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Is the Return on Investment of Norwegian Pension Funds a Result of Luck or Managers' Skills? Is it Possible to Predict Which Pension Funds that Will Outperform the Market?

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Master of Science in Business with Major in Business Law, Tax and Accounting

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Executive Summary

The purpose of this research is to get insight into the Norwegian pension fund market. We will look further into the performance of pension funds by analyzing the drivers of the return of the funds. The data of study consists of 70 Norwegian pension funds delivered from Pensjon Norge AS with period from 2014-2017.

In this thesis, we will study whether the performance of the pension funds is a result of luck or the stock-picking skills of managers by using bootstrap simulations. In addition, we will investigate the persistence of pension fund performance. Firstly, we use the four-factor model of Carhart (1997) to compute residuals, factor loadings and alphas of each pension fund. Further, we bootstrap a new dataset of alphas, and generate t-statistics of alpha, for each fund which is used to compare with the original four-factor alphas and t-statistics of alpha. We also compute the parametric and bootstrapped p-values for each fund to conclude our hypotheses. The main analysis in this study is over a period of three years (2015-2017). Besides, we also test three different subperiods as robustness tests. We operate with two different datasets, one dataset which contains gross numbers while the other dataset is net numbers.

Our main findings in this analysis are that there is some degree of stock-picking skills of managers for several pension funds. By evaluating the bootstrapped p-values, we can reject the null hypothesis for significant p-values and hence, rule the return of some funds as a result of managers' skills. On the contrary, we are not able to make any conclusions if the bootstrapped p-values are insignificant. In general, there are indications of some persistence in the performance of the pension funds. However, we are not able to predict which pension fund that will outperform the market since the ranking of the funds varies across the percentiles.

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1. Introduction

"Retirement income is generally assumed to be built on three pillars: national social security plans, supplementary pension schemes and private pension funds" (Boulier et al., 2001). In this research, we are going to focus on the return of pension funds in Norway. Each year, huge amounts are invested in Norwegian pension funds, which makes this a business that generates substantial investments and capital. According to Finans Norge, the pension and life insurance markets combined capital was 1364 billion NOK in 2016 where pension funds in private sector were 551 billion NOK. An obstacle related to pension funds is the unpredictability of performance. To explore which pension fund to invest in, it is of importance to analyze how the pension fund performs and what drives the performance. Thus, it is interesting to research whether the performance is a result of the stock-picking skills of managers or simply due to luck.

This research examines pension fund performance while controlling for luck. Specifically, we analyze the significance of the alphas of extreme funds by applying a bootstrap technique. In other words, we analyze funds with large positive estimated alphas. In preparation for the bootstrap analysis, we use the four-factor model of Carhart to calculate the ordinary least squares estimated alphas, factor loadings and residuals. Following this, the bootstrap method is applied to simulate 1000 alphas for each individual pension fund. The bootstrap approach is superior in reducing the difference between true and nominal probabilities of correctly rejecting a given null hypothesis (Kosowski et al., 2006). Further, pension funds are a current topic due to its relevance regarding the upcoming retirement boom. The governmental pension payments are decreasing which causes the employees and companies to depend on private pension savings. The reason behind this research is that there are more studies done on mutual funds than on pension funds. In addition, we have observed little research about pension funds conducted in Norway. By analyzing the pension funds, we want to see which funds that outperform the market and which funds that are most profitable to allocate capital. If the manager has stock-picking skills, it indicates that the pension fund may be a safer investment because it suggests a more reliable future performance.

In our research, we observe more significant bootstrapped p-values than parametric p-values. Hence, this enables us to assess the null hypothesis for more pension funds when analyzing the bootstrapped p-values compared to the parametric p-values. In general, our results report a varying amount of significant p-values depending on how many years that are included in the test period. When testing our main analysis, three years (2014-2016), we find the lowest amount of significant p-values indicating that the funds have been rebalanced after three years. For comparison, the research generates the most significant amount of p-values when only testing for one year (2014). A reasonable explanation is that it is easier to perform satisfactorily in a short period rather than for a long period of time. Throughout the analysis, we find some funds which remain among the top funds for all the test periods. For example, KLP Pengemarked and Skagen 100 are consistent among the top funds. Thus, investing in these funds will be a more secure investment than funds where the performance is due to luck.

A pension fund is defined as “a fund set up to pay the pension benefits of a company’s workers after retirement” (Nasdaq). Further, pension funds manage assets, this is called assets under management (AuM) and is defined as the total market value of assets that an investment company or financial institution manages on behalf of investors (Statistisk Sentralbyrå). Another way to look at AuM’s is as the share of the investors’ capital the company controls. We limit Assets under Management to funds where an investor has responsibility for managing the fund. Thus, we exclude mutual funds and cash in our calculations. The total Assets under Management was 1364 billion NOK in 2016, shows a positive trend from 2015 and 2014, with 1283 and 1202 billion NOK.

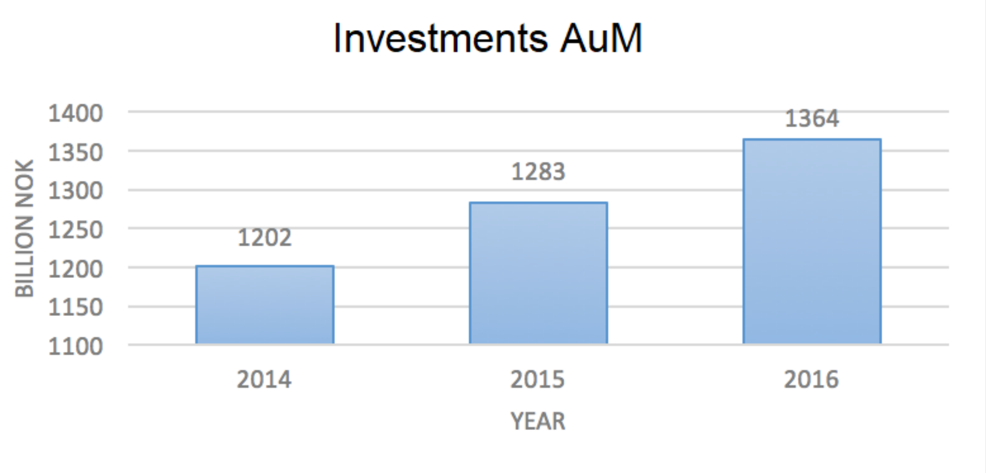

Figure 1 – Investments AuM (Reference: Finans Norge)

1.1 Literature Review

There is a considerable amount of literature that researches the topic of mutual funds and pension funds. One important contribution to the literature is Kosowski et al., (2006) which focuses on whether the performance of mutual funds is due to luck or managers' skills. To test their hypothesis, they use bootstrap simulations to assess their sampling estimates of statistical estimates. This research is one of the first thorough studies of the performance of mutual funds, measured as alpha while using luck as a control variable in the model. Alpha is a measure of pension fund performance and reports how the return is compared to the security market line. If the alpha is positive, it indicates that the fund is outperforming the market while a negative alpha reports a return worse than the market.

Similar to the method of Kosowski et al. (2006), Fama and French (2008) use the bootstrap method to perform a bootstrap simulation to test the persistence of mutual funds to determine the skills of the managers. Fama and French use Kosowski et al. (2006) as a baseline for their research and their approach. What separates the articles, is that Fama and French emphasize access to information for the managers, while Kosowski et al. (2006) focus their research on luck versus skills. Throughout the article, Fama and French conclude that a long return history may mask the effects of temporary access to information. Thus, persistence tests are a better measure of short-term performance of the mutual funds because they are better at identifying when funds have access to private information. The persistence tests suggest that the ranking of the performance of the funds are temporary and therefore of little of use for investors when they choose their funds. Additionally, the mutual fund industry will rarely deviate from market performance since the mutual fund industry contains a portfolio similar to the market portfolio.

Mark Carhart on the other hand, attempts to explain persistence in equity mutual funds mean and return by common factors in returns and investment expenses. Carhart argues that the performance of mutual funds is *not* a measure of superior stock-picking skills and that common factors can explain the majority of predictability in mutual fund returns of stock returns and investment expenses. In his research, Carhart shows that funds with previous high alphas frequently generate high alphas and returns in the following time periods. In contrast to Carhart, Kosowski et al. (2006) report results which indicate that the persistence of mutual funds is a consequence of managers' skills. The results of Kosowski et al. (2006) is supported by Berk and Green (2004) who report that investments are allocated to profitable investment opportunities by identifying skilled managers. They explore whether past performance influence where capital is allocated. Even though past performance is not a secure indicator of future performance, investors prefer to invest capital in mutual funds that have performed satisfactorily in the previous years. Moreover, Bernhardt, Davies and Westbrook (2002) studied short-term return persistence and how managers maximized the return of the fund. They found that competence was an essential factor affecting differences in performance.

To perform their analysis, Kosowski et al. (2006) use the four-factor model of Carhart in their research. However, they have a different method for testing the significance of the alphas. Similar, Busse et al. (2010) use factor models to explore persistent performance in pension funds, however, the different models give an inconsistent result. This separates the study of Busse et al. (2010) from both Carhart (1997) and Kosowski et al. (2006), where they do not experience considerable inconsistency in their results from the three-factor model to the four-factor model.

Existing literature has explored conditional performance evaluation in mutual funds. Ferson and Schadt (1996) have researched the effect of including lagged information variables when analyzing the performance of mutual funds. It is suggested that there is a need to include more public information variables when analyzing performance measures. This is similar to Fama and French (2008) who emphasize the importance of the managers' access to information from the market. In the research of Ferson and Schadt (1996). One of the disadvantages of standard performance measures is that they suffer from some biases. An example of this is that alphas, which is a traditional measure of performance, often generate negative numbers that can be interpreted as inferior performance. However, when lagged instruments are used to control variation, the traditional models improve the performance of the funds in their sample. As a contrast, there are examples of researches that have experienced negative alphas in their results. One example of this is Kosowski et al. (2006) that have several negative alphas in their research. However, due to their bootstrap methodology, negative alphas do not cause noise when analyzing performance.

Additionally, pension funds can be managed two ways; active or passive. An actively managed pension fund is, in general, an expensive form, and further, an actively managed fund is more effective in making a profit (Bauer et al., 2010). Typically, these funds have a higher expected return on their investments. However, they have more substantial costs and are riskier. Compared to the actively managed fund, a passive fund is less expensive, and they have a lower expected return on their investments. Bauer et al. (2010) have contributed to literature by focusing their research on the context of the cost structure of pension funds and their performance. They found that compared to mutual funds, pension funds have lower costs because pension funds, in general, are larger, which leads to more efficient operations. In addition, Andonov et al. (2012) analyzed whether large pension funds increased their return by having passive management. There are several reasons why large, passive funds may be more profitable, for example, active management is much more expensive than passive management. However, on average, pension funds have had a substantial risk-adjusted security selection performance. Further, a larger fund has more bargaining power that allows them to supervise managers and to keep the costs to a minimum.

