NORWEGIAN SCHOOL OF ECONOMICS

BERGEN, Spring 2017

Performance Prediction in

Dine Penger's Norwegian Mutual Fund Ratings

Evidence from ratings in the financial media

By

Haakon Markus Madsen

&

Ole Andreas Stensland Dahl

Thesis advisor: Thore Johnsen

Master Thesis – Financial Economics

NORWEGIAN SCHOOL OF ECONOMICS

KONFIDENSIALITETSERKLÆRING

Undertegnede, Haakon Markus Madsen og Ole Andreas Dahl, har fått tilgang til data for Dine Pengers fondsevaluering innsamlet av førstelektor Jon Mjølhus ved Høgskolen i Sørøst-Norge. Målet er å studere prediksjonsevnen til for fondsrangeringer. Materiale som er hentet inn er tenkt brukt i avhandlinger og/eller publisert forskning ved Høgskolen i Sørøst-Norge og Norges Handelshøyskole.

Med unntak av de data som Mjølhus godkjenner til bruk i publisering, skal intet av datagrunnlaget kopieres, videreformidles eller -distribueres.

Bergen, 14. februar 2017

Haakon Markus Madsen

Ole Andreas Dahl

Foreword

This master thesis concludes our Master of Science degree in Economics and Business Administration at the Norwegian School of Economics. Both candidates have specialized in Financial Economics, and have throughout the Master's programme gained invaluable insights about the financial universe. The writing process has been both challenging and inspiring, where we have had the possibility to implement knowledge that we have acquired throughout the Master's programme.

The final semester has been spent investigating the abilities of Dine Penger's rating system to forecast future performance in Norwegian mutual funds. More than one-third of the Norwegian population has invested capital in mutual funds. We believe that many of these investors rely on fund ratings when deciding which fund to invest in. As such, our main motivation is to provide insightful information about the true value of ratings to both unprofessional and professional investors. Hopefully this research will provide a significant contribution to a large part of the Norwegian society, in the question of deciding which fund to trust with their personal savings. We recommend interested parties to consider our findings when collecting information regarding future fund investments.

First and foremost, we would gratefully like to thank our master thesis supervisor, Professor Thore Johnsen, for invaluable insight about mechanisms in the financial markets and for the sharing of knowledge regarding mutual fund performances. His academic advices throughout the process have been critical and important for the quality of the research. Furthermore, we would like to express our gratitude to both Jon Olav Mjølhus and Espen Sirnes for the original and unique set of data. To our knowledge, we are the first individuals to apply this data of Norwegian mutual funds in academic research. For the confidence in our abilities, we are thankful. Lastly, we would like to thank the Department of Finance of the Norwegian School of Economics for motivational and inspiring curricula, which have truly been decisive for our future career paths.

As a final note, the opinions, results, and conclusions in this thesis are solely provided by the authors.

Bergen, June 2017

Haakon Markus Madsen

Ole Andreas Stensland Dahl

Performance Prediction in Dine Penger's Norwegian Mutual Fund Ratings

Haakon Markus Madsen & Ole Andreas Stensland Dahl

June 20, 2017

Abstract

The academic literature appears to lack comprehensive studies on the credibility of Norwegian mutual fund ratings issued by the Norwegian financial media. In this thesis, we implement a data set free of survivorship bias to investigate the performance persistence of Norwegian mutual fund ratings issued by Dine Penger in the period 2002-2013. As such, we examine whether investors will benefit from investing according to these ratings or not. The data set is to our knowledge completely unique, which implies that we are the first individuals to apply this data in academic research. To evaluate mutual fund performance, we employ the Jensen's and the Carhart 4-factor alphas as performance measurements. To comprehensively test for predictive abilities in the rating system, we conduct both several out-of-sample random effects panel regressions and J/K-strategies of buying top rated and short-selling bottom rated funds. Our findings indicate a substantial difference in the results when separating the total sample period into ex-ante and ex-post periods relative to the financial crisis in 2008. We find evidence that investors were more likely to benefit from the rating system before the financial crisis in 2008, as the rating system possessed better predictive abilities. Hence, in the ex-ante period, investors could implement various J/K-strategies to generate zero-pay returns. However, these strategies are no longer sufficient as the rating system has lost its predictability in the recent years.

Table of Contents

1. Introduction

There has been and still is an ongoing discussion around the relevance of certain rating systems that aims to distinguish between top and low quality equity funds. How is it possible to recognize a top quality fund that will outperform their benchmarks or peer group in the following period? This inquiry is widely discussed and highly relevant for different agents in the financial industry, such as academics and investors. The efficient market hypothesis[1], developed by Fama, Fisher and Roll (1969) has had a fundamental impact on the academic literature. According to this theorem, all asset prices fully reflect all available information at all time. Hence, in theory, it is impossible to continuously beat the market on a risk-adjusted basis since asset prices only will react to new information or changes in discount rates. Any results that prove persistence in the outperformance for a given fund would hence be directly contradictory to the semi-strong form of the efficient market hypothesis of Fama (1970). For investors, it is relevant to investigate the efficiency of the rating systems to decide which fund to invest in.

Early research literature is ambiguous whether some funds possess abilities to continuously outperform the market. Jensen (1968) argues that that mutual funds were on average not able to predict future performance of individual stocks well enough to outperform the market, also when measuring the returns gross management expenses. However, the question of diversification and the job of minimizing insurable risk were not discussed in this paper. Other studies such as Friend et al. (1962), Friend et al. (1970) and Sharpe (1966) also reports evidence of negative alphas for mutual funds. On the other hand, research by De Bondt and Thaler (1985, 1987) suggest that stock prices tend to overreact to information. Hence, funds can generate abnormal returns by following a contrarian strategy of

[1] The efficient market hypothesis can be categorized into three basic levels: the weak form reflecting all market information, the semi-strong reflecting all public information and strong form reflecting all public and private information available.

buying past losers and selling past winners over the previous three to five years, and holding that portfolio over a period of three to five years. Later academic research, such as Ippolito (1989), finds however that mutual funds, net of all fees and expenses[2], outperformed passive index funds on a risk-adjusted basis. Nevertheless, there is limited evidence of academic literature that supports this view. Still, there will always be funds that deliver abnormal positive (negative) returns to their investors. Here, two key questions arise: Is there any persistence in the outperformance (underperformance) of these funds, and is it possible to distinguish between top and low quality funds?

Earlier research papers have broadly touched upon similar questions. Jensen (1968) finds that applying his own made "Jensen's alpha" as a performance measurement, presents no evidence that past performance history is superior to a randomly constructed portfolio. On the other hand, several other studies indicate persistence in mutual fund performance.

A study by Grinblatt and Titman (1992) indicate a positive persistence in mutual fund performance, and an assertion that past performance provides useful information for investors who are considering an investment in mutual funds. This finding is further supported by Brown and Goetzmann (1995) that find evidence of relative performance persistence, such that investors can use historical information to beat the pack. However, this paper also suggests that "chasing the winners" strategy, although generating positive alphas, provides a high level of total risk. Because of high correlation between the winning funds, the total risk is not diversifiable, and would thus matter to risk-averse investors. Applying Jensen's alpha (1968) as a performance measurement, Hendricks, Patel and Zeckhauser (1993) infer that well performing funds in a one year evaluation period will continue to generate superior performance in the following year. This is referred to as the hot hands phenomenon. The result is supported by Carhart (1997), who additionally challenges the hot hands phenomenon and argues that this effect is closely related

[2] Excluded for load charges. A load charge is a one-time sales commission meant to compensate investment advisors when investing in funds.

to the one-year momentum effect of Jegadeesh and Titman (1993). Furthermore, Carhart (1997) finds evidence that investors should avoid funds with poor performance, as these funds are likely to underperform in the future. This finding is popularly referred to as the cold hands phenomenon. Also, Sharpe (1996) finds evidence that past performance explains some of the differences between fund performances, but he emphasizes that the view of highly efficient markets remains intact.

Considering that there is no perfect performance metric various alternatives have been developed to distinguish between top and average funds, more specifically rating systems. A well-recognized rating system is the Morningstar fund rating, which several academics have studied. According to the extensive study by Gottesman and Morey (2005), Morningstar's rating system is capable of predicting future performance for a minimum of three years. They also find that higher rated funds, consistently, tend to outperform lower rated funds. However, these results are contrary to those of Black and Morey (2000) and Morey (2002b), which indicate poor predictability of the rating system.

An important issue with most of previous empirical literature is the use of US data, which may not be directly transferable to other equity markets, more specially the Norwegian equity market which is the focus area in this research paper. There is limited research on the persistence in performance for Norwegian mutual funds, which might be of high relevance for both Norwegian and international investors. Nevertheless, Sørensen (2009) finds no proof of persistence in the performance of either winners or losers among Norwegian mutual funds listed on the Oslo Stock Exchange between 1982 and 2008. The same paper also finds weak signs of skill when analysing the cross-sectional distribution of alphas, but several inferior funds in the left tail of the distribution. Furthermore, Hansen, Haukaas and Gallefoss (2012) find evidence of short-term persistence in performance for Norwegian mutual funds, where the strongest persistency is related to abnormally weak performers. These findings are consistent with Bolle and Busse (2005). Another paper by Kilanger and Ingier (2008) conclude that the rating system of Morningstar is only applicable when analysing short-term performance of three months.

Multiple academic papers have been written on international fund rating systems, with some already presented. However, limited research has been conducted on Norwegian mutual funds and rating systems. Will similar results as seen in the US market apply to the Norwegian financial sector? In this paper, we will try to answer whether there is any persistence in the outperformance (underperformance) of Norwegian mutual funds, and if it is possible to distinguish between top and low quality funds using the rating system of Dine Penger.

2. Dine Penger Rating System

Dine Penger is the largest private finance magazine in Norway. The magazine publishes elven issues annually, which contain various articles about the Norwegian economy, including their ratings of Norwegian funds. The rating system, constructed by the prominent Norwegian economist Frank Asche and statistician Harald Haukås, rates mutual funds on a dice scale from six to one, where *six* is the highest and *one* is the lowest rating (Table 1). According to Dine Penger, its dice ratings are a quantitative measure, based solely upon returns, volatility and fees.

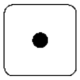
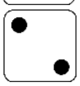
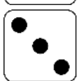
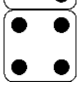
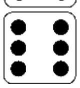
There are certain criteria that need to be satisfied for a fund to be included in the rating evaluation. Firstly, a fund must have existed for a minimum of three years, which is the evaluation period of the index. This criterion eliminates a potential bias with respect to the lifespan of the funds. Funds that are rated shortly after a period of superior return, will also be rated based on the past three years. This will decrease the possibility of new funds to receive higher ratings than funds with a greater longevity, which may have experienced a full market cycle and periods with below average returns. Secondly, all funds must be open-ended which implies no restrictions on the amount of shares a fund can issue.

Furthermore, the dice ratings are *non-normally* distributed, where the fund rating is determined based on specific value ranges. Because of this rating methodology, there are periods with zero 1 or 2-dice funds and other periods with few 6-dice funds.

Table 1

Interpretation of Dices

Table 1 explains the different dice ratings. From 1-dice, which is a definitely sell, to 6-dice funds, which means to buy/hold the fund.

	Sell, the fund is poorly managed.
	Sell, the fund is not good enough.
	Sell the fund if you find funds with dice 5 or 6 in the same region/industry, or want to change region/industry.
	Follow the fund carefully. If downgraded to dice 3, you should look for a better fund.
	Buy/Keep. Some equity funds range between 5 and 6.
	Buy/Keep.

2.1. Calculation of the Dine Penger Index

Dine Penger uses their in-house rating system, Dine Penger Index, to evaluate fund performance. The first step of the index is to measure the fund's logarithmic excess return in each period relative to the risk-free rate (ST1X). This process is completed for each month over the past three years. Table 2 reports these calculations for a fictional fund for a period of four months.

Table 2

First Step of Dine Penger Index Calculations

Table 2 illustrates the first step of the calculations in the Dine Penger Index using a hypothetical fund with four months of returns. First the new value of the fund is calculated based on the fund's previous monthly return. The return is then compared to the risk-free rate, to determine whether the fund has had excess gains or losses in the period. Then the logarithmic excess gains (losses) are calculated for each month in the evaluation period.

Monthly return of the fund	The funds new value	Risk-free rate	Gain or loss?	Gains to be summed	Losses to be summed
1%	101%	0.50%	0.5% = gain	ln(1.01/1.005) = 0.00496	
-5%	95%	0.50%	(5.5%) = loss		ln(0.95/1.005) = (0.0563)
10%	110%	0.50%	9.5% = gain	ln(1.1/1.005) = 0.0903	
-2%	98%	0.50%	(2.5%) = loss		ln(0.98/1.005) = (0.0252)

The second step is to compute a ratio between the absolute value of the gains and losses for each fund. Accordingly, we compute an expression of how much excess return the fund has gained for every percent of loss. The fund performance is then evaluated against its benchmark index, creating the funds DP-value. The DP value, as illustrated in Table 3, expresses the performance of the fund relative to the benchmark index. A shortfall of the index is that it does not measure the realized risk of the fund, but instead uses the ratio as measure of variance-based risk between gains and losses.

Table 3
Second Step of Dine Penger Index Calculations

Table 3 illustrates the last step of the Dine Penger Index using the hypothetical fund from Table 2. First, a ratio between the absolute value of the gains and losses are calculated for each fund. The ratio is evaluated against the benchmark index ratio to create the DP-value. The DP-value is then used to determine the dice according to specific range values. In this example, the fund has achieved a DP-value of 1.03, and would accordingly receive a 4-dice rating.

Sum gains and losses for the fund	9.53%	(8.15%)
Ratio gain/loss for the fund:	**9.53%/8.15%**	**= 1.17**
Sum gains and loss for the reference index:	8.00%	(7.00%)
Ratio gain/loss for the reference index:	**8.00%/7.00%**	**= 1.14**
The fund's DP-value:	**1.17/1.14**	**= 1.03**

DP-value:	**<0.75**	**0.75 - 0.9**	**0.9 - 1**	**1 - 1.1**	**1.1 - 1.25**	**1.25 - 1.5**
Dice:	1	2	3	4	5	6

Due to confidentiality issues, there are some limitations with the calculations of the Dine Penger Index. The DP-value only accounts for 50% of the dice estimation, while fees and other factors account for respectively 30% and 20%. How these factors affect the dice value have not been released by Dine Penger and are thus not explained in the model. However, the main emphasis in this paper is to evaluate the persistency and predictability of Norwegian mutual fund performance based on the dice ratings. Hence, missing information about the dice rating methodology should not have significant impact on our results.

3. Data

3.1. Norwegian Mutual Funds

The data set is obtained from Jon Olav Mjølhus and Espen Sirnes, who have both prominent roles and many years of experience in the Norwegian financial sector. The data is originally obtained from Dine Penger and is both unique and confidential.

