)	(4.65)	(5.11)	(4.99)	(4.86)	(4.99)	(4.81)	(4.63)	(4.95)	(4.58)	(4.55)
hml	-0.019	-0.026	-0.017	-0.018	-0.022	-0.024	-0.022	-0.026	-0.025	-0.021	-0.027	-0.025
	(-1.13)	(-1.48)	(-0.99)	(-1.13)	(-1.29)	(-1.44)	(-1.44)	(-1.58)	(-1.53)	(-1.34)	(-1.60)	(-1.54)
pr1yr	0.009	0.005	0.003	0.019	0.017	0.009	0.017	0.011	0.012	0.015	0.013	0.011
	(0.58)	(0.30)	(0.18)	(1.31)	(1.09)	(0.61)	(1.18)	(0.74)	(0.77)	(1.08)	(0.83)	(0.72)
liq	-0.095***	-0.102***	-0.091***	-0.084	-0.087***	-0.091***	-0.081***	-0.087***	-0.076***	-0.087	-0.090***	-0.085***
	(-3.63)	(-3.79)	(-3.32)	(-3.29)	(-3.33)	(-3.46)	(-3.24)	(-3.35)	(-2.91)	(-3.49)	(3.49)	(-3.29)

Table C.2. Factor loadings of low-rated funds

This table reports exposure of low-rated funds to the common risk factors. For a 1-month holding period, a portfolio of low-rated funds is formed from funds that had a low Morningstar rating (one or two stars) in the previous month. For 2- and 3-month holding periods, portfolios are formed from funds that had a low rating two and three months ago, respectively. Factor loadings are obtained using the four different asset-pricing models: the CAPM, the Fama-French three-factor, the Fama-French four-factor and the five-factor model. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. The t-statistics are reported in parentheses.

	Low-rated funds											
	CAPM-sorted			FF three-factor sorted			Carhart four-factor sorted			Five-factor model sorted		
	1m	2m	3m	1m	2m	3m	1m	2m	3m	1m	2m	3m
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CAPM												
rmrf	0.952***	0.945***	0.957***	0.959***	0.959***	0.969***	0.960***	0.959***	0.967***	0.961***	0.962***	0.964***
	(57.86)	(55.78)	(57.16)	(55.46)	(55.14)	(56.41)	(55.03)	(55.02)	(56.38)	(55.40)	(55.30)	(57.00)
FF three-factor												
rmrf	1.014***	1.011***	1.024***	1.028***	1.030***	1.037***	1.030***	1.028***	1.035***	1.030***	1.029***	1.032***
	(54.89)	(52.87)	(54.21)	(52.90)	(52.44)	(53.37)	(52.64)	(52.17)	(53.48)	(53.16)	(52.49)	(54.24)
smb	0.195***	0.200***	0.201***	0.209***	0.209***	0.204***	0.213***	0.206***	0.205***	0.212***	0.205***	0.205***
	(6.38)	(6.32)	(6.46)	(6.52)	(6.44)	(6.38)	(6.57)	(6.34)	(6.43)	(6.63)	(6.34)	(6.54)
hml	-0.048**	-0.051**	-0.036	-0.036	-0.037	-0.032	-0.040	-0.043*	-0.037	-0.048*	-0.052**	-0.038
	(-2.01)	(-2.04)	(-1.50)	(-1.43)	(-1.42)	(-1.29)	(-1.58)	(-1.68)	(-1.49)	(-1.93)	(-2.04)	(-1.55)
Carhart four-factor												
rmrf	1.002***	0.997***	1.009***	1.013***	1.014***	1.021***	1.014***	1.012***	1.019***	1.015***	1.013***	1.015***
	(53.81)	(52.23)	(53.24)	(52.13)	(52.14)	(52.60)	(51.92)	(51.98)	(52.74)	(52.41)	(52.27)	(53.60)
smb	0.191***	0.197***	0.196***	0.205***	0.206***	0.198***	0.208***	0.204***	0.200***	0.208***	0.203***	0.199***
	(6.36)	(6.40)	(6.43)	(6.53)	(6.57)	(6.37)	(6.59)	(6.48)	(6.43)	(6.65)	(6.47)	(6.55)
hml	-0.047**	-0.054**	-0.035	-0.034	-0.040	-0.031	-0.038	-0.047*	-0.036	-0.047*	-0.056**	-0.037
	(-2.01)	(-2.20)	(-1.49)	(-1.42)	(-1.59)	(-1.27)	(-1.57)	(-1.87)	(-1.48)	(-1.93)	(-2.24)	(-1.55)
pr1yr	-0.061***	-0.073***	-0.070***	-0.076***	-0.086***	-0.078***	-0.078***	-0.089***	-0.079***	-0.076***	-0.088***	-0.080***
	(-2.92)	(-3.31)	(-3.28)	(-3.44)	(-3.82)	(-3.59)	(-3.52)	(-3.98)	(-3.65)	(-3.47)	(-3.93)	(-3.78)
Five-factor model												
rmrf	0.928***	0.920***	0.938***	0.939***	0.945***	0.954***	0.939***	0.939***	0.955***	0.938***	0.937***	0.950***
	(36.97)	(36.04)	(36.89)	(35.72)	(35.95)	(36.41)	(35.56)	(35.84)	(36.52)	(35.93)	(36.06)	(37.15)
smb	0.216***	0.224***	0.221***	0.229***	0.231***	0.222***	0.233***	0.229***	0.222***	0.233***	0.229***	0.222***
	(7.33)	(7.44)	(7.37)	(7.44)	(7.42)	(7.18)	(7.52)	(7.39)	(7.20)	(7.61)	(7.46)	(7.36)
hml	-0.044**	-0.052**	-0.033	-0.032	-0.038	-0.029	-0.036	-0.045*	-0.034	-0.044*	-0.054**	-0.035
	(-1.98)	(-2.24)	(-1.46)	(-1.36)	(-1.59)	(-1.24)	(-1.52)	(-1.88)	(-1.45)	(-1.90)	(-2.27)	(-1.53)
pr1yr	-0.067***	-0.079***	-0.075***	-0.080***	-0.091***	-0.083***	-0.083***	-0.095***	-0.084***	-0.081***	-0.094***	-0.085***
	(-3.30)	(-3.74)	(-3.65)	(-3.81)	(-4.19)	(-3.92)	(-3.90)	(-4.38)	(-3.96)	(-3.87)	(-4.37)	(-4.12)
liq	-0.150***	-0.158***	-0.146***	-0.149***	-0.141***	-0.137***	-0.152***	-0.148***	-0.131***	-0.154***	-0.155***	-0.133***
	(-4.22)	(-4.37)	(-4.07)	(-4.02)	(-3.78)	(-3.70)	(-4.08)	(-3.99)	(-3.54)	(-4.17)	(-4.20)	(-3.69)