For comparison, Kosowski et al. (2006) and Fama and French (2008) eliminates the effect of the size of the fund as they use the bootstrap approach to test their hypotheses. Further, Bauer et al. (2010) conclude that the size of the fund and liquidity are negatively correlated, and this result is supported by Chen, Hong, Huang and Kubik (2004). The liquidity limits the performance of the funds, causing only small-cap mandates to outperform the market. Even though large pension funds are cost-effective compared to small funds, they are outperformed in equity performance. These results are substantiated by Andonov et al. (2012) who research whether the role of size has an impact on the performance of US pension funds. They analyze the three components of active management; asset allocation, market timing and security selection. The results illustrate that funds with high equity allocations often differ from their benchmark by choosing illiquid shares. However, only the relatively small funds benefit from this, because small funds are more flexible regulated.

In general, previous literature has emphasized more on analyzing mutual fund performance rather than pension fund performance. Mutual fund performance is a much-researched topic internationally. However, there are few studies on mutual funds conducted in Norway. Due to the fact that there are more thorough studies done on mutual funds, we will research pension funds. From reviewing the literature, there are several studies conducted in the United States on pension fund performance, and there are quite large differences in how pension funds in USA and Norway are structured (Stewart and Yermo, 2008). Due to these significant differences in the form of the pension funds, the results from American studies cannot be generalized to Norwegian pension funds.

Moreover, the studies that focus on pension funds do not analyze whether performance is a result of luck or managers' stock-picking skills. Alternatively, they aim to explain how the cost structure of the pension fund is affecting the return. In addition, some research explores whether the pension funds are active or passive managed to explain the performance of the funds. On the other hand, the study of Kosowski et al. (2006) includes stock-picking skills and luck as factors in their study while the cost structure of funds is excluded. To combine these gaps, we want to research whether the performance is a result of luck or managers' skills using returns before and after costs and fees. Hence, the research problem is: *Is the return on investment of Norwegian pension funds a result of luck or managers' skills? Is it possible to predict which pension funds that will outperform the market?*

To fill the knowledge gaps, this research uses the gross and net return of Norwegian pension funds to predict fund performance, alpha. The estimated alphas are used to calculate parametric p-values. After using the dataset, we bootstrap new alphas and their corresponding bootstrapped p-values. These types of bootstrap simulations can notably reduce the difference between true and nominal probabilities of correctly rejecting a given null hypothesis (Kosowski et al., 2006). Further, the parametric and bootstrapped p-values are analyzed to evaluate the significance of the pension fund return on investments.

Overall, the results provide evidence that the shorter the test period is, the more significant p-values are generated. This applies to both bootstrapped and parametric p-values. For the funds which have a significant p-value, the null hypothesis can be rejected, and this indicates that the performance of the funds is a result of the stock-picking skills of managers. The main analysis separates from the sub-periods by estimating fewer significant p-values which can be explained by the managers rebalancing the portfolio. When the test period is three years, we observe three significant bootstrapped p-values for both gross and net numbers when the funds are ranked by their four-factor alpha. For comparison, when we test for one year, all bootstrapped p-values are significant, while nine bootstrapped p-values generated from net numbers are significant. The bootstrap approach is used because of the high degree of nonnormality of the sample, and it generates p-values closer to the unknown true p-values. Further, there is some consistency in which funds that remain among the top and bottom fund when ranking the funds by their four-factor alpha and t-statistic of alpha for the different test periods. Examples of this are fund number 7 and 24, Skagen 100 and KLP Pengemarked, which are funds that remain among the top funds throughout the test periods. Even though all pension funds have corresponding p-values, we are only able to identify stock-picking skills of managers for the funds with significant p-values. Thus, the insignificant p-values do not enable us to assess the null hypothesis. However, it is reasonable to assume that they indicate that the performance of the pension funds may be a result of luck and not managers' skills.

2. Hypothesis

Along the lines of the literature review, we will formulate our hypothesis in this section. As mentioned above, previous research has focused on mutual funds. However, few studies engage in research on pension funds and even fewer studies about Norwegian pension funds. Based on what we have learned so far, we will define four hypothesis that we will test throughout this thesis.

Kosowski et al. (2006) test whether alphas of mutual funds are a result of luck or the stock-picking skills of managers. In their concluding remarks, they have indications of stock-picking skills affecting the return of mutual funds which suggest that the alphas are not solely due to luck. On the other hand, Carhart (1997) disagrees with Kosowski et al. (2006) and argues that performance of mutual funds is not a result of managers' skills but rather a combination of common factors in stock returns and investment expenses. Therefore, our null hypothesis is that high alphas are a result of luck.

Another assumption of Kosowski et al. (2006) is that in the long run, the mutual funds do not outperform the market. Kosowski et al. use the model of Carhart (1997) which is an extension of the Fama and French three-factor model. This model is based on the CAPM assumptions which assume that no funds can outperform the market. Hence, the hypothesis is that in the long run, true performance of Norwegian pension funds is zero, alpha = 0.

In accordance with Berk and Green (2004), the performance of mutual fund managers is unpredictable from past performance. Nevertheless, pension funds are always striving to outperform the market. Kosowski et al. (2006) conclude that there is some degree of persistence in performance. However, Lynch and Musto (2003) predict some degree of persistence in performance among the winning mutual funds, although they do not have the same indications for the losing funds. Based on this, our hypothesis is that the pension fund that is the most effective will vary because it is impossible to predict from past earnings.

To summarize, we have formulated three hypotheses:

- *High alphas are a result of luck and not managers' skills*
- *In the long run, true performance of pension funds is zero (alpha = 0)*
- *The most effective pension fund will vary because it is impossible to predict from past earnings*

3. Efficient Market Hypothesis

The efficient market hypothesis (EMH) implies that prices fully reflect all available information in the market. Market efficiency is desirable because it indicates optimal allocation of capital. However, efficient markets separate from perfect markets due to transaction costs and market imperfections. According to the hypothesis, the ideal market is a market that contains prices which functions as signals for where to allocate resources. Therefore, we desire a market where it is possible to make investment decisions by prices that fully reflect all available information. "*A market in which prices "fully reflect" available information is called efficient."* (Fama, 1970).

Eugene Fama first described the hypothesis of efficient markets in 1965. According to Fama, it is impossible for investors to outperform the market because prices at all time reflect all information. Three factors contribute to efficient markets; rationality, the independent deviation from rationality and arbitrage (Jain, 2012). The first factor, rationality, assumes rational investors that adjust their investments when new information is released. Secondly, independent deviation of rationality states that the optimistic investors are offset by pessimistic investors and thereby creating efficient capital markets. The third assumption is that the market will still be viewed as efficient as long as the rational professional investors outperform the irrational amateurs (Hillier et al., 2016).

Further, the EMH is supported by many economists worldwide, one of them is Harvard economist, Michael Jensen. Jensen claims that there exists solid evidence than other research that supports this hypothesis and therefore he believes that the market will outperform the investors. However, some analysts do not agree with Fama's studies. One of them is Peter Lynch who is claiming to have beaten the market over an extended period (Clarke et al., 2001). Other examples of investors outperforming the market, is Warren Buffet.

4. Data

4.1 Data Collection

The data of study is the monthly returns of Norwegian pension funds collected from Norsk Pensjon AS. Norsk Pensjon is a Norwegian pension portal, founded in 2006, that gives public individuals an overview of different pension schemes (Norsk Pensjon). Seven life insurance companies provide information about their pension schemes to Norsk Pensjon, and this information from the pension portal is incorporated in our database.

Other variables included in our study is collected from Asset Pricing Data at OSE published by BI and the Norwegian Stock Exchange Data Service. BI has computed variables (SMB, HML and PR1YR) from market data from Oslo Stock Exchange Data Service in a similar manner as Eugene Fama and Kenneth French in "Mutual Fund Performance" (2008).

4.2 Sample

The database generated from Norsk Pensjon AS initially consisted of 97 different pension profiles from seven different life insurance companies: DNB Liv, Storebrand, KLP, Sparebank1, Gjensidige, Nordea Liv and Danica.

To include as much as possible of the pension market in this research, our sample consists of pension funds targeting both companies and private individuals. The initial dataset consisted of observations from 2000 to 2017. However, some of the pension profiles did not provide observations for all years which made us limit the test period to three years (36 months). A consequence of missing observations is that our final dataset consists of 70 different pension funds. 27 pension funds are eliminated which makes it possible to compare the return of the funds for the same period. As a robustness test, we decided to include testing of different time periods to review the consistency of our results. The most extended period we analyzed, was four years (48 months) while the shortest interval was one year (12 months).

We have included both gross and net returns in our analysis to see if the results are depending on the costs of the pension funds. This leads the analysis to include one dataset that incorporates both gross and net return. However, the gross and net return is tested separately when applying the methodology. In addition, previous literature (for example Berk and Green 2004) indicates differences when testing gross and net returns which makes it interesting to see if gross and net numbers also provide different conclusions in Norwegian pension fund returns. Gross return is defined as the return of the pension funds before costs and fees and net return defined as after costs and fees have been paid. Further, the dataset is consisting of pension funds with different degrees of risk, including low, medium and high volatility.

Table I
PENSION FUND IDENTIFICATION NUMBERS

Identification	Name	Identification	Name
1	Sparebank 1 100 % aksjer	36	Kombinert Pensjonsprofil Balansert
2	Sparebank 1 Forsiktig	37	Kombinert Pensjonsprofil Offensiv
3	Sparebank 1 Moderat	38	Kombinert Pensjonsprofil Trygg
4	Sparebank 1 Offensiv	39	Kombinert Pensjonsprofil Aksjer Privat
5	Skagen 60	40	Kombinert Pensjonsprofil Renter Privat
6	Skagen 80	41	Aktiva Bedrift 10
7	Skagen 100	42	Aktiva Bedrift 30
8	Sparebank 1 BM Bank	43	Aktiva Bedrift 50
9	Danica Valg Forsiktig	44	Aktiva Bedrift 65
10	Danica Valg Moderat	45	Aktiva Bedrift 80
11	Danica Valg Offensiv	46	Aktiva Bedrift 100
12	DNB Pensjonsprofil 80	47	Kombinert Pensjonsprofil Aksjer
13	DNB Pensjonsprofil 0	48	Kombinert Pensjonsprofil Renter
14	DNB Pensjonsprofil 10	49	Aktiv Pensjonsprofil Aksjer
15	DNB Pensjonsprofil 30	50	Kombinert Pensjonsprofil Balansert Valutasikret
16	DNB Pensjonsprofil 50	51	Kombinert Pensjonsprofil Offensiv Valutasikret
17	DNB Pensjonsprofil 100	52	Kombinert Pensjonsprofil Trygg Valutasikret
18	Storebrand Balansert Pensjon	53	Eika 100 % Aksjer
19	Storebrand Forsiktig Pensjon	54	Eika Forsiktig
20	Storebrand Offensiv Pensjon	55	Eika Moderat
21	Danica Valg Aksjer	56	Eika Offensiv
22	Danica Pensjon Norge Aksje	57	Kombinert Pensjonsprofil Aksjer Valutasikret
23	Danica Pensjon Norge Obligasjon	58	Handelsbanken 50
24	KLP Pengemarked	59	Handelsbanken 75
25	KLP P30	60	Handelsbanken 100
26	KLP P50	61	Storebrand Ekstra Forsiktig Pensjon
27	KLP P70	62	Storebrand Ekstra Offensiv Pensjon
28	KLP P90	63	Sparebank 1 100 % Aksjer basis
29	Sparebank 1 Moderat Basis	64	Sparebank 1 Forsiktig Basis
30	Kombinert Pensjonsprofil Balansert Privat	65	Sparebank 1 Offensiv Basis
31	Kombinert Pensjonsprofil Offensiv Privat	66	Storebrand Balansert Pensjon P
32	Kombinert Pensjonsprofil Trygg Privat	67	Storebrand Ekstra Offensiv Pensjon P
33	Aktiv Pensjonsprofil Balansert	68	Storebrand Forsiktig Pensjon P
34	Aktiv Pensjonsprofil Offensiv	69	Storebrand Offensiv Pensjon P
35	Aktiv Pensjonsprofil Trygg	70	Storebrand Ekstra Forsiktig Pensjon P

4.3 Variables

As preparation for further analysis of data, the four-factor model of Carhart is used to compute ordinary least squares-estimated alphas and residuals. We considered using the three-factor model of Fama and French, but since the four-factor model has the better fit (Kosowski et al., 2006), we decided to use the model of Carhart as the primary model. However, previous literature that uses both models has experienced similar results. The variables included in the four-factor model are:

Table II

REGRESSION VARIABLES

Table 2 illustrates the dependent and independent variables under study.