The database is characterized as *panel data*, also called cross-sectional time series, as it includes observations of funds over multiple time periods. It comprises 74 Norwegian open-ended equity funds from January 2002 to December 2013[3], which is divided into two main elements. Firstly, daily net asset values (NAV) for each respective fund adjusted for dividend reinvestments, but ignoring cost elements such as management, entry and exit fees and load charges. Secondly, the database contains ratings for each respective fund. The rating system is structured in a similar way as a regular dice methodology from one to six, where the best funds are assigned a six rating. Each fund receives eleven ratings a year. Hence, a fund that remains throughout the entire sample period, will receive a cumulative number of 143 ratings. The ratings are issued on predetermined dates each year, illustrated in Table 4.

Table 4

The Issue Dates of Fund Ratings

Dine Penger evaluates Norwegian mutual funds eleven times a year, where each fund receives a rating ranging from 1 (weakest) to 6 (best). Table 4 examines the consistent eleven issue dates a year (yy):

Issue number	Issue date	Issue number	Issue date
1	1/5/yy	7	6/21/yy
2	2/2/yy	8	8/16/yy
3	3/1/yy	9	9/13/yy
4	3/29/yy	10	10/11/yy
5	4/26/yy	11	11/8/yy
6	5/24/yy		

[3] See Appendix 1 for a detailed overview of the fund list.

The return per trading day for each respective fund is calculated as follows:

$$r_{i,t} = ln\frac{NAV_{i,t}}{NAV_{i,t-1}}$$

Where $NAV_{i,t}$ represents the net asset value of fund i at trading day t, and $r_{i,t}$ reflects the logarithmic return of fund i at day t. We argue that logarithmic returns are preferred to simple returns as this provides a more precise estimation of the actual returns.

Furthermore, we calculate the logarithmic returns per fund ***between each issue*** as follows:

$$r_{i,t} = ln\frac{NAV_{i,t}}{NAV_{i,t-1}}$$

Here, the $NAV_{i,t}$ represents the net asset value of fund i at issue day t, and $NAV_{i,t-1}$ represents the net asset value of fund i at the previous issue day t. The $r_{i,t}$ reflects the logarithmic return of fund i between the issue dates t.

In addition, the sample size contains data for both actively and passively managed Norwegian mutual funds (Table 5). Active funds aim to outperform a pre-determined benchmark by conducting active bets in various stocks. This differentiates from a passive strategy that targets to track the performance of a benchmark. Because actively managed funds are promising outperformance of the benchmark to their customers, and consequently higher returns than passively managed funds, they typically have costlier fee structures. Moreover, all funds must have an investment mandate of minimum 80% exposure to Norwegian equities registered on Oslo Stock Exchange or unlisted shares registered in Norway. Funds that invest more than 20% of their investment capital in international equities, bonds, currency or any types of derivatives are excluded from the sample. This is the industry standard, approved by Verdipapirfondenes Forening (2012), for a fund to be classified as a Norwegian mutual fund.

Table 5

Summary Statistics of Database for Norwegian Funds

Table 5 illustrates a detailed overview of our fund data set, for instance the annual number of funds included and excluded from Dine Penger ratings, the average excess return of the risk-free rate and Jensen's alpha of the equal weighted portfolio between *issues* from 2002-2013. The equal weighted portfolio consists of all funds in the database for the given year. As shown, the total number of funds vary each year. On aggregate, the total number of funds included in our data set represent approximately 95% of all Norwegian open-ended equity funds as of 31 December 2012.

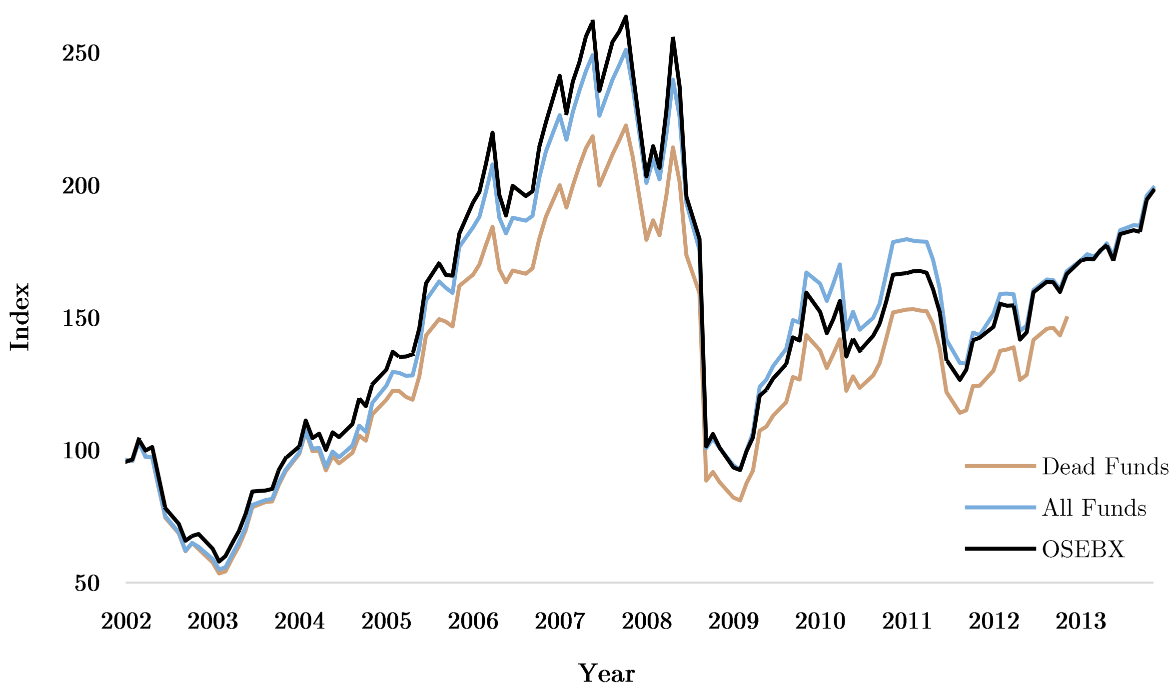
	Number of Funds				**Excess Return of Equal Weighted Portfolio**	**Jensen`s Alpha of Equal Weighted Portfolio**
Year	Beg. of Year	End of Year	New Funds Included	Dropped from Rating		
2002	57	63	6	0	-4.44%	-0.90%
2003	64	61	1	3	3.19%	0.59%
2004	61	61	1	3	2.19%	0.47%
2005	59	59	3	3	3.72%	0.91%
2006	59	56	1	7	1.56%	0.21%
2007	53	55	2	1	0.71%	0.26%
2008	54	54	0	0	-6.75%	-0.76%
2009	54	55	1	0	4.70%	1.08%
2010	55	55	1	1	0.62%	0.41%
2011	56	56	1	1	-2.02%	-0.60%
2012	55	54	0	3	1.39%	0.08%
2013	52	48	0	4	1.43%	0.18%
Total	**74**		**17**	**26**		
Average	**57**	**56**	**1**	**2**	**0.53%**	**0.16%**

A commonly known problem in the estimation and prediction of fund performance is the survivorship bias, introduced by Brown et al. (1992). This phenomenon is related to the bias of the result from excluding funds that have been liquidated, shut down or merged into other funds, often due to poor performance or low asset allocation (Appendix 2). Such exclusion would lead to misleading results, more specifically an overestimation of historical returns for mutual funds (Figure 1). We solve this issue by including these liquidated or merged funds in our analyses.

Figure 1

Return of OSEBX, All Fund and Dead Funds Portfolio

Figure 1 presents the returns of OSEBX, the equally weighted portfolio of all 74 funds and the equal weighted portfolio of funds that have been liquidated or merged within the data set. Every index is computed based on the equal weighted average returns of all funds between each issue period. The index "All Funds" comprises all funds, including both new included and liquidated funds, whereas the index "Dead Funds" only comprises funds that have been liquidated, acquired or merged into other funds. As expected, we can observe that the index "Dead Funds" on average delivers inferior returns throughout the whole period when compared to OSEBX and "All Funds". To avoid the survivorship bias, where returns and performance are overestimated, we need to include all dead funds.



3.2. Benchmark – Oslo Stock Exchange

Dine Penger uses the Oslo Stock Exchange Benchmark Index (OSEBX) as the main benchmark index for most of the funds. There exist a few exceptions, as some funds have either OBX[4] or OSESX[5] as their reference index. However, this only applies for a minority of the funds, with less than five having the OSESX as a benchmark. When testing for correlation between OBX and OSEBX in the sample period, we find a correlation of 94.8% indicating that both indices approximately follow the same pattern (Appendix 3). For simplicity, we want to use one benchmark and therefore OSEBX is a natural choice as the reference index. Figure 2 illustrates the excess logarithmic return for dices relative to OSEBX.

OSEBX, which currently consists of 60[6] independent Norwegian companies, is updated on a semi-annual basis, and should therefore, at all time, be a representative of the conditions in the Norwegian equity market. For the risk-free rate, we use the Norwegian three-month government bond (ST1X), which is the most common benchmark for risk-free placements. The data is obtained from Oslo Børs, which has a large database of all relevant securities and indices of the Norwegian financial market.

We have also applied time-series of daily returns of the variables in the Carhart 4-factor model. Developed by Carhart (1997), the 4-factor model is an extension of the famous Fama-French three factor-model (1993). All 4-factor model factors for the Norwegian equity market, excluding the market risk, have been acquired from Professor Bernt Arne Ødegaard (2017).

[4] OBX comprises the 25 most liquid stocks on Oslo Børs according to their trading volumes over the past six months (Oslo Børs , 2017).

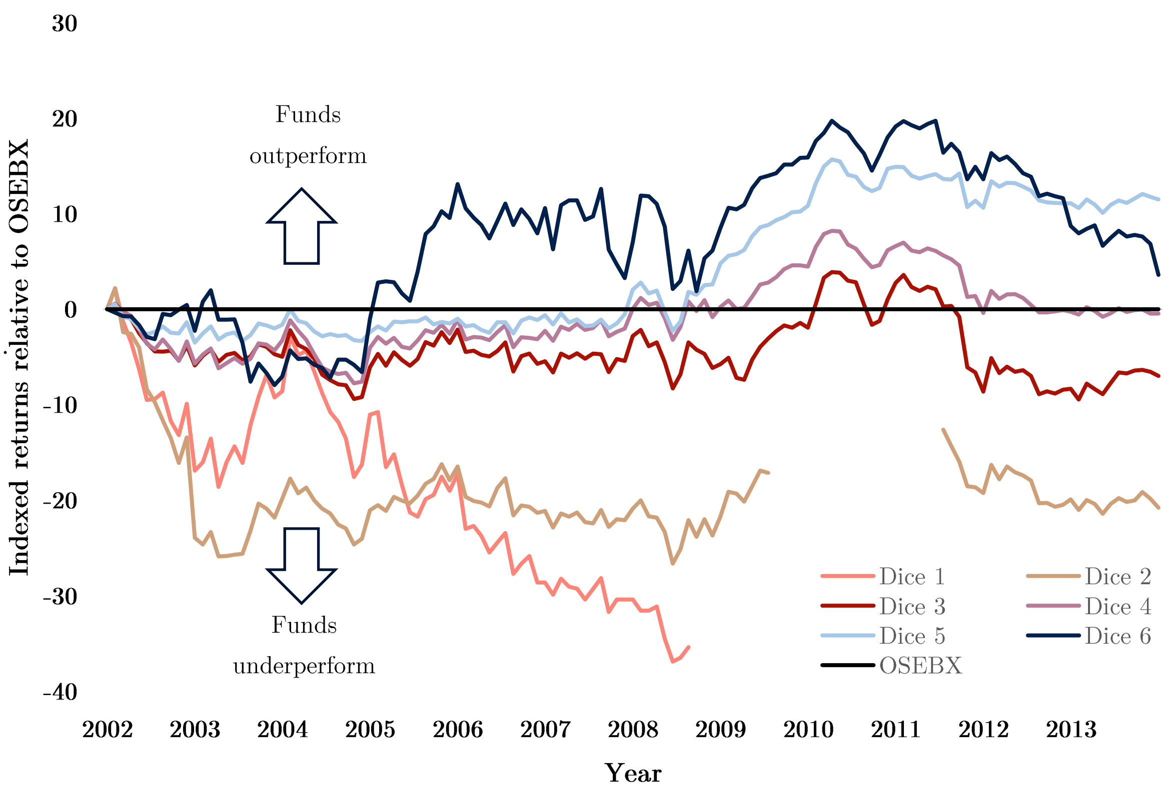
[5] OSESX, earlier known as the SMB-index, consists of the 10% lowest capitalized shares on Oslo Børs. The index is semi-annually revised and adjusted for dividend payments (Oslo Børs , 2017).

[6] Per 04.05.2017 (Oslo Børs , 2017).

Figure 2

Excess Returns for Dices Relative to Benchmark

Figure 2 illustrates the excess logarithmic returns for dices relative to OSEBX from 2002-2013. Each fund within each group of dices is equally weighted. In general, higher ranked funds outperform the benchmark, while lower ranked funds underperform relative to the OSEBX. Dices above (below) the OSEBX benchmark line outperform (underperform) the reference index. Please note the lack of data for both Dice 1 and Dice 2 funds, as there are periods in the sample data where no funds are ranked in these categories. For the calculation of the indexed return of Dice 2 between the missing value periods, we have continued the computation from the previous observable indexed value.



3.3. Limitations of the Set of Data

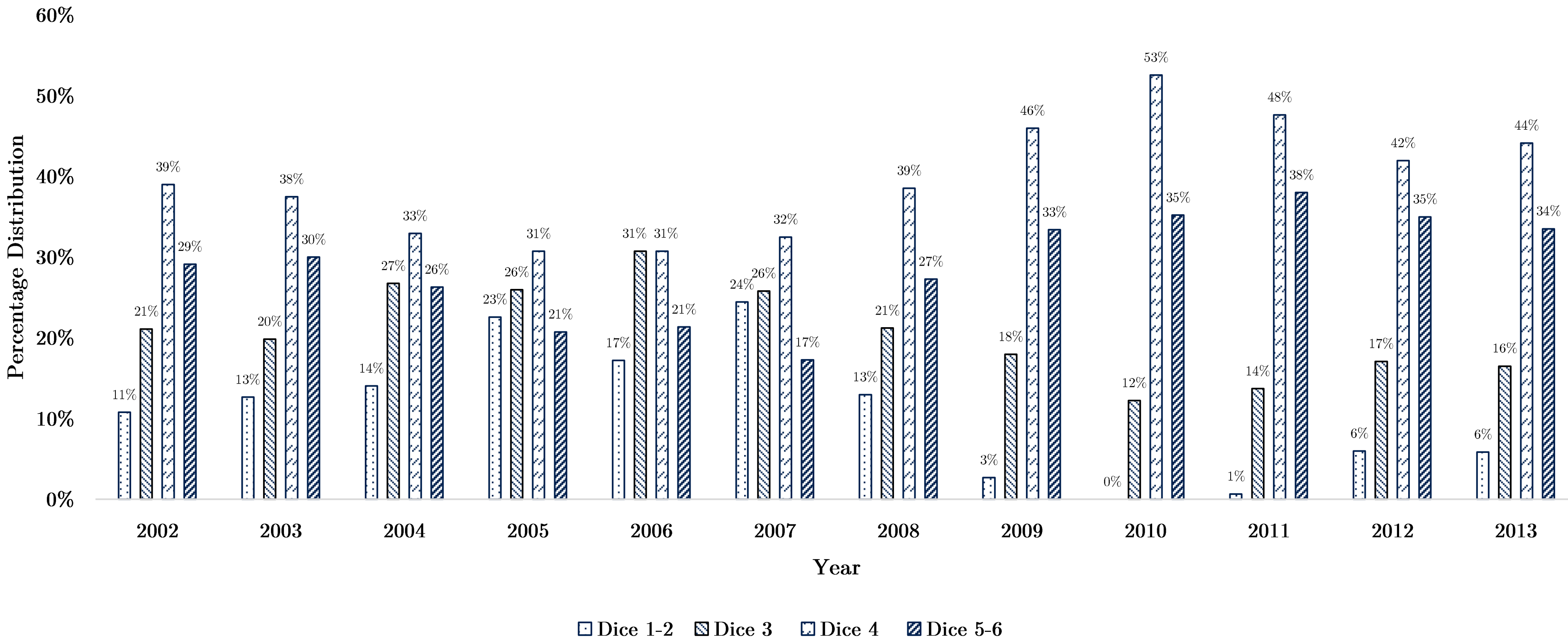
There are certain limitations with the data set that we want to highlight, as these limitations may impact some of the results in this paper. The first issue is the non-normal distribution of funds in the rating groups (Figure 3). Accordingly, there are periods with zero 1- and 2-dice ratings and few 6-dice ratings. The period with no bottom dice ratings begins at the end of 2008 and continues throughout most of the sample to 2013. This property could make it harder to distinguish between funds, as we need to group bottom and top ratings to minimize the likelihood of periodic variations and get more reliable results. Similar studies like Bolle and Busse (2005) and Sørensen (2009) found no evidence of dissimilarities in performance between top and median funds. This suggests that it could be even more difficult to find disparity between fund performances, as the range between top and bottom funds has decreased.

Another limitation with the data is that Dine Penger did not fully disclose all the components of the rating system. Even though the main components of the index were explained, Dine Penger did not disclose how fund fees are incorporated in the rating system. Furthermore, the various fund fees were not included in the data set and is therefore excluded from most of our analyses. As mentioned earlier, the emphasis of this research is to evaluate the predictability of dice ratings for fund performance, thus the lack of this information should not have significant influence on the results.

Figure 3

Distribution of Dices in the Sample Period

Figure 3 exhibits the distribution of funds within each dice-group over the sample period. As illustrated, most of the funds are ranked in the Dice 4 category. Notably, the number of funds ranked either 1 or 2 fall substantially after the financial crisis representing only a single-digit share of total funds. Also note, that there were no funds in this category in 2010. Another remark is the rise in higher ranked funds after 2008.



4. Methodology

In this section, we examine the different models used to evaluate the performance of Norwegian mutual funds compared to the risk-adjusted benchmark. To be consistent with other fund performance studies, and because different performance metrics can produce different results, we use two different performance metrics to measure performance: the Jensen's alpha (1967) and the Carhart (1997) 4-factor alpha. Further, we disclose two models used to evaluate whether the rating system contains any predictive abilities. These models are (1) the random effects panel data regression, and (2) the buying winners and short-selling loser strategy introduced by Jegadeesh and Titman (1993).

4.1. Performance Metrics

Various performance metrics have been developed to evaluate the risk-adjusted excess return of funds. To achieve robust results, we will evaluate fund performance on two performance measures presented below:

4.1.1. Jensen`s Alpha

Jensen's alpha, developed by Jensen (1967) is a simple asset-pricing model that measures the risk-adjusted performance of mutual funds. The measure is an extension from the earlier theory of the pricing of capital assets by Sharpe (1964), Lintner (1965) and Treynor (1962). The model is based on the assumption that (1) investors are risk-averse and wealth maximizers, (2) investors have indentical investment horizons and similar profit expectations regarding their investments, (3) investors are rational and choose portfolios based on the expected return and volatily, (4) zero transaction and tax costs, and (5) all assets are infinetely divisable which implies that fractional shares can be purchased.

The model is used to evaluate the risk-adjusted performance between mutual funds, to determine whether the fund is earning the proper return compared to its systematic level of risk. The unsystematic risk is not included, as the model assumes that investors have adequately diversified portfolios. A positive (negative) Jensen's alpha implies that the fund has outperformed (underperformed) compared to the benchmark index, in this case the OSEBX.

The model is specified as:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + \epsilon_{i,t}$$

Where $r_{i,t}$ is the return of fund i in period t, $r_{f,t}$ is the risk-free rate in period t and $r_{m,t}$ is the return of the benchmark portfolio in period t. The alpha $\alpha_{i,t}$ is the fund's abnormal return and β_i is the fund's sensitivity to the benchmark return. The error term $\epsilon_{i,t}$ is assumed serially independent with an expected mean of zero.

We find that, on average, Norwegian mutual funds realize a yearly Jensen's alpha of -0.45% in the period from 2002-2013. By studying individual funds, we find that there exist fund managers that can generate higher returns than what is expected for a given level of risk. For instance, the top five funds have generated an average yearly alpha of 4.18% during the sample period (Table 6). This might indicate that some fund managers inhabit stock-picking abilities. Similarly, we find funds that have exhibited a relative underperformance in returns compared to the risk.

Table 6

Jensen's Alpha for Top and Bottom Funds

Table 6 illustrates the top and bottom five funds in the sample set when considering the Jensen's alpha. Note, that the top funds have a higher average dice rating than the bottom funds. Still, some of the bottom performing funds exhibit dice ratings above what would be expected from the worst performing funds. The alphas have been calculated by running individual regressions on each fund, with the regression equation: $Y_{i,t} = \alpha_i + \beta_1 MKT_t + \epsilon_t$. Where $Y_{i,t}$ is the fund's excess return of risk-free rate, α_i is the intercept and MKT_t is the benchmark premium returns (OSEBX-$r_{f,t}$).

Top Five Funds			**Bottom Five Funds**		
Name	Alpha	Average Dice	Name	Alpha	Average Dice
Warren Wicklund Norge	4.88%	4	Globus Aktiv	-10.47%	4
Pareto Aksje Norge	4.74%	6	Globus Norge II	-10.43%	2
DNB SMB	4.07%	4	Globus Norge	-8.53%	2
Fondsfinans Spar	4.03%	5	Fondsfinans Aktiv II	-3.83%	5
Alfred Berg Gambak	3.17%	3	Nordea Kapital II	-3.60%	5
Average:	**4.18%**	**4.5**		**-7.37%**	**3.3**

4.1.2. The Carhart 4-Factor Model

The Carhart (1997) 4-factor model is commonly used as an active management and mutual fund evaluation model. The model is an extension from the Fama-French three-factor model (1993). In addition to factors such as company size (SMB)[7], price-to-book ratio (HML)[8] and market risk (MKT), the extended 4-factor model includes a momentum factor (PR1YR)[9], originally identified by Jegadeesh and Titman (1993). By adding the momentum factor to the original model, the new model contains four risk factors that have proved the ability to generate premium returns compared to the market index. The model is specified as follows:

$$r_{i,t} - rf_t = \alpha_i + \beta_{m,i} MKT_t + \beta_{SMB,i} SMB_t + \beta_{HML,i} HML_t + \beta_{PR1YR,i} PR1YR_t + \varepsilon_{i,t}$$

[7] Small Minus Big (SMB) reflects the return of a portfolio that has a long position in small companies and a short position in large companies.

[8] High Minus Low (HML) is the return of a portfolio that has a long position in companies with a high book-to-market ratio and a short position in companies with a low book-to-market ratio.

[9] The momentum factor (PR1YR) is created by holding a portfolio consisting of a long position in the top tertile and a short position in the bottom tertile, based on the returns of the past 12-months.

Where the betas $\beta_{m,i}$, $\beta_{SMB,i}$, $\beta_{HML,i}$ and $\beta_{PR1YR,i}$ represent the funds' exposure to the MKT, SMB, HML and PR1YR factors. The error term $\varepsilon_{i,t}$ is a measure for the unsystematic risk of fund i in time period t, with an expected mean of zero. The abnormal return, α_i is the average return left unexplained by the model. Carhart (1997) finds evidence that the explanatory power of the 4-factor model is significantly higher than the well-known Capital Asset Pricing Model (CAPM).

To evaluate the appropriateness of the 4-factor model, we estimate the factor loadings for each individual fund and the equal weighted fund portfolio. Factor loadings explain how the fund is exposed to each of the four risk factors in Carhart's model. A factor loading of one indicates that the fund has a perfect correlation with the respective factor, whereas a factor of zero means no exposure to the risk factor. Furthermore, a negative factor loading indicates a negative correlation and exposure to the respective factor.

The factor loading regression results indicate that the Norwegian mutual fund market, in aggregate, is not heavily loaded in any of the SMB, HML or PR1YR factors (Table 7). This observation is expected considering that few funds are likely to hold both a long position in the top funds and a short position in the bottom funds with the factor characteristics. Although, the average load in the SMB factor is 0.073, implying that the average fund has some exposure to the size risk. DNB SMB has the biggest load in the SMB factor with an average exposure of 0.371 through the period of 2002-2013.

Moreover, the average load in the MKT factor is 0.953. This value represents the average fund's exposure to the market (OSEBX) or systematic risk. As this value is relatively close to one, the average fund shares many of the similar risk attributes as the overall Norwegian equity market. Thus, the market is the most prominent risk factor, indicating that Jensen's alpha is a suitable evaluation metric. However, the regressions on each of the 74 funds show that the factor loadings in the SMB, HML and PR1YR vary across funds (Table 7). The factor loading variations between funds, signals that we also should consider these factors when analysing the respective alphas for each fund.

Table 7

Carhart 4-Factor Loadings in Fund Sample

Table 7 provides an overview of the factor loadings in the equal weighted portfolio (average load), and the maximum, median and minimum loadings for the sample set from 2002-2013. The first column presents the average load for the fund population. The second and third columns report the minimum and maximum loads for the 74 funds. The last column reports the median factor loadings, which is the midpoint of the fund distribution.

	Average Load	Minimum Load	Maximum Load	Median Load
MKT	0.953	0.697	1.14	0.973
SMB	0.073	-0.041	0.371	0.052
HML	-0.03	-0.138	0.041	-0.029
PR1YR	-0.014	-0.197	0.053	-0.010

4.1.3. Single or Multi-Period Carhart 4-Factor Model?

The previous paragraph explains the Carhart single period 4-factor model. An extension of this model is the Carhart multi-period 4-factor model. The multi-period 4-factor model is constructed similarly as the single-period model, except that we allow for yearly beta variations instead of a fixed beta. The multi-period model is calculated as follows:

$$r_{i,t} = \alpha_{i,k} + \sum_j \beta_{i,j,k} r_{j,t} + \epsilon_{i,t}$$

Where $\alpha_{i,k}$ is the alpha of fund i in year k and $\beta_{i,j,k}$ is the coefficient risk factor j for fund i in year k for every year from 2002-2013. Further, $r_{j,t}$ is the return on the risk factor j in period t. Since we regress on logarithmic returns, the average alpha will have the same interpretation as the alpha for the single-period model. The average multi-period alpha is calculated as:

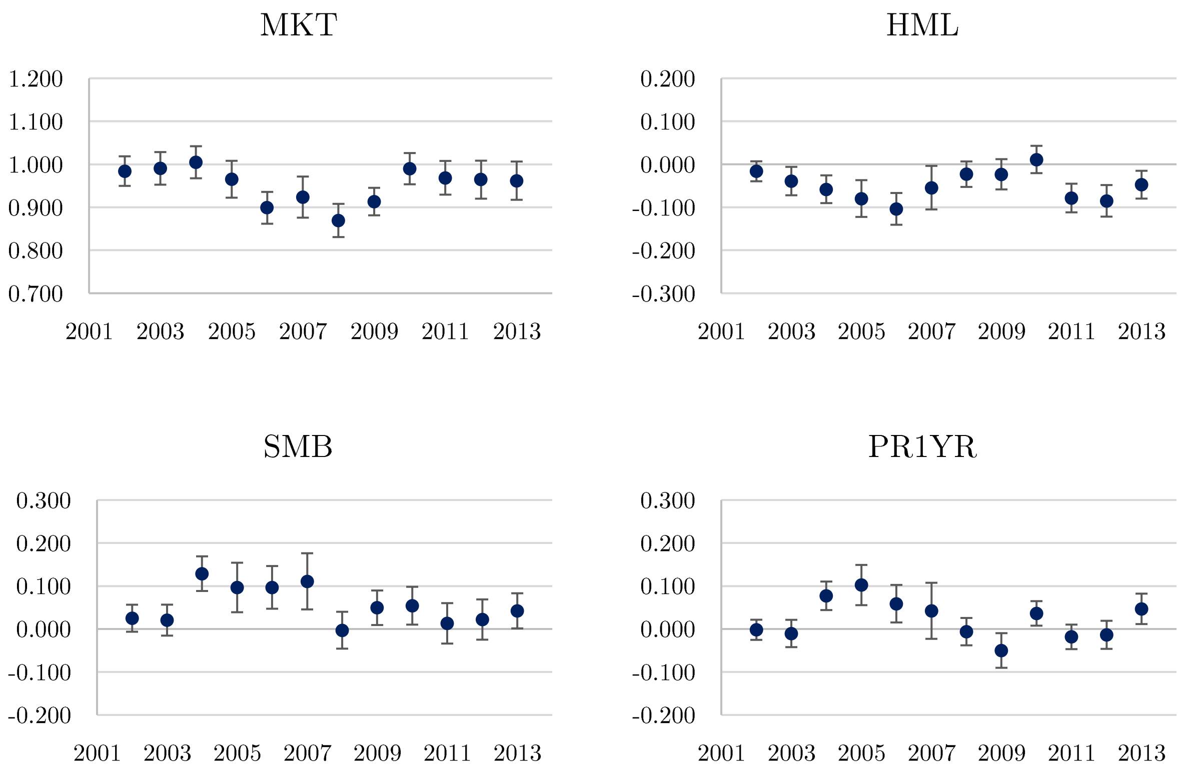
$$\alpha_i = \frac{\sum_i \alpha_{i,k}}{k}$$

Figure 4 illustrates the load variations throughout the sample period of a randomly selected fund. As shown, there are some yearly variations in the coefficients in respect to the risk loading factors. This might indicate that the multi-period model is desirable as it allows and account for these beta variations when calculating the alpha for the respective fund.

Figure 4

Variations in Factor Loadings during the Sample Period

Figure 4 illustrates how the factor loadings vary each year for Alfred Berg Norge+ in the sample period 2002-2013. The fund is randomly chosen, but all funds show some time-varying tendencies. The blue dot is the point estimate of the factor loading of the given year, while the vertical lines represent the 95% confident interval of the estimated point value.