Nature of Variable	Variable
Dependent variable	Excess return on pension funds
Independent variable	Excess return on aggregate market portfolio
	Small portfolio minus big portfolio
	High portfolio minus low portfolio
	1-year momentum in stock returns

The dependent variable is the monthly excess return on a managed portfolio. This variable is the outcome of the analysis and therefore is the main focus in the study (Foldnes et al., 2018). It is possible to have several dependent variables in a study. However, we only operate with one. In this research, r_{it} is the monthly excess return on a managed portfolio, which means that it is net return minus the risk-free rate. Independent variables, also called predictor variables, are used to explain the dependent variable. It is of interest to attempt to explain how other variables affect the main focus of the study, which is the dependent variable (Foldnes et al., 2018). The independent variables in this model are as follows:

$RMRF_t$ denotes the monthly excess return of the aggregate market portfolio. SMB_t (SMB: Small minus big) measures the difference between the return on a small portfolio minus the return on a big portfolio. This is also called “the small firm effect,” for the reason that smaller firms usually outperform larger ones. It can also be defined as the spread in returns between small and large portfolio/firms. For example, by including the SMB effect, the model will show if the small firm effect would cause the abnormal return. HML_t (HML: High minus low) explains the return on a portfolio of high-book-to-market stocks minus the return on a portfolio of low-book-to-market stocks (Fama and French, 1996). This variable is also known as "the value premium" which is the spread in return between value and growth stocks. Normally, the value stocks (high-book-to-market ratios) outperform the growth stocks (low-book-to-market ratios). Moreover, HML_t can be used to predict the future performance of the security. $PR1YR_t$ illustrates 1-year momentum in stock returns, which is a short time measure of the stock return.

4.3.1 Descriptive Statistics

The sample consists of return on 70 different pension funds. The dataset is cleaned of missing values which is making it easier to compare results in the same period. The table below illustrates a summary of descriptive statistics of the variables included in the study.

Table III

DESCRIPTIVE STATISTICS

Panel A

Sample Distribution

No. of Months	**No. of Obs.**	**No. of Funds**
12	840	70
24	1680	70
36	2520	70
48	3360	70

Panel B

Summary Statistics

Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
r_{it}	2520	0,006	0,019	-0,099	0,098
$RMRF_t$	2520	0,010	0,031	-0,072	0,057
SMB_t	2520	0,007	0,031	-0,062	0,103
HML_t	2520	-0,002	0,032	-0,070	0,060
$PR1YR_t$	2520	0,017	0,041	-0,088	0,121
R_f	2520	0,001	0,000	0,001	0,001
OSEAX	2520	0,011	0,031	-0,071	0,058

5. Methodology

5.1 Bootstrapping

Bootstrapping is a relatively straightforward method to estimate standard errors and confidence intervals, even when the data consists of complex parameters. It is an effective method when controlling and reviewing output, which makes the method easy to interpret and conclude by comparing the results, in this case, the alphas. In addition, bootstrapping fits both normal and nonnormal distribution of data, which causes this to be an attractive method to use when heterogeneous risk characterizes the dataset. Our dataset has a nonnormal distribution and heterogeneous risk which makes bootstrapping a suitable technique for testing our hypotheses that are similar to the hypotheses of Kosowski et al. (2006). Likewise, this technique is advantageous when the test is a natural experiment, which is equivalent to using past and present data rather than future estimations. Another main advantage of bootstrapping is that it is an attractive method when analyzing a cross-section of data similar to what we use in our study. To compare, we will study the returns of Norwegian pension funds while Kosowski et al. (2006) use the return of mutual funds as their main source of data.

The two test statistics in this research, is the estimated alpha, α, and the estimated t-statistic of alpha, t_{α}. Hence, the main focus of the analysis is on the alphas, and the t-statistic of alpha before and after bootstrapping is applied. Alpha is a measure of abnormal performance. Moreover, the alpha is a number which indicates if the return of the pension fund is above, equal to or below the market, indicated by the security market line (SML). One of the weaknesses regarding alpha as a test-statistics is that it is not an accurate measurement when constructing confidence intervals.

A test-statistic is usually used when performing hypothesis tests. The first step is to define a null hypothesis (H_0), which is the main hypothesis to be tested against a second hypothesis, also called the alternative hypothesis (H_A). In this research, the null hypothesis is "*High alphas are a result of luck and not managers' skills.*" If the null hypothesis is rejected, then the alternative hypothesis is accepted, and the alphas are a result of stock-picking skills of managers. When performing a hypothesis test, one or more rejection levels can be included in determining when the null hypothesis is being rejected or accepted. One of the most commonly used rejection levels is 5 %, which indicates a 95 % probability of accepting a correct null hypothesis and a 5 % chance of wrongfully accepting a null hypothesis. Other commonly used rejection levels are 10 % and 1 %.

t-statistic of alpha, t_α, is a pivotal statistic with better sampling properties. Further, the t-statistic has an attractive statistical property, that aids in eliminating spurious outliers by normalizing the estimated alpha by the predicted variance of the alpha estimate (Kosowski et al., 2006). This statistical property is useful when the sample includes funds with short lives or excessive risk-taking, typically small funds since they often generate alphas that tend to be spurious outliers. Another advantage of using the t-statistic is that this test statistic controls for differences in risk-taking which causes risk to have less impact on the results (Kosowski et al., 2006).

The first step towards running the bootstrap analysis is to perform a regression analysis.[1] Here, Carhart's four-factor model is used to compute ordinary least squares estimated alphas, factor loadings and residuals.[2] The time series of monthly net returns (minus the risk-free rate) for fund i, is used to calculate the input for the bootstrapping models. The model in use can be written as:

$$r_{i,t} = \hat{\alpha}_i + \hat{\beta}_i * RMRF_t + \hat{s}_i * SMB_t + \hat{h}_i * HML_t + \hat{p}_i * PR1YR_t + \hat{\varepsilon}_{i,t}, \qquad (1)$$

In equation 1, the monthly excess return is computed by the four independent variables in addition to the constant, alpha, and the error term, ε. $RMRF_t$ is a measure of the market return minus the risk-free rate of the aggregated market

[1] In general, regression analysis is one of the most commonly used techniques in econometrics (Brooks, 2014). The regression analysis attempts to explain variation in the dependent variable by using independent variables.

[2] To estimate linear regression models, ordinary least squares (OLS) is the most common approach where the goal is to achieve a regression line that fits the observed data the best. OLS aims to minimize the sum of squares of the differences between each data point and each point on the regression line[2]. Further, to measure the fit of the regression line, "*the closeness is measured by the sum of the squared mistakes made in predicting Y given X*" (Stock and Watson, 2015, p. 162).
For the OLS estimator to present useful estimates of the regression coefficients, several assumptions should be met (Brooks, 2014).

1. $E(u_t) = 0$ - The errors have zero mean.
2. $Var(u_t) = \sigma^2 < \infty$ - The error has constant variance and is finite over all values of x_t
3. $Cov(u_i,u_j) = 0$ - The error terms are linearly independent. There is no correlation between the error terms.
4. $Cov(u_t,x_t) = 0$ - There is no correlation between the error term and the x-value
5. ut ~$N(0, \sigma^2)$ - u_t is Normally distributed

portfolio. The following variable is SMB_t which denotes the difference between the return of a small portfolio and a big portfolio. This variable is also named the small firm effect because smaller firms normally perform better than larger firms. Further, HML_t, also called "the value premium," is a measure of the difference between the return on a portfolio of low-book-to-market stocks and high-book-to-market stocks. Lastly, $PR1YR_t$ is the 1-year momentum in stock returns.

After using the four-factor model to estimate alphas, the next step is to bootstrap new alphas and t-statistics of alphas and corresponding p-values. The baseline bootstrap model is used for each fund i in the sample, and in this method, the estimated residuals from the four-factor model are used and thereby creating a pseudo-time series of resampled residuals. These residuals are used to evaluate whether the sample is characterized as normal or nonnormal. Below is an example of the analysis of fund 1. Here we have calculated the residuals and use these to characterize the sample as normal or nonnormal. For fund 1, the sample is characterized as nonnormal as the histogram do not show a normal distribution. The majority of the residuals of the pension funds, indicate a nonnormal sample and thus bootstrapping is an appropriate technique in this research.