However, Blume (1971) finds evidence that the market beta coefficients were highly stable for portfolios comprising a high number of individual stocks, but unstable for each individual stock. Baesel (1974) finds results indicating that the market beta becomes substantially more stable as the length of the evalutaion period increases from one to nine years. Comparing the single and multi-period factor loadings from Table 7 and 8, we observe that both the average and median loads are approximately similar. The minor differences between the median and average loads in the models along with the findings from Blume (1971) and Baesel (1974), suggest that the single-period model will be just as reliable as the multi-period model for our mutual fund data. Hence, we will only use the single-period model as a risk-adjusted performance metric for further analyses.

Table 8

Multi-Period Carhart Four Factor Loadings in Fund Sample

Table 8 provides an overview of the multi-period annual factor loadings in the equal weighted portfolio (average load), and the maximum, median and minimum loadings for the sample set from 2002-2013. The first column presents the average yearly load of the entire fund sample. The second and third columns report the yearly minimum and maximum loads of the 74 funds. The variations in factor loadings are higher than the fixed loadings in Table 7, as yearly deviations from the long-term risk loads become evident. The last column reports the yearly median factor loadings, which is the midpoint of the fund distribution.

	Average Load	Minimum Load	Maximum Load	Median Load
MKT	0.946	0.445	1.214	0.972
SMB	0.091	-0.121	0.619	0.055
HML	-0.049	-0.405	0.318	-0.034
PR1YR	0.008	-0.386	0.319	-0.001

4.2. Random Effects Panel Data Regression

To find out whether the highest rated funds systematically outperform the lower rated funds, we will use a *random* effects panel data regression. Similar mutual fund performance studies have been conducted with the random effects model, such as Gerrans (2006) and Blake and Morey (2000).

The random effects model assumes that there is no individual fixed characteristic. Hence, the variations across funds are both random and uncorrelated with the other independent variables. In contrast, a fixed effects model assumes that there exist time-invariant characteristics, unique errors, which are constant across individuals. In our scenario, we expect that most of the fund characteristics are not constant across funds in respect to e.g. size, investment strategy (factor loadings), fee structure and portfolio managers. This expectation is further supported by the Hausman test (1978), which determines if a random or a fixed effects model is the most efficient regression (Appendix 4). It tests if the unique errors are correlated with the independent variables, where the null hypothesis[10] assumes zero correlation. In other words, that the random effects model is preferred.

The model is calculated as follows:

$$Y_{i,t} = \beta_0 + \beta_i X_{i,t} + u_i + \epsilon_{i,t}$$

Where $Y_{i,t}$ is the performance metric i in period t, β_0 is the constant term, β_i is the coefficients for the independent variables, $X_{i,t}$ is the dummy variable for the different dice ratings i in period t, u_i is the unobserved individual unique error and $\epsilon_{i,t}$ is the error term. Since the individual specific error u_i and the error term $\epsilon_{i,t}$ is uncorrelated with the independent variables, we can assume that $W_{i,t} = u_i + \epsilon_{i,t}$.

In the equation above, the highest rated fund portfolio (6- and 5-dice) is the reference group for the dummy variable regressions. To measure out-of-sample performance for the different dices, we use two performance metrics: the Jensen's alpha and the Carhart 4-factor alpha. If higher rated funds do not outperform lower rated funds, we expect β_i to not be statistically different from zero. However, if the ratings accurately predict performance we should see increasingly negative and significant coefficients as we move from β_5 (5 dice) to β_1 (1 dice). The findings of Morey and Gottesman (2006) confirm these results for the Morningstar methodology, when applied to US mutual funds in the period of 2002-2005.

4.2.1. In- and Out-of-Sample Periods

To examine the relationship between the Dine Penger ratings and subsequent performance, it is important to distinguish between the in-sample periods from 2002-2005 and 2009-2011 and the out-of-sample periods from 2006-2008 and 2012-2013. In the in-sample regression we fit the data so the dice portfolios are continuously updated between each issue. This should technically provide the best possible representation of the performance in each dice portfolio, as the funds always represent their respective rating. In contrast, the out-of-sample regressions are

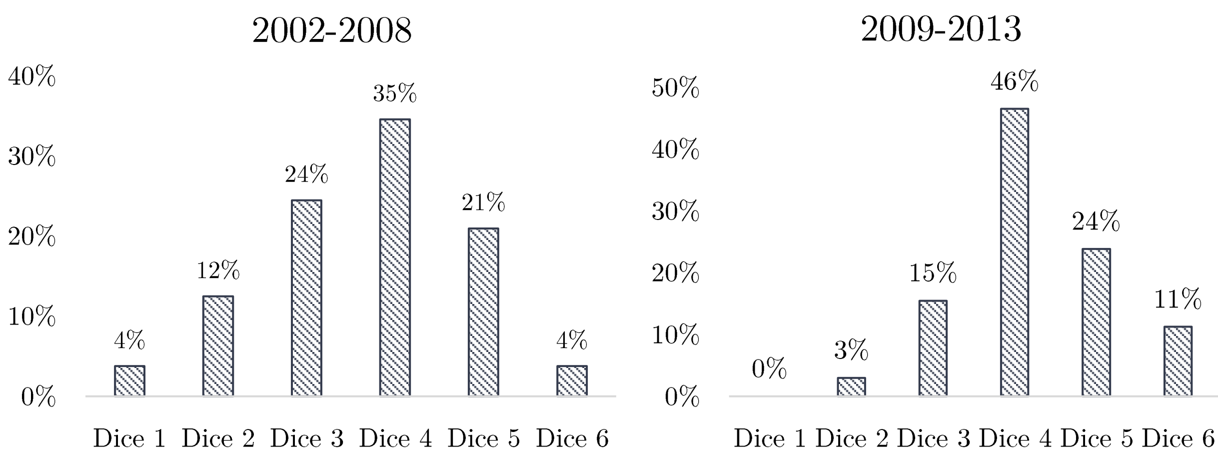
[10] Covariance $(u_i, X_{i,t}) = 0$

estimated based on the dice ratings given at the end of the in-sample periods. Accordingly, we can interpret the persistence and predictive abilities of the ratings, as each fund is fixed to their dice portfolio throughout the out-of-sample period. The performance of the mutual funds is tested on two different periods, before and after the financial crisis in 2008. These periods are identical for all funds. Further, we have compiled funds ranked 1-2 and 5-6 before 2008 and funds ranked 1-3 and 5-6 after 2008, as portfolios comprising too few funds could lead to misleading results (Figure 5).

Figure 5

Dice Distribution Before and After the Financial Crisis in 2008

Figure 5 presents the average dice distribution for both out-of-sample periods. As we can observe, there are zero 1-dice and few 2-dice funds after 2008. There are also few 6 and 1-dice funds in the pre-financial crisis sample. Hence, we have compiled funds ranked 1-2 and 5-6 before the financial crisis, and funds ranked from 1-3 and 5-6 after 2008 in our analysis.



4.3. Strategy of Buying Winners and Selling Losers

A well-respected research paper by Jegadeesh and Titman (1993) indicates that trading strategies that buy past winners and sell past losers realize significant abnormal returns. As we want to test whether investors can benefit from the rating system of Dine Penger, we apply this strategy with minor modifications. Instead of creating portfolios based on historical performance, we create the trading portfolios based on fund ratings from Dine Penger. Previous literature points out that the length of the evaluation period has a substantial effect on the results. A too short evaluation period may increase the amount of noise in the results, and make it harder to recognize pure managerial skills. On the contrary, a too long evaluation period may dilute recent abnormal performance. Therefore, we select funds based on their average rating over the past 1, 3, 6 and 12 months. These funds are evaluated over a holding period of 1, 3, 6 and 12 months. In total, this yields 16 different trading strategies, which is consistent with the original paper of Jegadeesh and Titman (1993).

The trading strategies can easily be explained: In any given month t, decile portfolios consisting of unique equal weighted funds are formed based on their average rating in the past J months. The top decile portfolio, consisting of the highest ranked funds, is called the "winners" decile whereas the bottom decile portfolio, consisting of the lowest ranked funds, is referred to as the "losers" decile. Then, in each period t, the strategy invests long in the winner portfolio and short-sell the loser portfolio, holding this portfolio for K months. This strategy is known as the J-month/K-month strategy or only the J/K-strategy. Earlier research by Jegadeesh and Titman (1993) use portfolios with overlapping holding periods to increase the power of the test. Therefore, in any given month t, the strategies hold a series of portfolios that are selected in the current month, as well as in the previous $K - 1$ months, where K is the holding period. The strategy mentioned above, will also be conducted with the top and bottom quartile portfolios. By using quartile portfolios, the results are less affected by deviations in individual fund returns. Therefore, it is likely that the results will be more robust to divergences in performance of individual top or bottom funds.

4.3.1. Limitations of the *J*-month/*K*-month Strategy

A more comprehensive analysis could investigate the *J*-month/*K*-month strategy over a shorter time perspective, e.g. weeks or even days. Increasing the frequency of portfolio formations could potentially lead to different or more significant results. One may also argue that it would be better to rank the funds into dice groups rather than quartiles and deciles. Ranking the funds into quartiles implies that funds with different ratings are likely to appear in the same portfolio. As such, it may be problematic to segregate rating and performance. However, as there in some periods are very few funds rated 1 or 2, the low rated funds would have higher influence than funds included in other portfolios. This would also impact our findings, and create an asymmetric distribution between the fund groups. Nevertheless, the asymmetry of the fund distribution is an overall limitation with the rating system and the set of data.

5. Empirical Analyses and Results

In this section, we analyse the rating system of Dine Penger to conclude whether the dices can predict future performance among Norwegian mutual funds in the period 2002-2013. The analyses implement the metrics and models from Chapter 4 such as (1) Jensen's alpha, (2) Carhart 4-factor alpha, (3) the Random Effects Panel Model Regressions and (4) the J/K-strategy of Jegadeesh and Titman (1993) of buying past winners and selling past losers.

5.1. In-Sample Random Effects Regressions

To provide the best representation of the performance between dice groups and to determine whether Dine Penger ratings manage to differentiate between top and bottom funds, we conduct in-sample regressions on the periods 2002-2005 and 2009-2011. These periods have been set to differentiate between the periods before and after the financial crisis in 2008. All dice portfolios are continuously updated, implying that investors would need to reallocate their portfolio after every issue, to constantly hold the top rated dice portfolio.

From the in-sample regression before the financial crisis (2002-2005) we find that the top rated portfolio, consisting of 5 and 6-dice funds, outperformed all the other portfolios when analysing the Jensen's alpha and 4-factor alpha (Table 9). However, the analysis only indicates weak significance levels when comparing the 3-dice funds to the top rated funds. Further, the regression signals that 3-dice funds perform slightly better than 4-dice funds, implying that there are small variations between the median ratings. We can also observe that both performance metrics provide approximately similar results.

Regression Equation for Table 9 and Table 10

$$Fund\ return_{i,t} = \beta_0 + \beta_1 MKT_t + (\beta_2 SMB_t + \beta_3 HML_t + \beta_4 PR1YR_t) + \beta_i Dice_{i,t} + u_i + \epsilon_{i,t}$$

Where β_0 is the constant term, $\beta_1 - \beta_4$ are the coefficients for the risk factors, $Dice_{i,t}$ is the dummy variables for the dice portfolios, while u_i is the individual specific error and $\epsilon_{i,t}$ is the error term. The term in parenthesis is only used in the 4-factor alpha regression. The time period is denoted by t, reflecting the in-sample period.

Table 9

In-Sample Regression From 2002-2005

Table 9 illustrates the in-sample regression between the periods 01.01.2002 - 31.12.2005. The top rated dice portfolio outperformed all portfolios, seen by the fact that the coefficients $\boldsymbol{\beta_4}$ through $\boldsymbol{\beta_{12}}$ are all both negative and significant. The regression shows resemblance to the findings of Morey and Gottesman (2006), which show increasingly more negative and significant coefficients as we move from the top to bottom portfolios. This indicates that the top rated funds outperform the bottom portfolio to a larger degree than median dice portfolios.

In-Sample Performance Measure	β0 (Constant)	β4 (4 dice)	β3 (3 dice)	β12 (1-2 dice)	N	Adj-R2
Jensen's Alpha	0.0017	-0.0030**	-0.0024*	-0.0060***	68	0.90
	(1.49)	(-2.48)	(-1.95)	(-2.83)		
4-Factor Alpha	0.0006	-0.0028**	-0.0023*	-0.0060***	68	0.92
	(0.56)	(-2.53)	(-1.95)	(-2.96)		

*** indicates significance at the 1 percent level
** indicates significance at the 5 percent level
* indicates significance at the 10 percent level

Compared to the first in-sample regression, the second regression from 2009-2011 yields less significant results. We find that the top portfolio outperforms the 1-3 dice portfolio for both metrics, but only at a 10% significance level (Table 10). Furthermore, we cannot infer that there exist any differences between the top and the 4-dice portfolio.

Table 10

In-Sample Regression From 2009-2011

Table 10 displays the in-sample regression between the period 01.01.2009-31.12.2011. Both Jensen's alpha and the 4-factor alpha provide weak statistical evidence that the top rated portfolio outperforms the bottom rated portfolio. Evaluating the top rated funds against the 4-dice portfolio, we find no statistical evidence of any outperformance.

In-Sample Performance Measure	β0 (Constant)	β4 (4 dice)	β13 (1-3 dice)	N	Adj-R2
Jensen's Alpha	0.0050***	-0.0006	-0.0034*	56	0.94
	(7.99)	(-0.72)	(-1.86)		
4-Factor Alpha	0.0054***	-0.0007	-0.0029*	56	0.94
	(8.70)	(-0.91)	(-1.67)		

*** indicates significance at the 1 percent level
** indicates significance at the 5 percent level
* indicates significance at the 10 percent level

5.2. Out-of-Sample Fund Performance Predictions

Our main finding suggests that after 2008 Dine Penger dices has no predictive ability to separate top from bottom ranked funds. Furthermore, when comparing the two out-of-sample prediction results, we find evidence that the predictive abilities were greater before the financial crisis in 2008. In addition, before 2008, we find indications of persistence in weak performance among the lower rated funds. The results conclude that the value of dices for investors have diminished as they have increasingly lost the ability to forecast future performance.

5.2.1. Predictive Abilities of Dice Ratings (2006-2007)

The results from the out-of-sample period 2006-2007 show evidence for the hypothesis that Dine Penger's dice ratings can predict future performance for Norwegian mutual funds. We also find certain characteristics that are similar with earlier studies conducted on fund rating performance.

Firstly, low ratings in the Dine Penger Index indicate relatively poor future performance (Table 11). As previously mentioned, funds ranked 1 or 2 are grouped into the lowest ranked portfolio, whereas fund ranked 5 or 6 are formed into the top ranked portfolio. We find evidence that the lower rated portfolio performs significantly worse than the top rated portfolio during the first twelve months of the prediction period. This finding is consistent with Hansen, Haukaas and Gallefoss (2012), and Bolle and Busse (2005), who both find short-term persistence in performance among the abnormally weak performers. Furthermore, we highlight that the top rated portfolio shows persistently better performance than the 3-dice portfolio after 9, 12, 18 and 24 months (Table 11). Secondly, there is no statistical evidence that we can separate the performance between the 4-dice portfolio and the top rated portfolio.

Our results from the first out-of-sample period indicate some predictive abilities of Dine Penger dices. Furthermore, the results show a tendency of increasingly lower alphas as we move from the top to the lowest rated portfolio.

Table 11

Out-of-Sample Performance Prediction (2006-2007)

Table 11 shows the out-of-sample regression for the period 2006-2007. During the first twelve months, the results indicate that the lower rated funds (1-2-dice) underperform compared to the highest rated funds (5-6-dice). This indicates persistence in weak performance among lower rated funds. Furthermore, we find evidence that top rated funds perform consistently better than 3-dice funds after nine to twenty-four months. Lastly, we find no significant difference in performance between top funds and 4-dice funds over the total prediction period. The z-statistics are reported in parenthesis, where *** is 1%, ** is 5% and * is 10% significance levels.

Out-of-Sample Performance Prediction from 01.01.2006 - 31.12.2007							
Prediction	Performance Measure	β0 (Constant)	β4 (4 dice)	β3 (3 dice)	β12 (1-2 dice)	N	Adj-R2
1 Month	Jensen's Alpha	0.0544***	-0.0109**	-0.0137**	-0.0397***	59	0.30
		(18.33)	(-2.10)	(-2.27)	(-4.89)		
	4-Factor Alpha	0.0554***	-0.0067**	-0.0078**	-0.0257***	59	0.33
		(18.88)	(-2.20)	(-2.44)	(-4.93)		
2 Months	Jensen's Alpha	0.0190***	-0.0038	-0.0061	-0.0213***	59	0.33
		(5.20)	(-1.20)	(-1.50)	(-4.70)		
	4-Factor Alpha	0.0352***	-0.0028	-0.0051*	-0.0165***	59	0.36
		(17.33)	(-1.09)	(-1.83)	(-3.50)		
3 Months	Jensen's Alpha	0.0176***	-0.0021	-0.0038	-0.0143***	59	0.30
		(5.42)	(-0.84)	(-1.23)	(-3.64)		
	4-Factor Alpha	0.0908***	-0.0020	-0.0038	-0.0153***	59	0.39
		(18.12)	(-0.83)	(-1.22)	(-3.66)		
6 Months	Jensen's Alpha	0.0026***	-0.0007	-0.0021	-0.0075**	60	0.91
		(3.74)	(-0.49)	(-1.20)	(-2.55)		
	4-Factor Alpha	0.0108***	-0.0005	-0.0020	-0.0075**	60	0.92
		(3.10)	(-0.32)	(-1.19)	(-2.54)		
9 Months	Jensen's Alpha	0.0033***	-0.0015	-0.0041***	-0.0076***	60	0.86
		(4.03)	(-1.07)	(-2.70)	(-2.69)		
	4-Factor Alpha	0.0089***	-0.0014	-0.0042***	-0.0077***	60	0.90
		(9.03)	(-1.01)	(-2.68)	(-2.69)		
12 Months	Jensen's Alpha	0.0052***	-0.0013	-0.0038***	-0.0068**	60	0.86
		(8.61)	(-1.05)	(-3.09)	(-2.27)		
	4-Factor Alpha	0.0031***	-0.0015	-0.0038***	-0.0068***	60	0.88
		(4.54)	(-1.16)	(-3.06)	(-2.28)		
18 Months	Jensen's Alpha	0.0044***	-0.0005	-0.0020**	-0.0045*	60	0.87
		(8.23)	(-0.51)	(-1.98)	(-1.72)		
	4-Factor Alpha	0.0021***	-0.0004	-0.0021**	-0.0044*	60	0.88
		(3.69)	(-0.48)	(-1.98)	(-1.71)		
24 Months	Jensen's Alpha	0.0043***	-0.0006	-0.0019**	-0.0036	62	0.92
		(8.33)	(-0.72)	(-2.06)	(-1.49)		
	4-Factor Alpha	0.0021***	-0.0007	-0.0019**	-0.0037	62	0.93
		(3.74)	(-0.78)	(-2.04)	-1.52		

Regression Equation for Table 11

$$Fund\ return_{i,t} = \beta_0 + \beta_1 MKT_t + (\beta_2 SMB_t + \beta_3 HML_t + \beta_4 PR1YR_t) + \beta_i Dice_{i,t} + u_i + \epsilon_{i,t}$$

Where β_0 is the constant term, $\beta_1 - \beta_4$ are the coefficients for the risk factors, $Dice_{i,t}$ is the dummy variables for the dice portfolios, while u_i is the individual specific error and $\epsilon_{i,t}$ is the error term. The term in parenthesis is only used in the 4-factor alpha regression. The time period is denoted by t, reflecting the out-of-sample period.

5.2.2. Predictive Abilities of Dice Ratings (2012-2013)

During the period 2012-2013 we find that Dine Penger dices have no predictive abilities (Table 12). In fact, we find weak evidence that the 1-3 dice portfolio slightly outperforms the highest rated portfolio after one month, with a relative higher Jensen's alpha of 1.33%. When analysing the alphas, we find no statistical evidence that the highest rated portfolio outperforms either the bottom rated or median portfolios at any time in the prediction period. Figure 6 illustrates the indexed returns for the respective dice portfolios in the out-of-sample period. As we can observe, there are only minor differences in returns between the portfolios.

The findings from the two out-of-sample regressions indicate that Dine Penger dices managed to distinguish between top and bottom funds before 2008, but lost this ability after the financial crisis. This change can to some extent be explained by the increase in correlation[11] between individual stocks, industry sectors and regional markets over the past ten years, with the largest rise in correlation recorded in the years just after the financial crisis (J.P. Morgan, 2010). Previous research by Sullivan and Xiong (2012) finds that the correlation between stocks has risen, and that the equity betas have converged in recent years. This infers that stocks, to a higher degree, tend to move based on macroeconomic factors[12] rather than fundamental value. In other words, mutual fund portfolios are increasingly moving in equivalence with swings in the overall market. Therefore, fund performance is more influenced by the short-term market timing rather than pure managerial stock-picking skills.

[11] Correlation measures the degree to which prices of stocks move together (J.P. Morgan, 2010).

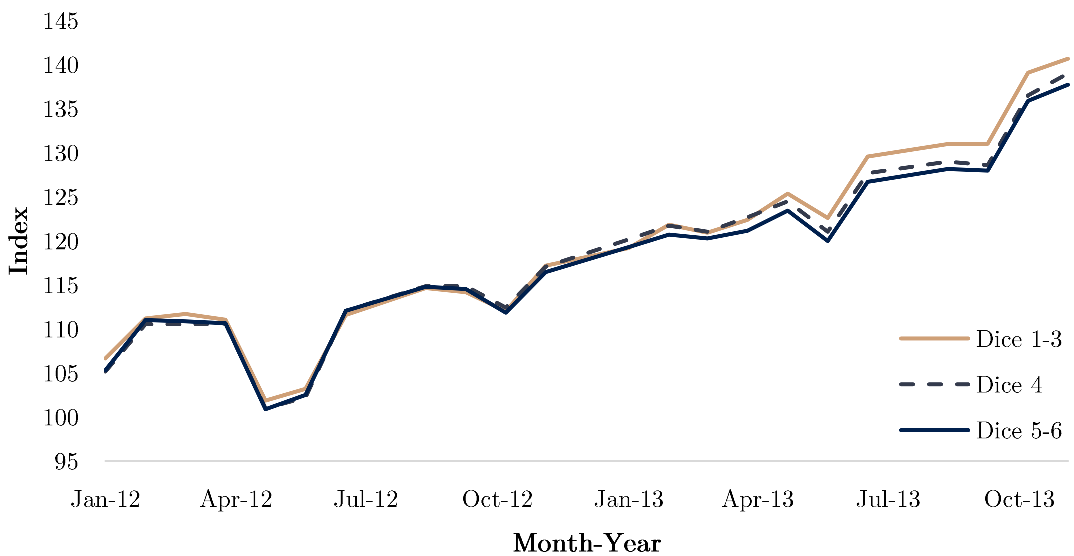
[12] Macroeconomic factors include elements such as economic growth, interest rate changes, inflation expectations, labor market conditions, the global political situation, etc.

This might explain the results in Table 12, where we observe no difference in performance between the dice portfolios. Furthermore, Sullivan and Xiong (2012) explain that the observed rise in systematic risk in part springs from the growth in passive index funds, which leads to more similar trading patterns in the overall market.

Figure 6

Indexed Returns for the Dice Portfolios

Figure 6 illustrates the indexed returns for the respective dice groups in the second out-of-sample period from 2012-2013. As we can observe, all dice portfolios provide approximately similar returns. This is in line with our findings from Table 12, where we find no evidence of predictive abilities in the dice ratings from Dine Penger.



The reason why the 1-3 dice funds are compressed into one portfolio is related to the fact that Dine Penger has given few or zero 1- and 2-dice ratings during this period. This implies that all funds in the set of data performed better than the Dine Penger Index 1- and 2-dice criteria. As mentioned, earlier research found it difficult to distinguish between top and median funds. Thus, this might also explain why there were no significant findings in Table 12.

Table 12

Out-of-Sample Performance Prediction (2012 – 2013)

Table 12 shows the out-of-sample regression results in the period 2012-2013. The results find no evidence of persistence in the dice ratings. In fact, the regression presents weak evidence that, after one month, the bottom portfolio outperforms the top rated portfolio when considering the Jensen's alpha. The z-statistics are reported in parenthesis, where *** is 1%, ** 5% and * 10% significance levels.

Out-of-Sample Performance Prediction from 01.01.2012 - 31.12.2013						
Prediction	**Performance Measure**	**β0 (Constant)**	**β4 (4 dice)**	**β13 (1-3 dice)**	**N**	**Adj-R2**
1 Month	Jensen's Alpha	0.0533***	-0.0016	0.0133*	55	0.07
		(8.61)	(-0.21)	(1.76)		
	4-Factor Alpha	0.0206***	0.0000	0.0109	55	0.09
		(3.82)	(0.01)	(1.64)		
2 Months	Jensen's Alpha	0.0612***	-0.0029	0.0012	55	0.04
		(8.21)	(-0.97)	(0.38)		
	4-Factor Alpha	0.0082***	-0.0011	0.0021	55	0.04
		(3.63)	(-0.39)	(0.64)		
3 Months	Jensen's Alpha	0.0145***	-0.0015	0.0028	55	0.52
		(7.18)	(-0.66)	(1.13)		
	4-Factor Alpha	-0.0125***	-0.0015	0.0028	55	0.74
		(-5.07)	(-0.67)	(1.12)		
6 Months	Jensen's Alpha	0.0031***	-0.0005	0.0005	55	0.87
		(3.61)	(-0.42)	(0.37)		
	4-Factor Alpha	-0.0031***	-0.0005	(0.35)	55	0.93
		(-2.79)	(-0.43)	-0.35		
9 Months	Jensen's Alpha	0.0024***	-0.0005	-0.0012	55	0.87
		(2.87)	(-0.37)	(-0.80)		
	4-Factor Alpha	0.0066***	-0.0005	-0.0013	55	0.91
		(5.62)	(-0.38)	(-0.79)		
12 Months	Jensen's Alpha	0.0017	0.0002	0.0000	55	0.87
		(1.55)	(0.16)	(0.01)		
	4-Factor Alpha	0.0005	0.0002	0.0001	55	0.90
		(0.42)	(0.16)	(0.09)		
18 Months	Jensen's Alpha	0.0016*	0.0004	0.0008	55	0.85
		(1.90)	(0.38)	(0.60)		
	4-Factor Alpha	-0.0031***	-0.0005	0.0005	55	0.88
		(-2.79)	(-0.42)	(0.37)		
24 Months	Jensen's Alpha	0.0018**	0.0003	0.0005	55	0.85
		(2.54)	(0.35)	(0.52)		
	4-Factor Alpha	0.0017**	0.0003	0.0006	55	0.87
		(2.28)	(0.35)	(0.56)		

Regression Equation for Table 12

$$Fund\ return_{i,t} = \beta_0 + \beta_1 MKT_t + (\beta_2 SMB_t + \beta_3 HML_t + \beta_4 PR1YR_t) + \beta_i Dice_{i,t} + u_i + \epsilon_{i,t}$$

Where β_0 is the constant term, $\beta_1 - \beta_4$ are the coefficients for the risk factors, $Dice_{i,t}$ is the dummy variables for the dice portfolios, while u_i is the individual specific error and $\epsilon_{i,t}$ is the error term. The term in parenthesis is only used in the 4-factor alpha regression. The time period is denoted by t, reflecting the out-of-sample period.

5.3. Main Results from the J/K-Strategy

Implementing a reformulated version of the J/K-strategy of Jegadeesh and Titman (1993), we evaluate the persistence in performance of Norwegian mutual funds from 2002-2013. More specifically, the implementation of a zero-pay strategy of investing in past winners and short-selling past losers. The following paragraphs will introduce the main findings and results when implementing the J/K-strategy for both *decile* and *quartile* portfolios on different sample periods.

The results from the *decile* J/K-strategy, in the period 2002-2013, find a zero-pay[13] strategy that is expected to yield annual returns of 4.37%, by creating a portfolio with an evaluation period of one month and a holding period of three months. Further, we find evidence that the return is related to persistent weak performance among the lower rated funds, rather than strong performance among the highest rated funds.

When analysing the *decile* J/K-strategy for the sample in (1) the ex-ante and during the financial crisis period of 2002-2008 and (2) the ex-post period of 2009-2013, we find contradictory results. In the ex-ante period, we find that it would be possible to achieve a yearly return of 7.67%, considerable higher than the whole sample analysis. However, during the period 2009-2013 no zero-pay portfolios were statistically different from zero. This result is consistent with the results from the random effects regressions from Chapter 5.1.2., suggesting that Dine Penger dices

[13] A zero-pay strategy refers to a strategy that involves the simultaneous purchase and sale of fund portfolios, such that the expenses related to the transaction cancel each other out. In this research paper we disregard the additional fees related to fund transactions.

had greater predictive abilities before the financial crisis. This can again be linked to the increased equity correlation over the past decade, as funds are more dependent on macroeconomic factors rather than individual stock movements.

The *quartile* J/K-strategy reveals relatively similar results as the decile portfolio strategy, however with some notable deviations. Firstly, the strategy also achieves positive zero-pay returns during the whole sample period, but with relatively lower returns. Another difference is that we find no evidence of persistence among weak performers, but rather strong continuing performance among the top quartile portfolio when observing the 4-factor alpha. This suggests that the Dine Penger dices hold some predictive abilities in picking out winner funds. We also find evidence in the quartile strategy that the ability to predict future performance were greater before 2008.

5.3.1. J/K-Strategy for the Whole Sample Period (2002-2013)

The results from the *decile* portfolio analysis are presented in Table 13-14, where the emphasis is put on the zero-pay strategy, called the buy-sell portfolio. Our main finding is that, when evaluating the whole period, dices seem to have short-term predictive abilities and persistence in foreseeing strategies that will achieve positive zero-pay returns. In particular, a shorter evaluation period yields both higher and more significant returns than zero-pay strategies with longer evaluation periods. The best trading strategy, according to our results, is to create overlapping portfolios with one-month evaluation periods and then hold the portfolios for three successive months. This strategy yields monthly zero-pay returns of 0.39%, which implies annualized returns of 4.37%. Compared to the findings in the original paper by Jegadeesh and Titman (1993), where a six-month evaluation and a six-month holding strategy realizes yearly zero-pay returns of 12.01%, we find relatively lower returns.