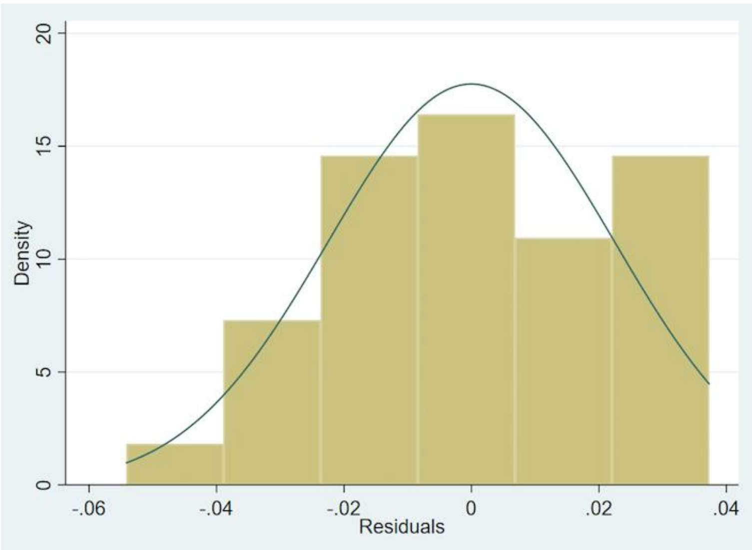

Figure 2 – Probability Distribution Residuals for Fund 1

When applying the bootstrap method, b is used as an index for the bootstrap number (b=1 for bootstrap 1) "*and where each of the time indices* $s^b_{T_{i0}}, \dots, s^b_{T_{i1}}$ *are drawn randomly from* $[T_{i0}, \dots, T_{i1}]$ *in such a way that reorders the original sample of*

$T_{i1} - T_{10} + 1$ *residuals for fund i* (Kosowski et al., 2006, p.2561). Below is a visualization of the bootstrap procedure for fund 1. Here, we observe the simulation of 1000 iterations where b is the index for each iteration. This means that b = 1 is the index for the first iteration which is illustrated by the first dot in the first row. In each row, there are 50 dots which indicates that there are 50 iterations per row and 1000 iterations in total.

```
. simulate _b _se, reps(1000) : bs_resid, res(resid) mat(b)

      command:  bs_resid, res(resid) mat(b)

Simulations (1000)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50
..................................................   100
..................................................   150
..................................................   200
..................................................   250
..................................................   300
..................................................   350
..................................................   400
..................................................   450
..................................................   500
..................................................   550
..................................................   600
..................................................   650
..................................................   700
..................................................   750
..................................................   800
..................................................   850
..................................................   900
..................................................   950
..................................................  1000
```

Figure 3 - Bootstrap Simulation for Fund 1

Secondly, a time series of pseudo-monthly excess returns for this fund is constructed which requires the null hypothesis to be $\alpha = 0$, or $t_\alpha = 0$. An alpha equal zero is called the true alpha since it indicates the long-term value of the coefficients. Alpha is converging towards zero because no stock or fund will outperform the market in the long run (Hillier et al., 2016). This is equivalent to the efficient market hypothesis, where it is assumed that no investor is able to outperform the market due to full access to information (Fama, 1970).

$$r^{b}{}_{i,t} = 0 + \hat{\beta}_i * RMRF_t + \hat{s}_i * SMB_t + \hat{h}_i * HML_t + \hat{p}_i * PR1YR_t + \hat{\epsilon}^{b}_{i,t_{\varepsilon}}, \qquad (2)$$

Here, the alpha (and t-statistic of alpha) is eliminated from the model since its true value, in the long run, is zero. When performing the regression for a given bootstrap, a positive alpha (or t-statistic of alpha) may generate abnormally high positive residuals, and a negative alpha (or t-statistic of alpha) may generate abnormally negative residuals. This step is repeated for all funds i and thereby creating a cross-section of bootstrapped alphas. The bootstrapped t-statistics of alpha is then calculated by dividing the alpha with the corresponding standard error. To build a distribution of the cross-sectional alphas (or t-statistics), this step is repeated for all bootstrap iterations. The number of bootstrap iterations is 1000 for all pension funds. An example of this is shown below in Figure 4, which illustrates an excerpt of the results of the bootstrap simulation for Fund 1. The Figure displays the results for bootstrap iteration 100 to 110. The three highlighted columns in Figure 4 show the bootstrapped alphas, "_b_cons", the standard error of the bootstrapped alpha, "_se_cons" and the t-statistic of the four-factor alpha, "tstat". The bootstrapped alphas divided by the standard error of the bootstrapped alphas are used to calculate the t-statistic of alpha which later leads to the computation of the corresponding bootstrapped p-values.

	_b_RMRF	_b_SMB	_b_HML	_b_PR1YR	_b_cons	_se_RMRF	_se_SMB	_se_HML	_se_PR1YR	_se_cons	tstat
100	-.2730869	-.1703193	-.4086236	.6053709	.057595	.1434227	.1780785	.1576775	.1323138	.1773296	.3247905
101	.0015603	-.0698938	-.0694341	.4283879	-.2997337	.1618573	.1873951	.1820916	.1359442	.2019709	-1.484044
102	-.4472189	-.1545521	-.1326106	.4424121	.0272099	.1344493	.1627063	.1819895	.1331943	.1543837	.1762487
103	-.2911765	-.2465986	-.3884892	.3026944	.1985609	.1448314	.188175	.171959	.1212338	.2075131	.9568595
104	-.2385812	-.1438886	-.2129643	.2910741	.04109	.1186921	.1421679	.148397	.1034771	.1381071	.2975227
105	-.1606927	-.1999767	-.216509	.6798601	-.2274923	.1309015	.1456834	.1409846	.104125	.1460534	-1.557596
106	-.3688537	-.0470213	-.0139598	.4488223	-.0796286	.1283097	.1287899	.1310217	.1111559	.1421437	-.5601981
107	-.2833668	-.1868307	.1312151	.3501858	-.0569837	.1295098	.1433471	.1418326	.1277736	.1479356	-.3851928
108	-.4463669	.1099221	.3050192	.4902241	-.3224204	.1274827	.1323895	.1192204	.1032648	.1445691	-2.230216
109	-.6552585	-.0228265	-.5048258	.3572389	.3192245	.1637776	.1752255	.1523345	.1434079	.1785653	1.787719
110	-.4449527	-.1616075	-.3931564	.6219574	.0452261	.1515772	.1689493	.1572203	.1425844	.1480819	.305413

Figure 4 - Excerpt of Bootstrap Results for Fund 1

Further, we evaluate the bootstrap iterations by comparing the estimated values of alpha, and the estimated t-statistic of alpha, to those that are observed in the actual data set. These comparisons lead to the computation of the p-values of each pension fund.

The p-value is considered as a complicated method to use when testing null hypotheses due to their difficult calculations (Wooldridge, 2016). In a case where the p-value is below the acceptable significance level, the null hypothesis is rejected, and the performance of the pension fund is a result of managers' stock-picking skills. We use p-values to conclude whether the observations in the dataset are surprisingly given a true null hypothesis. The p-value can be defined as the probability of observing output that is as extreme as our observations if the null hypothesis is true (Foldnes et al., 2018). Extreme observations are interpreted as unexpected values given that we accept the null hypothesis. An advantage of this method is that it gives more insight to the significance level of the regression coefficient.

To conclude the null hypothesis, the p-values are calculated using the t-statistics of alpha. The bootstrapped p-values are calculated by observing how many bootstrapped t-statistics of alpha that are larger than the estimated t-statistic of alpha divided by 1000, which is the number of bootstrap iterations.

Fund Number	**1**
tstat before bootstrapping	***0,831***
tstat after bootstrapping	-3,558
	-3,481
	-3,100
	-2,962
	-2,848
Bootstrapped p-value	**0,217**

Figure 5 – Calculation of the bootstrapped p-value

Figure 5 reports the p-value of Fund 1 calculated from gross numbers when the test period is three years (2014-2016). The number highlighted in cursive is the standard t-statistic of Fund 1 calculated from the four-factor regression model of Carhart before applying the bootstrap procedure. The excerpt displays five of the 1000 bootstrapped t-statistics. Moreover, the bold number is the calculated bootstrapped p-value for Fund 1. The bootstrapped p-value is calculated by observing how many of the bootstrapped p-values that are larger than 0,83112, which is the standard t-statistic from the four-factor model. This gives Fund 1 a bootstrapped p-value of 0,217.

These bootstrapped p-values determine whether the null hypothesis is to be accepted or rejected by comparing the values to three rejection levels. The rejection levels in this research are 10 %, 5 % and 1 %. As the rejection level is decreasing, the more accurate is the conclusion. When the p-value is significant, the null hypothesis is rejected, and the return of the pension fund is a result of the stock-picking skills of managers. For the insignificant p-values, we are not able to conclude that luck is the drive behind the performance of the pension fund. However, one may assume that luck is one of the factors affecting the return although one cannot conclude with certainty. Further, the null hypothesis can only be rejected for the individual pension fund with a corresponding significant p-value meaning that the result cannot be generalized for all funds in the sample. Due to the nonnormality distribution of the dataset, the main focus is on the bootstrapped p-values because they give a more accurate estimation.

Lastly, the pension funds are ranked by their four-factor model alpha and their t-statistic of alphas with their corresponding p-values. For example, the pension fund with the highest (lowest) alpha is ranked as the top (bottom) fund. An excerpt of this is illustrated in Figure 6 below. Further, the figure shows the top funds ranked by their t-statistic of alpha with corresponding p-values before and after bootstrapping (BS). The ranking of the pension funds is used when formulating Tables IV, V and VI where the results are displayed.

Ranking	**Fund Number**	**tstat**	**p-values Before BS**	**p-values After BS**
1	24	8,743	0,000	0,000
2	8	8,144	0,000	0,000
3	70	4,432	0,000	0,000
4	61	4,317	0,000	0,000
5	68	3,504	0,001	0,003
6	19	3,006	0,005	0,005
7	13	2,604	0,014	0,004
8	14	2,557	0,016	0,012
9	41	2,212	0,034	0,034
10	66	2,141	0,040	0,038
11	23	2,089	0,044	0,031
12	69	1,906	0,066	0,041
13	64	1,786	0,083	0,044
14	18	1,769	0,087	0,068
15	15	1,766	0,088	0,055

Figure 6 – Pension Funds Ranked by Their t-statistics of Alpha.

6. Empirical Results

6.1 The Normality of the sample

Before commenting on the bootstrap simulations, we have computed the residuals of each pension fund in the sample. These residuals are generated from the four-factor model and are used to determine whether there is a need for bootstrapping. If this analysis results in a high degree of nonnormality, it indicates that bootstrapping is a reasonable tool to assess the main research problem (Kosowski et al., 2006). The residuals are calculated from both gross and net returns, and our results show that normality is rejected for 61 % (gross) and 59 % of funds (net). In addition, the rejection of several funds with extreme estimated alphas is large which is another strong indicator of the need for bootstrapping. Moreover, the high degree of nonnormality challenges the use of standard t- and F-tests which substantiate the need for bootstrapping (Davison et al., 1986). Further, in this section, the results of the analysis will be discussed by comparing p-values generated from bootstrapping to the parametric (standard) p-values computed from the t-statistics of the individual pension funds.

6.2 Results Bootstrap Tests

Table IV illustrates Norwegian Pension funds with at least 36 monthly observations. Panel A displays the pension funds ranked on their four-factor alpha and bootstrapped p-values as well as parametric (standard) p-values calculated from the t-statistic of each pension fund. The first three rows report numbers calculated from gross returns while the three bottom rows show numbers that are generated from net returns. Further, the columns report the bottom and top three observations as well as the median and every tenth percentile. Throughout Panel A, there are small variations between the four-factor alphas of the pension funds, and there are small differences between gross and net numbers.