When conducting J/K-strategy on *quartile* portfolios, we find that the optimal strategy is a one-month evaluation period and a one-month holding period, which would yield yearly zero-pay returns of 3.29% (Appendix 5). This relatively lower return is expected as the decile portfolios only contain the very best and worst funds. From the quartile strategy, we also find evidence that it would be possible to achieve zero-pay returns over longer evaluation periods in comparison to the decile strategy. The results in Appendix 5 suggest that it would be possible to create a 12/12-strategy, and still achieve a zero-pay return of 1.69%. This finding infer that the dices hold predictive abilities up to a year, but the returns become increasingly lower as the length of both the holding and evaluation period increases.

An important difference between our result and Jegadeesh and Titman (1993) is the distinction between funds and stocks. Because our analysis evaluates funds instead of independent stocks, we would expect a higher degree of diversification and accordingly lower volatility in returns. This might explain the lower yearly zero-pay returns in our results. Another key point is the interpretation of the momentum factor. Even though mutual funds are likely to be invested in stocks with momentum factor attributes, they may not be as sensitive to the factor as independent stocks. In addition, our portfolios are formed on dices rather than historical returns, which can make it harder to pick up the momentum effect. Thus, we would expect our results on fund data to be smaller and less significant than previous studies on stock data.

Table 13

Decile Portfolio J/K-Strategy from 2002-2013

Table 13 reports the performance of the top decile portfolios (Buy), the bottom decile portfolio (Sell) and the zero-pay portfolio (Buy-Sell) from 2002-2013. The portfolios are formed on varying lengths of evaluation periods in *J* months, given by the rows in the table. The funds are then held for a period of *K* months illustrated by the columns. This process is continued throughout the whole sample period, with overlapping portfolios. The t-statistics are reported in parenthesis.

			Return			
J		**K =**	**1**	**3**	**6**	**12**
1	Sell		0.0055	0.0037	0.0062	0.0079**
			(0.82)	(0.70)	(1.52)	(2.52)
1	Buy		0.0095	0.0079	0.0104***	0.0108***
			(1.47)	(1.65)	(2.90)	(3.89)
1	**Buy-Sell**		**0.0037****	**0.0039*****	**0.0037*****	**0.0027*****
			(2.04)	**(2.81)**	**(3.58)**	**(3.39)**
3	Sell		0.0073	0.006	0.0083**	0.0095***
			(1.06)	(1.14)	(2.10)	(3.17)
3	Buy		0.0088	0.0077	0.0109***	0.0111***
			(1.36)	(1.60)	(3.00)	(4.09)
3	**Buy-Sell**		**0.0016**	**0.0017**	**0.0026*****	**0.0016****
			(0.86)	**(1.34)**	**(3.16)**	**(2.52)**
6	Sell		0.0093	0.0082	0.0107***	0.0117***
			(1.36)	(1.58)	(2.80)	(4.14)
6	Buy		0.0112*	0.0102**	0.0125***	0.0125***
			(1.70)	(2.13)	(3.69)	(4.82)
6	**Buy-Sell**		**0.0019**	**0.0021***	**0.0018****	**0.0007**
			(1.2)	**(1.93)**	**(2.37)**	**(1.32)**
12	Sell		0.0130*	0.0115**	0.0133***	0.0120***
			(1.89)	(2.22)	(3.44)	(4.05)
12	Buy		0.0139**	0.0123**	0.0139***	0.0127***
			(2.11)	(2.56)	(4.00)	(4.72)
12	**Buy-Sell**		**0.0009**	**0.0008**	**0.0007**	**0.0006**
			(0.68)	**(0.78)**	**(0.86)**	**(1.03)**

*** indicates significance at the 1 percent level
** indicates significance at the 5 percent level
* indicates significance at the 10 percent level

In addition to earlier results, we find evidence of persistence in poor performance among the bottom funds in the *decile* portfolios (Table 14). The bottom decile portfolio, consisting of loser funds, is generating negative 4-factor alphas in the entire sample period. This indicates persistence in weak performance among the bottom funds. Furthermore, these results are only statistically significant when implementing relatively short evaluation and holding periods, suggesting that the persistence is short-term. If we include the average annual fee of 1.77%[14], these alphas would be even more negative. Therefore, because returns are gross of fees, the negative alphas can be directly attributed to persistence in either lack of skill or bad luck, in essence fund managers are consistently either mistiming the market or picking bad stocks.

We can also deduce that the 4-factor alpha is statistically indistinguishable from zero when analysing the top *decile* performing funds (Table 14). This observation could infer that it is not the top funds that continue to perform well, but rather that poor performing funds continue to perform poorly.

Table 14

Decile Portfolio 4-Factor Alphas from 2002-2013

Table 14 reports the monthly performance of a) the top decile portfolios and b) the bottom decile portfolios. The portfolios are formed with varying lengths of the evaluation periods *J*, illustrated by the rows in the tables. The portfolios are then held for a given number of *K* months, with overlapping *K-1* portfolios, before being rebalanced. The 4-factor alpha reported in the table is the average monthly alpha from applying the J/K-strategy throughout the entire sample period (2002-2013). The t-statistics are reported in parenthesis, where *** is 1%, ** 5% and * 10% significance levels.

a) Top Decile

	K - Holding Period			
J - Evaluation Period	**1**	**3**	**6**	**12**
1	-0.0012	-0.0009	-0.0006	-0.0009
3	-0.0013	-0.0009	-0.0006	-0.0011
6	-0.0011	-0.0008	-0.0002	-0.0010
12	-0.0007	-0.0004	0.0001	-0.0009

b) Bottom Decile

	K - Holding Period			
J - Evaluation Period	**1**	**3**	**6**	**12**
1	-0.0059***	-0.0044**	-0.0030*	-0.0030
3	-0.0040**	-0.0024	-0.0035*	-0.0020
6	-0.0034*	-0.0034	-0.0021	-0.0011
12	-0.0024	-0.0020	-0.0011	-0.0019

[14] This number is obtained from Hansen, Haukaas and Gallefoss (2012).

We also find evidence of persistence in performance among the top *quartile* portfolio (Table 15). In contradiction to the decile strategy, we find that top quartile portfolios generate positive 4-factor alphas for the entire sample period. This indicates that zero-pay returns for the quartile strategy are related to persistent strong performance among top rated funds, rather than weak performance among lower rated funds. These inconsistent findings between the decile and quartile alpha analyses might be explained by the lack of poor performing funds. In fact, the bottom quartile portfolio, in some periods, consists of funds ranked from 1-4, whereas the top quartile portfolio normally only consists of funds rated 5 or 6. The large range of dices will decrease the probability of the bottom portfolios generating negative alphas. Moreover, the use of quartile portfolios also increases the probability of positive alphas in the top rated portfolios, as it is less likely to be affected by bad performance in outlying funds.

Table 15

Quartile Portfolio 4-Factor Alphas from 2002-2013

Table 15 reports the monthly performance of a) the top quartile portfolios and b) the bottom quartile portfolios. The portfolios are formed with varying lengths of the evaluation periods *J*, illustrated by the rows in the tables. The portfolios are then held for a given number of *K* months, with overlapping *K-1* portfolios, before being rebalanced. The results indicate persistent strong performance for the top quartile portfolios. The t-statistics are reported in parenthesis, where *** is 1%, ** 5% and * 10% significance levels.

a) Top Quartile

	K - Holding Period			
J - Evaluation Period	**1**	**3**	**6**	**12**
1	0.0028***	0.0030***	0.0033***	0.0033***
3	0.0026***	0.0032***	0.0031***	0.0033***
6	0.0028***	0.0031***	0.0032***	0.0035***
12	0.0029***	0.0033***	0.0038***	0.0038***

b) Bottom Quartile

	K - Holding Period			
J - Evaluation Period	**1**	**3**	**6**	**12**
1	-0.0008	0.0000	0.0005	0.0009
3	-0.0006	0.0002	0.0004	0.0012
6	-0.0003	0.0004	0.0008	0.0015
12	0.0008	0.0011	0.0016	0.0015

5.3.2. J/K-Strategy in the Period 2002-2008

When implementing the *decile* J/K-strategy for the period 2002-2008 we find evidence that it would be possible to create zero-pay portfolios that would produce substantial returns (Table 16). Similar to the decile whole sample analysis, the zero-pay portfolio with an evaluation period of one month and a holding period of three months generates the highest returns. However, the zero-pay returns are significantly higher in comparison to the whole sample, with average yearly returns of 7.67% against 4.37%. This indicates that the predictive abilities of the Dine Penger ratings were greater at the beginning of the sample.

Table 16

Decile Portfolio J/K-Strategy in Period 2002-2008

Table 16 reports the performance of the decile zero-pay portfolios (Buy-Sell) from 2002-2008. The table illustrates that the strategy yields better zero-pay returns with shorter evaluation and holding periods. The portfolios are formed on varying lengths of evaluation periods in months *J*, given by the row on the table. The funds are then held for a period of *K* months illustrated in the columns. This process is continued throughout the sample period, with overlapping portfolios. The t-statistics are reported in parenthesis, where *** is 1%, ** 5% and * 10% significance levels.

J		K =	1	3	6	12
1	Buy-Sell		0.0063**	0.00674***	0.00606***	0.00414***
			(2.21)	(3.05)	(3.60)	(3.22)
3	Buy-Sell		0.00265	0.003	0.00408***	0.00238**
			(0.90)	(1.46)	(3.14)	(2.29)
6	Buy-Sell		0.0027	0.00303*	0.0027**	0.0008
			(1.07)	(1.73)	(2.14)	(0.89)
12	Buy-Sell		0.0006	0.0007	0.0005	0.0007
			(0.30)	(0.45)	-0.48	(0.69)

Furthermore, we find that the 4-factor alphas for the bottom *decile* portfolios are even more negative when comparing with the whole sample decile analysis (Table 14 and Table 17). This result aligns with the random effects regression (Table 11), which suggests continuation of weak performance among bottom funds. Still, from Table 17 we see that the shorter the evaluation and holding period, the more negative and significant the 4-factor alphas become. Again, this signifies that dice ratings only predict short-term performance. There is no evidence of 4-factor alphas different from zero among the top decile portfolios, which implies that the top rated funds do not achieve abnormal returns during the period.

Table 17

Decile Portfolio 4-Factor Alphas from 2002-2008

Table 17 reports the monthly performance of a) the top decile portfolios and b) the bottom decile portfolios. The findings suggest short-term continuation in poor performance among the bottom portfolios. The portfolios are formed with varying lengths of the evaluation periods *J*, illustrated by the rows in the tables. The portfolios are then held for a given number of *K* months, with overlapping *K-1* portfolios, before being rebalanced. The 4-factor alpha reported in the table is the average monthly alpha from applying the J/K-strategy throughout the entire sample period (2002-2008). The t-statistics are reported in parenthesis, where *** is 1%, ** 5% and * 10% significance levels.

a) Top Decile

	K - Holding Period			
J - Evaluation Period	**1**	**3**	**6**	**12**
1	-0.0020	-0.0015	-0.0003	-0.0026
3	-0.0020	-0.0007	-0.0003	-0.0027
6	-0.0003	-0.0004	0.0017	-0.0009
12	0.0006	0.0014	0.0011	-0.0014

b) Bottom Decile

	K - Holding Period			
J - Evaluation Period	**1**	**3**	**6**	**12**
1	-0.0085***	-0.0067**	-0.0041	-0.0029
3	-0.0061**	-0.0036	-0.0049	-0.0024
6	-0.0055*	-0.0048	-0.0022	-0.0019
12	-0.0026	-0.0015	0.0001	-0.0036

Analysing the *quartile* J/K-strategy for the period 2002-2008, we find similar results as for the quartile whole sample analysis (Appendix 6). The most profitable portfolio is the 1/1-strategy, which generates zero-pay returns of 4.16%. The zero-pay returns are slightly higher in comparison to the whole sample analysis, which again infer that the Dine Penger dices where better at predicting performance before and during the financial crisis. Moreover, as found in the whole sample analysis, the 4-factor alphas the top portfolio display positive and significant 4-factor alphas (Appendix 7). This indicates that the ratings had capabilities to recognize quality funds.

5.3.3. J/K-Strategy in the Period 2009-2013

When analysing the *decile* portfolio from 2009-2013, we find contradicting results as to the period 2002-2008. We find no evidence that any of the zero-pay portfolios deliver returns different from zero (Table 18). This implies that Dine Penger dices have no ability to predict fund performance after 2008, in consistency to the results found in the random effects model (Table 12). However, there is weak significance that a 12/12-strategy could possibly generate positive returns. This differs from the earlier findings that suggest increasingly better performance, as the portfolios are more frequently rebalanced. One may argue that this result is due to continuing underperformance among the bottom funds, even though this finding is somewhat ambiguous.

Table 18

Decile Portfolio J/K-Strategy in Period 2009-2013

Table 18 reports the performance of the zero-pay portfolio (Buy-Sell) in the period 2009-2013, which shows that no zero-pay portfolios deliver significant returns. Also note, that there is a weak significance for the 12/12-strategy. The t-statistics are reported in parenthesis, where *** is 1%, ** 5% and * 10% significance levels.

J		**K =**	**1**	**3**	**6**	**12**
1	**Buy-Sell**		-0.0011	-0.0013	0.0003	0.0036
			(-0.45)	(-0.88)	(0.18)	(0.32)
3	**Buy-Sell**		-0.0010	-0.0008	0.0008	0.0002
			(-0.59)	(-0.59)	(0.54)	(0.18)
6	**Buy-Sell**		-0.0005	0.0002	0.0005	0.0002
			(-0.38)	(0.25)	(0.61)	(0.26)
12	**Buy-Sell**		0.0012	0.0013	0.0011	0.0012*
			(0.69)	(1.15)	(1.17)	(1.73)

The *decile* 4-factor alpha analyses also diverge from the earlier J/K-strategy conclusions. They are less significant and negative for the bottom decile portfolio during the short-term J/K-strategies, but progressively become more significant and negative with longer holding periods (Table 19). The alphas exhibit weak significance levels during the twelve-month evaluation period, which suggest some persistence among poor performers in the rating system. At a 5% significance level, only the

1/12-month strategy shows negative 4-factor alphas. This points towards the fact that some weak performers continue to perform poorly.

Table 19

Decile Portfolio 4-Factor Alphas from 2009-2013

Table 19 reports the monthly performance of a) the top decile portfolios and b) the bottom decile portfolios. As we can observe, there are no portfolios that deliver positive alphas. However, some low rated portfolios show a persistence in poor performance illustrated by the negative alphas. The t-statistics are reported in parenthesis, where *** is 1%, ** 5% and * 10% significance levels.

a) Top Decile

	K - Holding Period			
J - Evaluation Period	**1**	**3**	**6**	**12**
1	0.0004	0.0031	0.0000	-0.0019
3	0.0013	0.0024	-0.0003	-0.0015
6	-0.0004	0.0006	-0.0001	-0.0017
12	-0.0008	-0.0005	-0.0007	-0.0004

b) Bottom Decile

	K - Holding Period			
J - Evaluation Period	**1**	**3**	**6**	**12**
1	-0.0013	-0.0004	-0.0027	-0.0048**
3	-0.0012	-0.0017	-0.0028	-0.0034
6	-0.0011	-0.0020	-0.0037*	-0.0018
12	-0.0037*	-0.0033	-0.0039*	-0.0015

The less significant results after the financial crisis are also present for the top and bottom *quartile* portfolios (Appendix 8). The only strategy that yields a weak significant return is the 12/12-month strategy, with an annualized return of 1.21%. By evaluating the Jensen alpha, we still find some positive significant results, but the results are ambiguous as Dine Penger does not manage to distinguish between the top and bottom quartile portfolios (Appendix 9).

5.4. Robustness of the Prediction Results

A notable aspect of our data set and, in general, all other data sets of stock returns, is the element of autocorrelation. Put simply, autocorrelation is the correlation between a lagged variable in one or more time periods and itself. Earlier studies by Lehmann (1990) and Conrad, Hameed and Niden (1994) report significant negative autocorrelation in *weekly* individual stock returns, which implies a tendency of overreaction in prices. The theorem is well-known in the financial industry and investors use this technique to predict future movements of stock prices. The problem with autocorrelation is that it causes non-spherical errors. This means that the error terms $W_{i,t}$ are not uncorrelated and heteroscedastic[15], which conflicts with assumptions in the Gauss-Markov theorem.

First, note that we do not need the homoscedastic and autocorrelation assumptions to produce unbiased coefficient estimates in the random effects model. However, violations of the assumptions could lead to inconsistent and biased standard errors, making the regression model inefficient[16]. The presence of heteroscedasticity tends to overestimate standard errors, resulting in lower statistical power. While the presence of negative autocorrelation tends to underestimate standard errors, and therefore consequently misleading narrow confidence intervals, large t-statistics and low p-values. Over or underestimated t-statistics are a threat to the internal validity of the analysis, meaning that we cannot draw statistical inference of Norwegian fund performance based on our results. Heteroscedasticity and autocorrelation are closely related problems, which can be solved by implementing cluster[17] robust estimators introduced by White (1984), Arellano (1987) and Rogers (1993).

Cluster robust estimators deal with autocorrelation and heteroscedasticity by allowing the standard errors to be correlated within a fund, but uncorrelated across

[15] Heteroscedasticity is present when the size of the error term varies between values of independent variables.

[16] Efficiency is a measure of quality of an estimator. An efficient model needs fewer observations than less efficient models to achieve the same performance.

[17] A cluster consists of a single Norwegian mutual fund, separated based on their fund ID.

funds. This way both the violated assumptions in the Gauss-Markov theorem can be satisfied, producing standard error estimates that are robust and consistent to disturbances being heteroscedastic and autocorrelated. In practice, we can rarely be sure about correlated errors and it is better to always use cluster robust standard errors to achieve efficient and internally valid results from the random effects model.

6. Conclusion

This master thesis examines the ability of Dine Penger's rating system to predict future performance among Norwegian mutual funds. To test this ability, we implement a data set free of survivorship bias for 74 Norwegian mutual funds in the period from 2002-2013. We analyse whether investors can benefit from investing in accordance with the ratings. This topic provides a significant contribution for both individual and professional investors, in the question of deciding which fund to trust with their financial assets.

To comprehensively evaluate performance, we apply the Jensen's and the Carhart 4-factor alphas. Furthermore, we investigate the predictability in fund ratings by conducting several out-of-sample random effects panel regressions, and by using the J/K-strategy of buying past winners and short-selling past losers. To strengthen the analysis of the latter test, we have conducted the strategy for both top and bottom decile and quartile portfolios.

We find substantial evidence of differences in predictive abilities of the rating system when separating the sample period to ex-ante and ex-post periods relative to the financial crisis in 2008. Our results indicate that while the rating system did possess some predictive abilities ex-ante, it lost most of these abilities after the financial crisis.

Interestingly, before 2008, investors could rely on the rating system as an indicator for future fund performance as the ratings were capable of separating top and bottom funds. Our results from the random effects model conclude that funds ranked 5-6 outperformed funds ranked 1-3 for a short-term period of one to two years. By implementing the most promising J/K-strategy for decile portfolios, we find evidence of a zero-pay strategy that would yield annual returns of 7.67%. Moreover, by conducting the respective top strategy for the whole sample period, the investor would achieve a yearly zero-pay return of 4.37%. These results are consistent with the results from the J/K-strategy for quartile portfolios, however with a notable exception. While the zero-pay returns from the decile strategy mainly resulted from persistence in weak performance among the 10% lowest rated funds, the zero-pay returns from the quartile portfolios is explained by persistence in strong performance among the top 25% funds. This finding provides two interesting notes. Firstly, that the ratings manage to point out the 10% weakest performers. And secondly, that the rating system generally managed to give the highest rating to the top performing funds.

On the contrary, in the period after the financial crisis we find significantly weaker results, indicating that Dine Penger lost a large part of their forecasting ability. During the period 2009-2013, neither the decile nor the quartile J/K-strategy provide zero-pay portfolios that are statistically different from zero. This result is consistent with the findings from the random effects regressions, suggesting that Dine Penger dices had greater predictive abilities in the beginning of the sample period. One explanation for these contradictory results might be the increased equity correlation over the past decade, as funds are more dependent on macroeconomic factors rather than individual stock movements. This could make it harder to separate top and bottom funds. Another notable point during the period is the number of funds within each rating group. Some periods contain few or no funds ranked in the lowest rating groups (1-2 dice). We argue that this shortfall of the rating system might influence the results, as some of the anticipated "better" funds are included in the short portfolio in the J/K-strategy.

7. Suggestions for Further Research

Although this master thesis provides a comprehensive analysis of the abilities for Dine Penger's rating system to forecast future performance of Norwegian mutual funds, there are still some questions that remain unanswered. The following paragraphs will present our suggestions for further research, in which we encourage other academics to inquire for future research.

The first suggestion is directly related to Dine Penger as a recommendation of how the overall rating system can be improved. Throughout the entire thesis period, we questioned the rationality of non-normal distributed fund ratings. This distribution is directly contradictory to the well-respected Morningstar fund rating methodology that rank funds according to a normal distribution. Instead of using an absolute value for fund ratings, we would rather recommend Dine Penger to rate each individual fund relative to the performance of its peer group. This would make it easier to distinguish between top and bottom performing funds, and therefore to a better degree help investors pick the appropriate funds.

Further, we suggest Dine Penger to fully disclose all relevant information of the dice calculations. As previously explained, Dine Penger did not disclose how fees, and some other factors, are accounted for in the rating system. Future research should attempt to gather such information and compare the new results with the findings this paper.

Another suggestion would be to analyse the ability of dice ratings to predict performance based on fund characteristics. For instance, we would recommend a separation between active and passive funds. Other separation criteria could be dependent on factors such as investment strategies, capital under management or fee structures.

References

Arellano, M., 1987. Computing Robust Standard Errors for Within-Group Estimators. *Oxford Bulletin of Economics and Statistics,* Issue 49, pp. 431-434.

Baesel, J. B., 1974. On the Assessment of Risk: Some Further Considerations. *Journal of Finance,* 29(5), pp. 1491-1494.

Blake, C. R. & Morey, M. R., 2000. Morningstar Rating and Mutual Fund Performance. *The Jorunal of Financial and Quantitativ Analysis*, September, Issue 35, pp. 451-483.

Blume, M. E., 1971. On the Assessment of Risk. *Journal of Finance,* 26(1), pp. 1-10.

Bollen, N. P. B. & Busse, J. A., 2005. Short-term persistence in mutual fund performance. *Review of Financial Studies ,* 18(2), pp. 569-597.

Bondt, W. D. & Thaler, R., 1985. Does the Stock Market Overreact?. *Journal of Finance ,* Issue 42, pp. 793-808.

Bondt, W. D. & Thaler, R., 1987. Further evidence on investor overreaction and stock market seasonality. *Journal of Finance ,* Volume 42, pp. 557-581.

Brown, S. J. & Goetzmann, W. N., 1995. Performance Persistence. *The Journal of Finance ,* 50(2), pp. 679-698.

Brown, S. J., Goetzmann, W. N., Ibbotson, R. G. & Ross, S. A., 1992. Survivorship Bias in Performance Studies. *Review of Financial Studies,* Volume 5, pp. 553-580.

Carhart, M. M., 1997. On Persistence in Mutual Fund Performance. *Journal of Finance*, Mars, Issue 52, pp. 57-82.

Chevalier, J. & Ellison, G., 1997. Risk Taking by Mutual Funds as a Response to Incentives. *Journal of Political Economy ,* 105(6), pp. 1167-1200.

Conrad, J., Hameed, A. & Niden, C., 1994. Volume and autocovariances in short-horizon individual security returns. *The Journal of Finance* , Volume 49, pp. 1305-1329.

Fama, E., 1970. Efficient capital markets: A review of theory and empirical work. *Journal of Finance,* pp. 383-417.

Fama, E. F. & French, K. R., 1992. The Cross-Section of Expected Stock Returns. *The Journal of Finance*, June, Issue 47, pp. 427-465.

Fama, E. F. & French, K. R., 1993. Common risk factors in the returns on stocks and bonds. *Jounral of Financial Economics,* Volume 33, pp. 3-56.

Fama, E., Fisher, L., Jensen, M. & Roll, R., 1969. The Adjustment of Stock Prices to New Information. *International Economics Review.*

Friend, I., Blume, M. & Crockett, J., 1970. *Mutual funds and other institutional investors: A new perspective* , New York : McGraw-Hill .

Friend, et al., 1962. *A Study of Mutual Funds,* Washington, DC: U.S. Government Printing Office.

Gerrans, P., 2006. Morningstar ratings and future performance. *Accounting and Finance*, 12 October, Issue 46, pp. 605-628.

Grinblatt, M. & Titman, S., 1992. The Persistence of Mutual Fund Performance. *The Journal of Finance* , 47(5), pp. 1977-1984.

Hansen, H. H., Haukaas, E. S. & Gallefoss, K., 2012. *Performance and Persistence in Norwegian Mutual Funds,* Trondheim: NTNU.

Hausman, J. A., 1978. Specification tests in econometrics. *Econometrica* , 46(6), pp. 1251-1271.

Hendricks, D., Patel, J. & Zeckhauser, R., 1993. Hot hands in mutual funds. *The Journal of Finance* , 48(1), pp. 1974-1988.

Ippolito, R., 1989. Efficiency with costly information: A study of mutual fund performance, 1965-1984. *The Quarterly Journal of Economics* , 1(104), pp. 1-23.

J.P. Morgan, 2010. *Why We Have a Correlation bubble,* New York: Morgan Markets.

Jegadeesh, N. & Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance ,* 48(1), pp. 65-91.

Jensen, M., 1968. The performance of mutual funds in the period 1945-1964. *Journal of Finance,* 23(2), pp. 389-416.

Jensen, M. C., 1967. The Performance Of Mutual Funds In The Period 1945-1964. *Journal of Finance,* 23(2), pp. 389-416.

Kilanger, A. & Ingier, J., 2008. *Morningstar ratings as a predictor of future performance and flows for Norwegian mutual funds,* Oslo : BI Norwegian Business School .

Lehmann, B. N., 1990. Fads, martingales and market efficiency. *Quarterly Journal of Economics,* Volume 60, pp. 1-28.

Lintner, J., 1965. Security Prices, Risk, and Maximal Gains from Diversification. *Journal of Finance ,* 4(20), pp. 587-615.

Morey, M., 2002b. Mutual Fund Age and Morningstar Ratings. *Financial Analysts Journal ,* pp. 56-63.

Morey, M. R. & Gottesman, A. A., 2006. *Morningstar Mutual Fund Ratings Redux.* [Online]
Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=890128

Ødegaard, B. A., 2017. *Finance BI.* [Online]
Available at:
http://finance.bi.no/~bernt/financial_data/ose_asset_pricing_data/index.html
[Accessed 15 March 2017].

Oslo Børs , 2017. *Oslo Børs.* [Online]
Available at:
https://www.oslobors.no/markedsaktivitet/#/details/OBX.OSE/overview
[Accessed 08 06 2017].

Oslo Børs , 2017. *Oslo Børs.* [Online]
Available at:
https://www.oslobors.no/markedsaktivitet/#/details/OSEBX.OSE/overview
[Accessed 4 May 2017].

Oslo Børs, 2017. *Oslo Børs.* [Online]
Available at:
http://oslobors.no/markedsaktivitet/#/details/OSESX.OSE/overview
[Accessed 08 06 2017].

Rogers, W., 1993. Regression Standard Errors in Clustered Samples. *Stata Technical Bulletin,* 1(13), pp. 19-23.

Sharpe, W., 1966. Mutual fund performance. *Journal of Business ,* 39(2), pp. 119-138.

Sharpe, W. F., 1963. A Simplified Model for Portfolio Analysis. *Management Science*, Januar, Issue 9, pp. 277-293.

Sharpe, W. F., 1994. The Sharpe Ratio: Properly used, it can improve investment management. *The Journal of Portfolio Management*, Fall, Issue 21, pp. 49-58.

Sørensen, L. Q., 2009. *Mutual Fund Performance at the Oslo Stock Exchange,* Bergen: Norwegian School of Economics - Department of Finance.

Sullivan, R. N. & Xiong, J. X., 2012. How Index Trading Increases market Vulnerability. *Financial Analysts Journal ,* 68(2).

Treynor, J. L., 1962. *Toward a Theory of Market Value of Risky Assets ,* s.l.: Unpublished.

Verdipapirfondenes Forening, 2012. *VFF.* [Online]
Available at:
http://vff.no/assets/Bransjenormer/Bransjestandarder/Bransjestandard-for-informasjon-og-klassifisering-av-aksjefond-og-kombinasjonsfond-per-22.3.2012.pdf
[Accessed 08 06 2017].

White, H., 1984. *Asymptotic Theory for Econometricians,* San Diego: Academic Press.

Appendix

Appendix 1

List of All Norwegian Mutual Funds in Data Sample

Appendix 1 displays an overview of all 74 Norwegian mutual funds in the set of data. Please note that some of the funds have changed name both during and after the sample period from 2002-2013. Also note that funds have both been born and liquidated during the sample period. Therefore, Dine Penger have not given dice ratings to all funds during the period. See Appendix 2 for an overview of these funds.