The median fund in the gross sample has a four-factor alpha of 0,2 % per month (2,4 % annually), and the median fund that corresponds to the net sample has a four-factor alpha of 0,2 % per month (2,4% annually) as well. The bottom pension funds with four-factor alphas that corresponds to both gross and net returns are 0 %. However, the top fund with an alpha computed from the gross return is 0,5% per month while the alpha calculated from the net return is 0,3 % per month. Further examples are the alphas at the lower tenth-percentile for both gross and net return that takes the value of 0,1 % per month. At the upper tenth percentile, the alpha corresponding to gross return is 0,4 % per month, while the alpha calculated from the net return is 0,3 % per month. As an example, the upper tenth-percentile (net return numbers) has a bootstrapped p-value of 0,225 which is the probability of this pension fund to obtain an alpha of at least 0,3 % per month purely from sampling variation. For comparison, the standard p-value is generated from the t-statistic of four-factor alpha.

However, since a high degree of nonnormality characterizes the sample, the bootstrapped p-values are more accurate than the parametric p-values. As previously mentioned, the nonnormality indicates strong need to perform bootstrapped simulations to assess the null hypothesis and will, therefore, be the main focus of the analysis.

Overall, the results in Panel A shows few significant bootstrapped p-values for both gross and net numbers. For the gross returns, there are two significant bootstrapped p-values at 5 % acceptance level, both corresponding to the top and bottom 30-percentile. When the rejection level is at a 10 % level, there are three significant bootstrapped p-values. In addition to the 30-percentiles, the bootstrapped p-value that corresponds to the second highest ranked pension fund is significant as well. Moreover, there are three significant bootstrapped p-values at a 10 % rejection level which are generated from net return numbers. These p-values correspond to the bottom 10-percentile and the upper 40- and 30-percentile. Similar to the gross numbers, there are two bootstrapped p-values which are significant at 5 % rejection level, and these are located at the bottom 10- and upper 30-percentiles.

In general, Panel A reports higher parametric p-values than the bootstrapped p-values, which is acknowledged as a more precise measure (Engel, 2007). Generated from gross numbers, three pension funds have significant bootstrapped p-values. Table IV has in total fifteen columns that each represent one Norwegian pension fund, and out of these fifteen columns, twelve of these have an insignificant bootstrapped p-value. Consequently, it is only possible to reject the null hypothesis by using the significant bootstrapped p-values corresponding to each pension fund (Kosowski et al., 2006). From Panel A, the pension funds with significant p-values are the ones on the bottom and upper 30-percentiles, in addition to the fund that is ranked with the second highest alpha. Since these three funds have generated few extreme positive values of predicted alphas, then it can be concluded the return of the funds is affected by genuine stock-picking skills of the managers. Even though a low p-value represents stock-picking skills, a high p-value is not representative to conclude that luck is the main source of high alphas (Kosowski et al., 2006). This is because we are solely testing if the performance is a result of stock-picking skills of managers or not. The insignificant p-values indicate luck, in the absence of skills, but they are not an accurate measurement of luck. Thus, the insignificant p-values simply provide an explanation for lack of managers' skills.

Panel B rank pension funds by the t-statistics calculated for the estimated four-factor alpha. As mentioned in the methodology section, the t-statistic has an advantage when constructing bootstrapped distributions since it is eliminating the effect of heterogeneous risk between the pension funds in the sample. This advantage of the t-statistic is aiding in encountering fewer problems with high variance and survival bias in the sample (Davison et al.,1986). Similar to Panel A, this panel reports pension funds located in the bottom, on the percentiles and the top in the gross and net sample. On the contrary to Panel A, the pension funds are ranked by their t-statistics calculated from the four-factor alpha rather than their alphas. In addition, the rows in Panel B illustrate both the bootstrapped and parametric p-values for 15 individual pension funds. Row one to three show test statistics and p-values calculated from gross numbers, while rows four to six report the same measures calculated from net numbers.

Mostly, there are significant differences between the bootstrapped and the parametric p-values corresponding to the gross numbers. Compared to the right side of Panel B, there are larger gaps between the bootstrapped and parametric p-values on the left side of the panel. Further, the p-values located on the left side of Panel B takes a high value in general. For example, the bottom pension fund has a bootstrapped p-value equals 0,919, while the parametric p-value is 0,458 creating a gap between the p-values of 0,461 which is a substantial difference.

Equivalently to Panel A, the bootstrapped p-values is a more emphasized measurement due to the high degree of nonnormality in the sample. Compared to the left side of Panel B, on the right side, there are several p-values which are significant. In general, the gaps between the bootstrapped and parametric p-values are limited, and even for some pension funds, there are no noticeable gaps. For example, the upper 20-percentile has a bootstrapped p-value of 0,055, and a parametric p-value of 0,088 and both of these p-values are significant at a 10 % rejection-level. Moreover, the top three pension funds all have bootstrapped and parametric p-values equal to 0. To conclude whether the null hypothesis is accepted or rejected, the bootstrapped p-values are emphasized due to the nonnormality of the sample (Davison et al., 1986). The top 30-and 20-percentiles have bootstrapped p-values that are significant at a 10 % rejection level. Moreover, the null hypothesis can be rejected at a 5 % level for the 10-percentile and the top three pension funds since their bootstrapped p-values are significant. Thus, due to the significance of the bootstrapped p-values, there are strong indications that the return of these pension funds is a result of managers' skills.

Similarly, row four to six of Panel B displays t-statistics and both bootstrapped and parametric p-values based on net numbers. Equivalently to the gross numbers, there are considerable gaps between the bootstrapped and parametric p-values, especially on the left side. However, from the median to the upper funds, the gaps decrease before they disappear for the top two pension funds. To conclude whether to reject the null hypothesis, the p-value has to be significant either at a 10 %, 5 % or 1 % rejection-level. Here, the p-values for the upper 10-percentile and the top three funds are significance at a 5 % level. Hence, the stock-picking skills of managers are an important contributor to their alpha, and the null hypothesis for these individual funds can be rejected.

Table IV
Mutual Pension Fund Alphas

In Panel A, all pension funds with at least 36 monthly return observations are ranked on their four-factor alpha. The first to third row reports gross return numbers, while row four to six illustrates net returns. The first row shows the OLS estimate of Alphas calculated from gross returns, and the second row reports the bootstrapped p-values of Alphas. To compare, the third row describes the p-value of alphas before bootstrapping. Further, row four illustrates the OLS estimate of Alphas calculated from net returns, and the fifth and sixth row describes p-values after bootstrapping and parametric (standard) p-values. In the first row (fourth row) of Panel B, all pension funds with at least 36 monthly gross (net) return observations are ranked on their t-statistics of their four-factor alpha. The second row of Panel B shows the bootstrapped p-values of the t-statistics and row three reports results from bootstrapped p-values of the t-statistics based on gross numbers. Row four to six illustrate funds that are ranked based on the t-statistics of their net four-factor alpha. Row four shows the t-statistics of the pension funds, while row five and six describe bootstrapped p-values of the t-statistics and parametric (standard) p-values. In each panel, the first column left (right) report results with a three lowest (highest) alphas or t-statistics, followed by results for marginal pension funds at different percentiles in the left (right) tail of the distribution. All bootstrapped p-values are based on the distribution of the best (worst) funds in 1000 bootstrap iterations.

	Bottom	2.	3.	10 %	20 %	30 %	40 %	Median	40 %	30 %	20 %	10 %	3.	2.	Top
Panel A: Funds Ranked on Four-Factor Model Alphas															
Gross Alpha, α	0,000	0,001	0,001	0,001	0,002	0,002	0,002	0,002	0,003	0,003	0,003	0,004	0,004	0,004	0,005
Bootstrapped p-value	0,458	0,153	0,407	0,219	0,110	0,004***	0,111	0,176	0,180	0,003***	0,267	0,250	0,217	0,041**	0,254
Parametric p-value	0,919	0,858	0,859	0,374	0,202	0,014**	0,200	0,333	0,377	0,001***	0,491	0,483	0,412	0,066*	0,482
Net Alpha, α	0,000	0,000	0,000	0,001	0,001	0,001	0,002	0,002	0,002	0,002	0,003	0,003	0,003	0,003	0,003
Bootstrapped p-value	0,511	0,522	0,450	0,000***	0,386	0,418	0,196	0,115	0,043**	0,015**	0,228	0,225	0,278	0,314	0,132
Parametric p-value	0,984	0,999	0,946	0,000***	0,805	0,802	0,368	0,202	0,056*	0,014**	0,498	0,394	0,542	0,599	0,239
Panel B: Funds Ranked on t-Statistics of Four-Factor Model Alphas															
Gross t-Stat of Alpha, t_α	0,102	0,180	0,180	0,387	0,637	0,755	0,949	1,124	1,238	1,413	1,766	2,557	4,432	8,144	8,743
Bootstrapped p-value	0,919	0,859	0,858	0,358	0,292	0,251	0,155	0,137	0,147	0,094*	0,055*	0,012**	0,000***	0,000***	0,000***
Parametric p-value	0,458	0,407	0,153	0,701	0,529	0,457	0,350	0,270	0,227	0,168	0,088*	0,016**	0,000***	0,000***	0,000***
Net t-Stat of Alpha, t_α	-0,020	0,001	0,068	0,226	0,389	0,571	0,745	0,801	0,915	1,108	1,309	1,846	3,341	4,738	6,707
Bootstrapped p-value	0,511	0,522	0,450	0,413	0,358	0,284	0,229	0,212	0,196	0,157	0,121	0,050**	0,000***	0,000***	0,000***
Parametric p-value	0,984	0,999	0,946	0,823	0,698	0,572	0,461	0,430	0,368	0,275	0,199	0,074*	0,002***	0,000***	0,000***

6.3 Bootstrap Tests for Subperiods

To test whether the results are consistent, we perform robustness test for different subperiods by testing the same measurements as done in the main analysis. Three subperiods are tested, four years, two years and one year (48 months, 24 months and 12 months). These robustness tests enable us to either generalize the results or to conclude the outcome as an isolated case. In addition, these tests are tools to observe fluctuations through the test periods. Below, two tables illustrate pension funds ranked by their four-factor alphas and t-statistics. Further, the two tables include all three subperiods and are divided into gross and net numbers.

Table V reports results from the robustness tests generated from gross numbers. Similar to Table IV, the pension funds are ranked by their four-factor alphas and t-statistics. Panel A and B represent a test period of 4 years (48 months), Panel C and D display a period of 2 years (24 months), while Panel E and F show results for the test period of 1 year (12 months). For each period, the first panel illustrates the pension funds ranked by their four-factor alpha and the second panel shows the pension funds ranked by their t-statistics, both panels include corresponding t-values. In general, the bootstrapped p-values reports a lower value than the parametric p-values. Thus, when comparing bootstrapped and parametric p-values, there are a greater amount of significant bootstrapped p-values. Among the fifteen columns, the majority of the pension funds have a corresponding significant p-value. Furthermore, there is a tendency to an increase in significant bootstrapped p-values as the period is decreasing making test period of 1 year as the one with the most significant p-values. In the light of the fact that the majority of funds in Table V has significant bootstrapped p-values, there are strong indications of stock-picking skills of managers. This means that the null hypothesis can be rejected for the majority of the pension funds in Table V.