SID	Fund Name	SID	Fund Name	SID	Fund Name
104	Storebrand Norge	405	Postbanken Norge	42314	KLP AksjeNorge
106	Avanse Norge (I)	9206	KLP Aksjeinvest	45665	Alfred Berg Humanfond
109	Nordea Vekst	9237	Alfred Berg Aktiv	45731	ABIF Norge ++
110	Nordea Avkastning	9247	DnB NOR Norge (III)	45755	Storebrand Norge I
113	Orkla Finans Investment Fund	9256	DnB NOR Norge Selektiv (I)	45791	Danske Invest Norge Aksjer Inst.
117	DnB NOR Norge (I)	9262	Storebrand Aksje Innland	46372	Nordea Kapital III
169	Alfred Berg Gambak	9273	NB-Aksjefond	46770	Fondsfinans Aktiv II
195	Alfred Berg Norge	9287	PLUSS Aksje	47745	Storebrand Optima Norge A
212	Avanse Norge (II)	9379	SEB Norge LU	47764	Holberg Norge
213	Carnegie Norge Indeks	9419	Postbanken Aksjevekst	48106	DnB NOR SMB
230	Avanse OBX Indeks	9425	Nordea SMB	49339	Pareto Aksje Norge
240	ABN AMRO Indeks	9427	Nordea SMB II	50467	DnB NOR Norge Selektiv (II)
241	ODIN Norge	9468	Alfred Berg Aktiv II	50571	RF-Plussfond
253	Storebrand Vekst	9488	RF Aksjefond	51109	Alfred Berg Norge Etisk
264	Orkla Finans 30	9489	Delphi Vekst	52104	WarrenWicklund Alpha
267	PLUSS Index	9520	Alfred Berg Norge +	52707	Fondsfinans Spar
281	Danske Invest Norge II	9532	Storebrand Verdi	54974	WarrenWicklund Norge
283	Danske Invest Norge I	9546	Globus Norge	57759	Alfred Berg Indeks
284	Danske Invest Norge Vekst	9547	Atlas Norge	58528	DnB NOR OBX
305	Delphi Norge	9588	Terra SMB	58836	Handelsbanken XACT OBX
323	DnB NOR Norge Selektiv (III)	9610	Terra Norge	61094	Pareto Verdi
372	PLUSS Markedsverdi	9693	Globus Norge II	62523	Landkreditt Norge
374	Nordea Kapital	9717	Globus Aktiv	72887	KLP AksjeNorge Indeks II
375	Handelsbanken Norge	38688	Nordea Kapital II	1249628	DnB NOR Norge Indeks
404	Carnegie Aksje Norge	38944	WarrenWicklund Indeks+		

Appendix 2

Included and Excluded Funds during the Sample Period

Appendix 2 illustrates an overview of all funds that have been included or excluded from Dine Penger rating since the beginning of the sample period. In total, there are 17 new included and 26 excluded funds.

New Funds Included			Funds Excluded from Rating		
SID	**Fund Name**	**Year**	**SID**	**Fund Name**	**Year**
46372	Nordea Kapital III	2002	9206	KLP Aksjeinvest	2003
47745	Storebrand Optima Norge A	2002	9379	SEB Norge LU	2003
47764	Holberg Norge	2002	9427	Nordea SMB II	2003
48106	DnB SMB	2002	230	Avanse OBX Indeks	2004
49339	Pareto Aksje Norge	2002	45731	ABIF Norge ++	2004
50467	GNKF Norske Aksjer	2002	46770	Fondsfinans Aktiv II	2004
50571	RF-Plussfond	2003	9419	Postbanken Aksjevekst	2005
52104	WarrenWicklund Alpha	2004	38688	Nordea Kapital II	2005
51109	Banco Norge	2005	38944	WarrenWicklund Indeks+	2005
52707	Fondsfinans Spar	2005	264	Orkla Finans 30	2006
54974	WarrenWicklund Norge Verdi	2005	9468	ABN AMRO Kapital	2006
57759	ABN AMRO Indeks +	2006	9532	Storebrand Verdi	2006
58528	DnB NOR OBX	2007	9610	Terra Norge	2006
61094	Pareto Verdi	2007	9717	Globus Aktiv	2006
62523	Landkreditt Norge	2009	46372	Nordea Kapital III	2006
72887	KLP AksjeNorge Indeks II	2010	50571	RF-Plussfond	2006
1249628	DnB NOR Norge Indeks	2011	240	ABN AMRO Indeks	2007
			58528	DnB NOR OBX	2010
			58836	Handelsbanken XACT OBX	2011
			9262	Storebrand Aksje Innland	2012
			9468	Alfred Berg Aktiv II	2012
			45791	Danske Invest Norge Aksjer	2012
			9273	NB-Aksjefond	2013
			9489	Delphi Vekst	2013
			9588	Terra SMB	2013
			9610	Terra Norge	2013

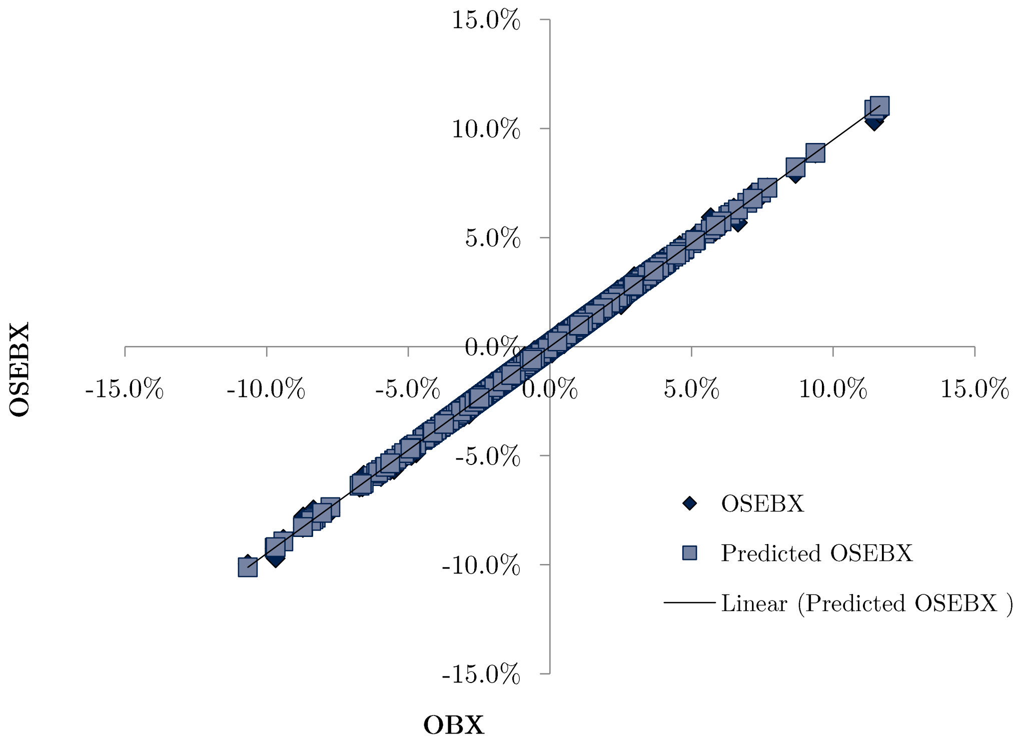
Appendix 3

Correlation OSEBX and OBX between 2002-2013

Appendix 3 illustrates the correlation between OSEBX and OBX in the sample period from 2002 to 2013. As we can observe, the OBX coefficient is statistical significant with a value of 0.948. This implies that a one percent increase in the OBX index leads to a 0.948% increase in the OSEBX index. Hence, we can conclude that there is a high correlation between both indices, indicating a close relationship between risk and return.

Regression Statistics	
Adjusted R Square	99.61%
Observations	3013

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.000	0.000	-0.805	0.421	0.000	0.000
OBX	0.948	0.001	871.871	0.000	0.946	0.951



Appendix 4

The Hausman Test for Random or Fixed Effects Model

Appendix 4 illustrates the results from the Hausman test. It tests whether the random effects model is preferred compared to a fixed effects model. The null hypothesis assumes zero correlation between unique errors and independent variables. As seen from the p-value of 13.44%, we cannot reject the null hypothesis. We can therefore conclude that the random effects model is the most efficient regression.

	Fixed	**Random**	**Difference**	**S.E.**
MKT	0.958	0.958	0.000	0.000
Star 1	-0.005	-0.008	0.003	0.001
Star 2	-0.001	-0.003	0.002	0.001
Star 3	-0.001	-0.002	0.001	0.001
Star 4	-0.002	-0.002	0.001	0.001
Star 5	-0.000	-0.001	0.000	0.001

Test: Ho: difference in coefficients are not systematic

chi2 = 9.78

Prob>chi2 = 0.1344

We cannot reject the null hypothesis

Appendix 5

Quartile Portfolio J/K-Strategy from 2002-2013

Appendix 5 reports the performance of the top quartile portfolios (Buy), the bottom quartile portfolio (Sell) and the zero-pay portfolio (Buy-Sell) from 2002-2013. We find that it is possible to achieve zero-pay returns for the quartile strategy, where the optimal strategy is a 1/1-strategy that yields yearly zero-pay returns of 3.29%. This return is related to persistent strong performance among top rated funds shown in Table 15. The t-statistics are reported in parenthesis.

			Return			
J		**K =**	**1**	**3**	**6**	**12**
1	Sell		0.0076	0.0056	0.0075*	0.0088***
			(1.13)	(1.11)	(1.95)	(3.31)
1	Buy		0.0102	0.0078	0.0093**	0.0102***
			(1.56)	(1.61)	(2.59)	(4.11)
1	**Buy-Sell**		**0.0027*** **	**0.0021*** **	**0.0018*** **	**0.0015*** **
			(2.84)	**(3.25)**	**(3.96)**	**(5.29)**
3	Sell		0.0073	0.0059	0.0087**	0.0098***
			(1.08)	(1.14)	(2.26)	(3.76)
3	Buy		0.0095	0.0077	0.0103***	0.0111***
			(1.43)	(1.56)	(2.83)	(4.53)
3	**Buy-Sell**		**0.0023** **	**0.0018*** **	**0.0016*** **	**0.0014*** **
			(2.42)	**(2.93)**	**(3.81)**	**(5.10)**
6	Sell		0.0093	0.0085*	0.0109***	0.0113***
			(1.37)	(1.68)	(2.94)	(4.45)
6	Buy		0.0112*	0.0099**	0.0122***	0.0124***
			(1.67)	(2.04)	(3.49)	(5.22)
6	**Buy-Sell**		**0.0019** **	**0.0014** **	**0.0013*** **	**0.0011*** **
			(2.00)	**(2.28)**	**(3.54)**	**(4.17)**
12	Sell		0.0129*	0.0120**	0.0129***	0.0110***
			(1.89)	(2.38)	(3.41)	(4.18)
12	Buy		0.0140**	0.0129***	0.0139***	0.0124***
			(2.07)	(2.65)	(3.89)	(5.00)
12	**Buy-Sell**		**0.0011**	**0.0009**	**0.0010** **	**0.0014*** **
			(1.24)	**(1.48)**	**(2.53)**	**(5.07)**

*** indicates significance at the 1 percent level
** indicates significance at the 5 percent level
* indicates significance at the 10 percent level

Appendix 6

Quartile J/K-Strategy on the Sample 2002-2008

Appendix 6 reports the performance of zero-pay portfolios (Buy-Sell) from 2002-2008. We find that the J/K-strategy generates positive returns slightly higher than for the quartile whole sample analysis. The t-statistics are reported in parenthesis.

			Return			
J		**K =**	**1**	**3**	**6**	**12**
1	**Buy-Sell**		0.0034**	0.0031***	0.0024***	0.0016***
			(2.53)	(3.38)	(3.69)	(4.32)
3	**Buy-Sell**		0.0028*	0.0025***	0.0019***	0.0014***
			(1.97)	(2.93)	(3.40)	(3.98)
6	**Buy-Sell**		0.0020	0.0017*	0.0014**	0.0011***
			(1.42)	(1.97)	(2.45)	(2.96)
12	**Buy-Sell**		0.0008	0.0011	0.0012**	0.0016***
			(0.63)	(1.39)	(2.17)	(4.25)

*** indicates significance at the 1 percent level
** indicates significance at the 5 percent level
* indicates significance at the 10 percent level

Appendix 7

Quartile Portfolio 4-Factor Alphas from 2002-2008

Appendix 7 reports the monthly performance of a) the top quartile portfolio and b) the bottom quartile portfolio. The top portfolio shows positive alphas, indicating that the ratings could predict quality funds. The 4-factor alphas reported in the table are the average monthly alphas from applying the J/K-strategy through the sample (2002-2008), where *** is 1%, ** 5% and * 10% significance levels.

a) Top Decile

	K - Holding Period			
J - Evaluation Period	**1**	**3**	**6**	**12**
1	0.0033***	0.0039***	0.0035***	0.0039***
3	0.0031**	0.0040***	0.0036***	0.0038***
6	0.0032**	0.0039***	0.0037***	0.0039***
12	0.0035***	0.0043***	0.0044***	0.0043***

b) Bottom Decile

	K - Holding Period			
J - Evaluation Period	**1**	**3**	**6**	**12**
1	-0.0013	-0.0001	0.0002	0.0017
3	-0.0010	0.0000	0.0006	0.0018
6	-0.0006	0.0006	0.0018	0.0023
12	0.0014	0.0019	0.0026	0.0025

Appendix 8

Quartile J/K-Strategy on the Sample 2009-2013

Appendix 8 reports the performance of zero-pay portfolios (Buy-Sell) from 2009-2013. During this period, we find no statistical evidence of zero-pay return in any of the J/K-strategies. This infer that Dine Penger did not manage to distinguish between top and bottom funds. The t-statistics are reported in parenthesis, where *** is 1%, ** 5% and * 10% significance levels.

			Return			
J		**K =**	**1**	**3**	**6**	**12**
1	**Buy-Sell**		-0.0000	-0.0006	-0.0008	-0.0003
			(-0.28)	(-0.54)	(-0.87)	(-0.40)
3	**Buy-Sell**		-0.0001	-0.0006	-0.0001	0.0003
			(-0.08)	(-0.60)	(-0.12)	(0.46)
6	**Buy-Sell**		0.0002	-0.0000	-0.0001	0.0003
			(0.15)	(-0.10)	(-0.18)	(0.69)
12	**Buy-Sell**		0.0008	0.0007	0.0005	0.0010*
			(0.63)	(0.69)	(0.65)	(1.81)

Appendix 9

Quartile Portfolio 4-Factor Alphas from 2009-2013

Appendix 9 reports the monthly performance of a) the top quartile portfolio and b) the bottom quartile portfolio. We find that a few portfolios seem to deliver positive alphas. These results are ambiguous as the rating system does not manage to separate top and bottom portfolios. The 4-factor alphas reported in the table are the average monthly alphas from applying the J/K-strategy through the sample (2002-2008), where *** is 1%, ** 5% and * 10% significance levels.

a) Top Decile

	K - Holding Period			
J - Evaluation Period	**1**	**3**	**6**	**12**
1	0.0035**	0.0036**	0.0026*	0.0010
3	0.0033**	0.0028*	0.0021	0.0016
6	0.0019	0.0023	0.0014	0.0013
12	0.0009	0.0017	0.0014	0.0013

b) Bottom Decile

	K - Holding Period			
J - Evaluation Period	**1**	**3**	**6**	**12**
1	0.0029	0.0051*	0.0032	0.0018
3	0.0037	0.0024	0.0022	0.0013
6	0.0020	0.0026	0.0011	0.0014
12	0.0005	0.0013	0.0014	0.0011