To compare to the previous table, Table VI shows pension funds ranked by their four-factor alphas and t-statistics with corresponding p-values for net numbers instead of gross returns. Even though the majority of pension funds have corresponding significant bootstrapped p-values, it is less significant p-values in the net sample than when analyzing gross numbers. In addition, we observe the same tendency of a decreasing number of significant p-values as the testing periods increase, as we did in Table V. Equivalently to table V, there is a higher number of pension funds where the bootstrapped p-value is significant than those that are inconclusive. Here, the majority of the pension funds have a significant bootstrapped p-value, which causes the null hypothesis to be rejected. Thus, the pension funds where the null hypothesis is rejected have strong indications of managers skills which are affecting the funds' alphas.

Table V

Mutual Pension Fund Alphas, for Subperiods

This table reports subperiods for the pension funds' performance measures, all numbers are calculated from gross returns. In Panel A, all pension funds in the sample with 48 observations during 2014-2017 are ranked on their four-factor model alphas. The first row reports the OLS estimate of alphas, while row two and three illustrates the bootstrapped p-values and the parametric (standard) p-values. In Panel B, the first row shows the t-statistics of the alpha. The second and third row shows the bootstrapped p-values and the parametric (standard) p-values which are based on the t-statistic of alphas. Panels C, D, E and F, all report the same measures as Panels A and B, but for the subperiods 2016-2017 (24 observations) and 2017 (12 observations). In each panel, the first column left (right) report results for marginal pension funds at different percentiles in the left (right) tail of the distribution. All bootstrapped p-values are based on the distribution of the best (worst) funds in 1000 bootstrap iterations.

	Bottom	2.	3.	10 %	20 %	30 %	40 %	Median	40 %	30 %	20 %	10 %	3.	2.	Top
Panel A: Funds Ranked on Four-Factor Model Alphas (2014 - 2017)															
Gross Alpha, α	0,001	0,002	0,002	0,003	0,003	0,003	0,004	0,004	0,004	0,004	0,005	0,005	0,006	0,007	0,007
Bootstrapped p-value	0,000***	0,000***	0,000***	0,010***	0,016**	0,043**	0,014**	0,012**	0,107	0,102	0,058*	0,136	0,086*	0,113	0,033**
Parametric p-value	0,000***	0,000***	0,000***	0,016**	0,031**	0,069*	0,022**	0,022**	0,210	0,194	0,125	0,265	0,185	0,211	0,050**
Panel B: Funds Ranked on t-Statistics of Four-Factor Model Alphas (2014 - 2017)															
Gross t-Stat of Alpha, t_α	0,956	1,036	1,045	1,139	1,270	1,410	1,573	1,852	2,127	2,321	2,661	3,530	6,026	10,647	11,064
Bootstrapped p-value	0,169	0,165	0,150	0,138	0,113	0,097*	0,085*	0,041**	0,028**	0,021**	0,008***	0,003***	0,000***	0,000***	0,000***
Parametric p-value	0,344	0,305	0,302	0,261	0,211	0,166	0,124	0,071*	0,039**	0,025**	0,011**	0,000***	0,000***	0,000***	0,000***
Panel C: Funds Ranked on Four-Factor Model Alphas (2016 - 2017)															
Gross Alpha, α	0,001	0,001	0,002	0,003	0,004	0,005	0,005	0,006	0,006	0,007	0,007	0,008	0,010	0,013	0,014
Bootstrapped p-value	0,000***	0,000***	0,341	0,216	0,035**	0,015**	0,003***	0,080*	0,027**	0,079*	0,028**	0,147	0,007***	0,070*	0,077*
Parametric p-value	0,000***	0,000***	0,671	0,461	0,051*	0,013**	0,001***	0,114	0,037**	0,153	0,039**	0,282	0,008***	0,100*	0,115
Panel D: Funds Ranked on t-Statistics of Four-Factor Model Alphas (2016 - 2017)															
Gross t-Stat of Alpha, t_α	0,430	0,529	0,583	1,049	1,333	1,491	1,754	2,065	2,335	2,618	2,950	3,829	6,947	8,239	10,725
Bootstrapped p-value	0,341	0,322	0,314	0,145	0,091*	0,079*	0,056*	0,046**	0,034**	0,011**	0,007***	0,004***	0,000***	0,000***	0,000***
Parametric p-value	0,671	0,603	0,568	0,307	0,199	0,153	0,097*	0,054*	0,03**	0,017**	0,008***	0,001***	0,000***	0,000***	0,000***
Panel E: Funds Ranked on Four-Factor Model Alphas (2017 - 2017)															
Gross Alpha, α	0,001	0,001	0,002	0,003	0,005	0,006	0,008	0,010	0,010	0,012	0,014	0,015	0,020	0,025	0,029
Bootstrapped p-value	0,000***	0,002***	0,002***	0,000***	0,001***	0,028**	0,012**	0,021**	0,009***	0,009***	0,012**	0,010***	0,038**	0,011**	0,022**
Parametric p-value	0,000***	0,000***	0,001	0,000***	0,001***	0,039**	0,007***	0,019**	0,005***	0,006***	0,004***	0,004***	0,034**	0,014**	0,016**
Panel F: Funds Ranked on t-Statistics of Four-Factor Model Alphas (2017 - 2017)															
Gross t-Stat of Alpha, t_α	1,874	2,152	2,257	2,622	3,173	3,252	3,552	3,869	4,211	4,268	4,578	5,797	7,619	7,619	8,026
Bootstrapped p-value	0,067*	0,085*	0,037**	0,038**	0,026**	0,026**	0,016**	0,006***	0,012**	0,007***	0,007***	0,001***	0,000***	0,000***	0,000***
Parametric p-value	0,103	0,068*	0,065*	0,034**	0,016**	0,014**	0,009***	0,009***	0,004***	0,004***	0,003***	0,001***	0,000***	0,000***	0,000***

Table VI

Mutual Pension Fund Alphas, for Subperiods

This table reports subperiods for the pension funds' performance measures, all numbers are calculated from net returns. In Panel A, all pension funds in the sample with 48 observations during 2014-2017 are ranked on their four-factor model alphas. The first row reports the OLS estimate of alphas, while row two and three illustrates the bootstrapped p-values and the parametric (standard) p-values. In Panel B, the first row shows the t-statistics of the alpha. The second and third row shows the bootstrapped p-values and the parametric (standard) p-values which are based on the t-statistic of alphas. Panels C, D, E and F, all report the same measures as Panels A and B, but for the subperiods 2016-2017 (24 observations) and 2017 (12 observations). In each panel, the first column left (right) report results for marginal pension funds at different percentiles in the left (right) tail of the distribution. All bootstrapped p-values are based on the distribution of the best (worst) funds in 1000 bootstrap iterations.

	Bottom	2.	3.	10 %	20 %	30 %	40 %	Median	40 %	30 %	20 %	10 %	3.	2.	Top
Panel A: Funds Ranked on Four-Factor Model Alphas (2014 - 2017)															
Net Alpha, α	0,001	0,002	0,002	0,003	0,003	0,003	0,004	0,004	0,004	0,004	0,005	0,005	0,006	0,007	0,007
Bootstrapped p-value	0,000***	0,000***	0,000***	0,010***	0,016**	0,043**	0,014**	0,0115**	0,107	0,102	0,057*	0,136	0,086*	0,113	0,033**
Parametric p-value	0,000***	0,000***	0,000***	0,016**	0,031**	0,069*	0,022**	0,0215**	0,210	0,194	0,125	0,265	0,185	0,211	0,050**
Panel B: Funds Ranked on t-Statistics of Four-Factor Model Alphas (2014 - 2017)															
Net t-Stat of Alpha, t_α	0,956	1,039	1,045	1,139	1,270	1,410	1,573	1,852	2,127	2,321	2,661	3,885	6,026	10,647	11,064
Bootstrapped p-value	0,169	0,164	0,150	0,138	0,113	0,097*	0,085*	0,041**	0,028**	0,021**	0,008***	0,000***	0,000***	0,000***	0,000***
Parametric p-value	0,344	0,305	0,302	0,261	0,211	0,166	0,124	0,071*	0,039**	0,025**	0,011**	0,000***	0,000***	0,000***	0,000***
Panel C: Funds Ranked on Four-Factor Model Alphas (2016 - 2017)															
Net Alpha, α	0,001	0,001	0,001	0,002	0,003	0,004	0,004	0,005	0,005	0,006	0,007	0,008	0,009	0,011	0,013
Bootstrapped p-value	0,000***	0,000***	0,395	0,000***	0,048**	0,014**	0,005***	0,052*	0,015**	0,102	0,167	0,105	0,047**	0,084*	0,096*
Parametric p-value	0,000***	0,000***	0,773	0,000***	0,069*	0,036**	0,002***	0,078*	0,016**	0,184	0,330	0,163	0,044**	0,134	0,151
Panel D: Funds Ranked on t-Statistics of Four-Factor Model Alphas (2016 - 2017)															
Net t-Stat of Alpha, t_α	0,293	0,470	0,497	0,804	1,103	1,281	1,561	1,927	2,111	2,275	2,652	3,431	5,672	5,718	8,333
Bootstrapped p-value	0,395	0,350	0,336	0,263	0,154	0,125	0,084*	0,0565*	0,048**	0,033**	0,017**	0,007***	0,000***	0,000***	0,000***
Parametric p-value	0,773	0,643	0,625	0,431	0,284	0,216	0,134	0,069*	0,048**	0,035**	0,016**	0,003***	0,000***	0,000***	0,000***
Panel E: Funds Ranked on Four-Factor Model Alphas (2017 - 2017)															
Net Alpha, α	0,001	0,001	0,001	0,002	0,005	0,006	0,007	0,009	0,010	0,011	0,013	0,014	0,019	0,023	0,027
Bootstrapped p-value	0,000***	0,000***	0,009***	0,000***	0,008***	0,083*	0,023**	0,123	0,014**	0,211	0,248	0,044**	0,447	0,134	0,151
Parametric p-value	0,002***	0,001***	0,058*	0,000***	0,004***	0,052*	0,005***	0,0105**	0,004***	0,024**	0,016**	0,005***	0,044**	0,016**	0,018**
Panel F: Funds Ranked on t-Statistics of Four-Factor Model Alphas (2017 - 2017)															
Net t-Stat of Alpha, t_α	1,640	1,714	1,939	2,254	2,562	3,128	3,314	3,620	3,820	4,056	4,234	4,795	5,725	6,280	6,296
Bootstrapped p-value	0,144	0,130	0,094*	0,076*	0,039**	0,019**	0,016**	0,017**	0,016**	0,014**	0,005***	0,004***	0,001***	0,001***	0,000***
Parametric p-value	0,146	0,079*	0,098*	0,058*	0,037**	0,017**	0,013**	0,009***	0,007***	0,005***	0,004***	0,002***	0,001***	0,000***	0,000***

6.4 Analysis Comparison

When comparing the subperiods (gross and net) to the main analysis, we observe several differences between the number of significant p-values. The main analysis shows substantially less significant bootstrapped p-values, while the subperiods show that the majority of the pension funds have corresponding significant p-values. A logical explanation for this is that it is somewhat easier to predict only one year as the task of obtaining high return is getting more complex and challenging over time. The most amount of significant p-values are generated when testing one year (2014), and the number of significant p-values is decreasing as the test period increases. On the other hand, we observe an increase in the number of significant bootstrapped p-values from test period three to four years. This may be a result of managers wanting to rebalance their pension fund after a certain period in an attempt to optimize the fund. The managers aspire to make the pension fund as efficient as possible by replacing posts that are no longer profitable or not contributing to an efficient portfolio. This is a contributor to the increase in the number of significant p-values from the period of three years to four years. Compared to subperiods, the null hypothesis can be rejected for fewer funds when the test period is three years. This is because of rebalancing the pension funds, and it is expected to see fluctuations in the number of significant bootstrapped p-values depending on the period.

In the light of our research problem, there is some degree of persistence in regard to the performance of the pension funds. Mostly, the three top and bottom pension funds for both gross and net numbers are the same. The following examples are based on panels' ranking funds by their four-factor alpha. However, the results are consistent with panels' ranking the funds on the t-statistic of alpha. An example of this, is the pension fund that is observed in the top three for gross numbers, pension fund number 24, KLP Pengemarked. For net numbers, one of the top funds is Skagen 100, fund number 7. However, when it comes to gross numbers, this fund is located around the median towards the bottom. A reason behind this may be that Skagen 100 has lower cost and fees than other pension funds in the sample. On the other hand, the opposite is observed with fund 8, Sparebank 1 BM Bank, which is among the bottom funds in the net sample but is one of the top funds when generated from gross numbers. This suggests that Sparebank 1 BM Bank has higher costs compared to other funds.

7. Concluding Remarks

The purpose of this research is to gain insight into the performance of Norwegian pension funds and to analyze the drivers of the return of the funds. We test whether the return of the pension funds is a result of the stock-picking skills of managers or solely due to luck. The motivation behind this research is to contribute to the literature on what is affecting the return of funds. Further, in this section, we will go through a summary of the method including our main findings from the analysis and some limitations of the study and further research.

That are seven different actors that provide information about their pension funds to Pensjon Norge AS. Pensjon Norge has provided us with data from 97 pension funds, however, after some adjustments only 70 pension funds were included in the final dataset. The model in use is the unconditional four-factor model of Carhart, which is applied to estimate residuals, factor loadings and alphas. Further, the bootstrap technique is used to simulate 1000 new iterations of alphas and t-statistics of alpha to each pension fund. Then the pension funds are ranked by their alphas and t-statistics of alpha with corresponding p-values.

The three years' period is the main focus of the analysis. To conclude whether the return of the pension funds is a result of luck or stock-picking skills of managers, we compare the bootstrapped p-values to rejection levels of 10 %, 5 % and 1 %. The bootstrapped p-values that are significant gives indications of managers' skills affecting the alphas of pension funds. In the main analysis, there are few significant bootstrapped p-values causing us not to be able to make a general conclusion regarding all pension funds. However, there are three significant bootstrapped p-values which lead us to conclude that the return of these pension funds is affected by the stock-picking skills of managers. In addition to the main analysis, robustness tests have been conducted. Three other time periods have been tested and compared to the main analysis, and these test periods generate more significant p-values compared to the analysis of three years (2014-2016). As the test period is decreasing (fewer observations), more significant bootstrapped p-values are generated for the subperiods. Thus, the null hypothesis can be rejected for more funds, and there is reasonable to conclude that the alphas of the pension funds are not solely due to luck, but rather a result of the stock-picking skills of managers.

Finally, based on all test periods in the analysis, we are not able to conclude whether to accept or reject the null hypothesis for all pension funds in the sample. It is impossible to make a generalizing conclusion based on this analysis to conclude whether the return for every Norwegian pension funds is a result of luck or managers' skills. When comparing the tests, there is some degree of persistence in the top and bottom funds. However, it is not enough evidence to predict which pension funds that are the most likely to outperform the market due to substantial variations in the rest of the results.

There are some limitations to this study. One important limitation is that some of the data we received of the pension funds contained missing values. This made it difficult to test for a longer period. Thus, we decided to test as many funds as possible and thereby to shorten our test periods. Further studies may focus on longer time periods to explore whether the results are consistent over time. Another interesting angle would be to use the conditional four-factor model to compare to the results of the unconditional model which we have used in this thesis. Other previous literature has used the three-factor model of Fama and French which may also be interesting to include in further studies.

Our contribution to the research is the effect luck and managers' skills have on Norwegian pension fund returns. By researching this topic, we have observed that the pension fund returns are a result of both luck and managers' stock-picking skills. Further, we have managed to identify a few pension funds which stand out as funds that are profitable over time.

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9. Appendix

9.1 Gross p-values

Fund	2014-2017	2015-2017	2016-2017	2017	Fund	2014-2017	2015-2017	2016-2017	2017
1	0,086	0,217	0,110	0,002	**36**	0,059	0,292	0,091	0,012
2	0,058	0,215	0,015	0,000	**37**	0,135	0,388	0,216	0,017
3	0,039	0,135	0,063	0,001	**38**	0,012	0,110	0,034	0,010
4	0,082	0,155	0,094	0,003	**39**	0,169	0,458	0,341	0,026
5	0,143	0,291	0,147	0,018	**40**	0,009	0,094	0,026	0,016
6	0,120	0,250	0,070	0,011	**41**	0,003	0,034	0,002	0,003
7	0,113	0,254	0,077	0,022	**42**	0,014	0,058	0,010	0,005
8	0,000	0,000	0,000	0,000	**43**	0,041	0,098	0,027	0,009
9	0,016	0,111	0,037	0,008	**44**	0,053	0,138	0,044	0,013
10	0,076	0,271	0,097	0,020	**45**	0,058	0,162	0,064	0,020
11	0,118	0,296	0,040	0,030	**46**	0,094	0,168	0,087	0,020
12	0,085	0,139	0,052	0,034	**47**	0,165	0,407	0,322	0,041
13	0,000	0,004	0,000	0,002	**48**	0,010	0,094	0,011	0,010
14	0,003	0,012	0,004	0,006	**49**	0,150	0,418	0,186	0,026
15	0,009	0,055	0,014	0,013	**50**	0,037	0,142	0,011	0,029
16	0,023	0,108	0,027	0,019	**51**	0,088	0,180	0,028	0,009
17	0,102	0,183	0,101	0,040	**52**	0,010	0,080	0,009	0,004
18	0,012	0,068	0,016	0,015	**53**	0,143	0,311	0,122	0,037
19	0,000	0,005	0,003	0,007	**54**	0,018	0,147	0,035	0,028
20	0,044	0,102	0,037	0,012	**55**	0,088	0,325	0,094	0,088
21	0,136	0,358	0,166	0,038	**56**	0,107	0,280	0,133	0,060
22	0,138	0,267	0,090	0,015	**57**	0,103	0,251	0,050	0,003
23	0,002	0,031	0,003	0,012	**58**	0,021	0,096	0,107	0,085
24	0,000	0,000	0,000	0,002	**59**	0,029	0,148	0,145	0,067
25	0,023	0,072	0,010	0,011	**60**	0,033	0,133	0,079	0,042
26	0,028	0,126	0,011	0,010	**61**	0,000	0,000	0,000	0,000
27	0,042	0,137	0,024	0,012	**62**	0,062	0,163	0,037	0,009
28	0,097	0,206	0,057	0,004	**63**	0,127	0,240	0,074	0,009
29	0,043	0,135	0,030	0,004	**64**	0,005	0,044	0,009	0,001
30	0,097	0,333	0,147	0,005	**65**	0,083	0,210	0,054	0,007
31	0,125	0,153	0,314	0,017	**66**	0,003	0,038	0,010	0,007
32	0,024	0,219	0,056	0,023	**67**	0,021	0,066	0,007	0,010
33	0,070	0,267	0,051	0,026	**68**	0,000	0,003	0,000	0,001
34	0,112	0,376	0,123	0,024	**69**	0,008	0,041	0,011	0,026
35	0,021	0,171	0,014	0,009	**70**	0,000	0,000	0,000	0,000

This table displays the calculated p-values for each individual pension fund after the bootstrapping procedure for gross numbers.

9.2 Net p-values

Fund	2014-2017	2015-2017	2016-2017	2017	Fund	2014-2017	2015-2017	2016-2017	2017
1	0,086	0,278	0,154	0,002	36	0,059	0,342	0,112	0,014
2	0,058	0,305	0,032	0,001	37	0,135	0,413	0,228	0,017
3	0,039	0,226	0,091	0,002	38	0,012	0,152	0,043	0,016
4	0,083	0,228	0,134	0,004	39	0,169	0,511	0,395	0,027
5	0,143	0,354	0,169	0,021	40	0,009	0,209	0,048	0,054
6	0,120	0,313	0,084	0,012	41	0,003	0,043	0,005	0,003
7	0,113	0,314	0,096	0,026	42	0,014	0,083	0,011	0,005
8	0,000	0,000	0,000	0,002	43	0,041	0,123	0,033	0,010
9	0,016	0,196	0,048	0,014	44	0,053	0,176	0,055	0,014
10	0,076	0,358	0,124	0,026	45	0,057	0,201	0,076	0,021
11	0,118	0,386	0,167	0,040	46	0,094	0,231	0,105	0,023
12	0,085	0,221	0,073	0,050	47	0,164	0,474	0,336	0,040
13	0,000	0,032	0,005	0,076	48	0,010	0,122	0,014	0,015
14	0,000	0,048	0,015	0,039	49	0,150	0,522	0,263	0,054
15	0,009	0,135	0,024	0,016	50	0,037	0,176	0,014	0,033
16	0,023	0,186	0,048	0,025	51	0,088	0,202	0,030	0,010
17	0,102	0,247	0,125	0,050	52	0,010	0,121	0,015	0,005
18	0,012	0,101	0,025	0,020	53	0,143	0,418	0,167	0,045
19	0,000	0,018	0,005	0,009	54	0,018	0,220	0,057	0,036
20	0,044	0,132	0,048	0,014	55	0,088	0,341	0,129	0,102
21	0,136	0,437	0,213	0,044	56	0,107	0,376	0,188	0,068
22	0,138	0,298	0,108	0,016	57	0,103	0,255	0,045	0,003
23	0,002	0,050	0,007	0,017	58	0,021	0,151	0,151	0,098
24	0,000	0,000	0,000	0,004	59	0,029	0,198	0,186	0,079
25	0,023	0,095	0,013	0,015	60	0,033	0,229	0,241	0,146
26	0,028	0,157	0,015	0,011	61	0,000	0,000	0,000	0,001
27	0,042	0,182	0,029	0,014	62	0,062	0,225	0,047	0,010
28	0,097	0,235	0,065	0,005	63	0,127	0,305	0,102	0,020
29	0,043	0,238	0,050	0,009	64	0,005	0,143	0,017	0,007
30	0,097	0,379	0,168	0,005	65	0,083	0,284	0,079	0,011
31	0,125	0,450	0,350	0,019	66	0,003	0,108	0,020	0,007
32	0,024	0,266	0,054	0,016	67	0,021	0,240	0,037	0,011
33	0,070	0,367	0,069	0,027	68	0,000	0,015	0,003	0,001
34	0,112	0,459	0,146	0,026	69	0,008	0,144	0,033	0,033
35	0,021	0,255	0,017	0,010	70	0,000	0,002	0,000	0,000

This table displays the calculated p-values for each individual pension fund after the bootstrapping procedure for net numbers.

BI Norwegian Business School - campus Oslo

GRA 19502

Master Thesis

Component of continuous assessment: Forprosjekt, Thesis MSc

How effective are pension funds in Norway and can this be reflected in the market?

Navn: Elise Gangnes, Karianne Hammarstrøm

Start: 01.01.2018 09.00

Finish: 15.01.2018 12.00

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1. Introduction

"Retirement income are generally assumed to be built on three pillars: national social security plans, supplementary pension schemes and private pension funds" (Boulier et al., 2001). In our master thesis we are going to focus on investments in private pension funds in Norway. Each year, there are huge amounts being invested in Norwegian pension funds, which means that this is a big business that generates a lot of investments and capital. According to Finans Norge, the pension and life insurance market's combined capital was 1364 billion NOK in 2016 where pension funds in private sector was 551 billion NOK.

In addition to pension funds being a huge market in Norway, this is a much-discussed topic because of the upcoming retirement boom. The retirement boom implies that the amount of retired people in Norway will increase dramatically compared to younger, working people. This means that there will be fewer employees, compared to the retired people, to generate taxes for the Norwegian government to set aside for future pensions. Based on this, it is inevitable that private pension savings will become more important in the subsequent years.

Furthermore, we find investments in private pension funds a very interesting topic due to its relevance the upcoming years. We believe that private pension savings will become more crucial as the older generation increases relative to the working generation. Based on this, we want to investigate whether the pension funds in Norway today are effective and if this can be reflected in the market. By doing this, we hope to gain insight in the Norwegian private pension fund market and to see how effective the market is.

1.1 Pension Funds

A pension fund is "*a fund set up to pay the pension benefits of a company's workers after retirement"* (Nasdaq). Pension funds can be managed two ways; active or passive. An actively managed pension fund is in general an expensive form, and further, an actively managed fund is more effective in making profit (Bauer et al., 2010). Normally, these funds have higher expected return on their investments. However, they have larger costs and are riskier. Compared to the actively managed fund, a passive fund is less expensive, and they have a lower expected return on their investments (Bauer et al., 2010).

There are two types of pension schemes, defined benefit scheme and defined contribution scheme. In the case of defined benefit scheme, the firm is responsible to provide retirement benefits for its employees of a predefined amount which normally is a percentage of the employee's future wage level (Lecture Notes GRA6211 Financial Accounting Theory, 2016). One disadvantage with this pension scheme is that the cost of the pension promise is not known in advance. The true costs of this scheme will fluctuate due to changes in actuarial and demographic factors (Andonov et al., 2012). The other pension scheme, is the defined contribution scheme "*in which the pension promise is an annual contribution to the employee's pension savings."*(Lecture Notes GRA6211 Financial Accounting Theory, 2016). Thus, the employer bears the risk of small pensions because they are responsible for the allocation of assets.

2. Literature Review

Bauer et. al wrote the article *Pension Fund Performance and Costs: Small is Beautiful* where they focused their research on the context between cost structure of pension funds and their performance. They found that compared to mutual funds, pension funds have lower costs because pension funds in general are larger, which leads to more efficient operations. In addition, a larger fund has more bargaining power that allows them to supervise managers and to keep the costs to a minimum. Another finding is that actively managed funds have higher costs compared to passive managed funds, because they are more time consuming for the manager. Further, they conclude that the size of the fund and liquidity is negatively correlated, and this result is supported by Chen, Hong, Huang and Kubik (2004). The liquidity limits the performance of the funds, causing only small cap mandates to outperform the market. Even though large pension funds are cost efficient compared to small funds, they are outperformed in equity performance.

Bauer et al. studied the results of Busse, Goy and Wahal (2010) who have one of the most thorough research on pension funds and persistence in performance. Busse et al. (2010) uses factor models to explore persistent performance in pension funds and the different models gives an inconsistent result. The three-factor models indicate modest persistent performance which will lead to investors using performance to evaluate various pension funds. The four-factor model, the conditional four-factor model and the seven-factor model, however, signal little to no persistence.

Previous research has analyzed the money flow to mutual funds combined with performance of the investments. Berk and Green wrote in 2004, *Mutual Fund Flows and Performance in Rational Markets*, where they investigate whether past performance influence where capital is allocated. Even though past performance is not a secure indicator of future performance, investors prefer to invest capital in mutual funds that have performed satisfactorily in the previous years. The logic behind these investment decisions can be related to corporate finance models where capital is allocated to investments with positive net present value. Berk and Green view the ability to identify profitable investment opportunities as the scarce resource, which means the managers of the funds and not the investors. The authors looked at Bernhardt, Davies and Westbrook and their study from 2002 about short-term return persistence and how managers maximized the return of the fund. They found that competence was an important factor affecting differences in performance.

Through the article “Can Large Pension Funds Beat the Market” Andonov et al. (2012) research whether the role of size has an impact on the performance of US pension funds. They analyze the three components of active management; asset allocation, market timing and security selection. The results illustrate that funds with high equity allocations often differ from their benchmark by choosing illiquid shares. However, only the relatively small funds benefit from this, because small funds are more flexible regulated. Andonov et al. (2012) also explore that large pension funds increase their return by having a passive management. There are several reasons why, for example, active management is much more expensive than passive management. However, on average, pension funds have had a substantial risk-adjusted security selection performance.

Existing literature has explored conditional performance evaluation in mutual funds. Ferson and Schadt (1996) have researched the effect of including lagged information variables when analyzing performance of mutual funds. In their study, they incorporate conditional returns rather than traditional, unconditional returns. One of the disadvantages with standard performance measures is that they suffer from a number of biases. One example of this, is that alphas, which are a traditional measure of performance, often generate negative numbers that can be interpreted as inferior performance. However, when lagged instruments are used to control variation, the traditional models improve the performance of the funds in their sample. Ferson and Schadt (1996) suggest there is a need to include more public information variables when analyzing performance measures. This topic has been researched for more than 30 years, and there are still multiple knowledge gaps to fill.

2.1 Research Gap

Throughout the literature review there are several noticeable knowledge gaps to fill. There is a lot of literature regarding mutual funds, however, there has not been done sufficient research on pension funds. The most thorough study in this area is "Performance and Persistence in Institutional Investment Management" by Busser et al. (2010), that focuses on pension funds and persistence in their performance. Since there are quite large differences in how pension funds in USA and Norway are structured, we see this as a current research area in Norway. Previous literature has focused on how cost efficient mutual and pension funds are and their characteristics. Despite being a researched topic in USA, there is a consensus among authors that there are several gaps that need to be filled. As a comparison, pension fund is a topic that is less researched, for example, in Norway, where there is a knowledge gap between the efficiency of pension funds and how efficient the market is. We see this as an opportunity to explore this context and therefore, we want to analyze how effective pension funds are in Norway and if this can be reflected in the market.

3. Theoretical Framework

3.1 Business Cycles

Since 2014, SSB has observed a recession in the economy, and it reached a low point the last quarter of 2016 before the trend turned to a positive development. Compared to previous rises in the economy, this growth has been moderately higher than the predicted trend growth (SSB, 2017). In the upcoming years, SSB expects the growth to continue moderately. There was also a deterioration in the central bank policy rate with a low point of 0,5 % in March 2016, and it is forecasted to remain at the same level until 2019.

The improved economic situation occurred after a period of recession which mainly was caused by a reduction of demand in the petroleum sector. This had ripple effects that lead to a fall in gross domestic product (GDP) of almost 10 % from the third quarter of 2014 to the beginning of 2017 (SSB, 2017). It is forecasted that the growth in activities in the economy will increase, and that the negative impact from the petroleum sector is reduced and that the sector will provide positive growth opportunities the subsequent years. The positive development in the petroleum sector, will be very beneficial to the industry sector in Norway. In addition, the industry benefits from an improvement of the competitive advantage through the weakened exchange rate and the low growth in salaries. All sectors combined, it is expected a growth in GDP for Mainland Norway of 1,9 % in 2017 and that this growth will continue the next three years. Thus, it is assumed that the cautious increase in the economy will last throughout the forecast period.

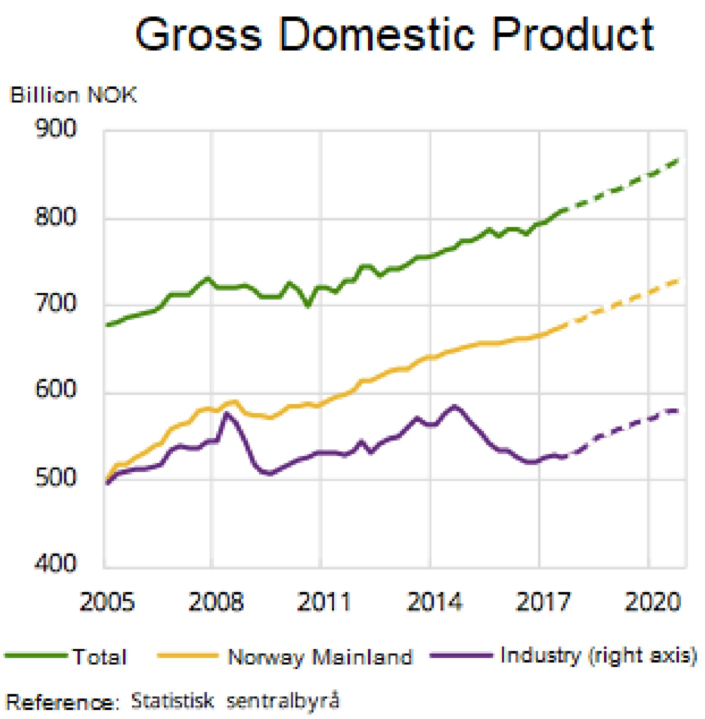

Figure 1 – Gross Domestic Product in Norway

It is expected that employees will receive higher salaries in the subsequent years. In general, the salaries are expected to grow because of increased productivity. However, the last years can be characterized as abnormal because of low growth in salaries (SSB, 2017). In accordance with the rise in the economy, SSB forecasts a 4 % salary growth in 2020.

The unemployment rate continues to deteriorate because there is a stronger growth in employment than in the workforce. This means that the proportion of the workforce that is employed is increasing. As previously mentioned in the introduction, the older generation is increasing which causes a decrease in the percentage of the population that are working. Another reason for this decrease is the economic situation, causing more employers to withdraw from the labor market. It is expected that the decrease will stagnate due to an improvement of the economy.

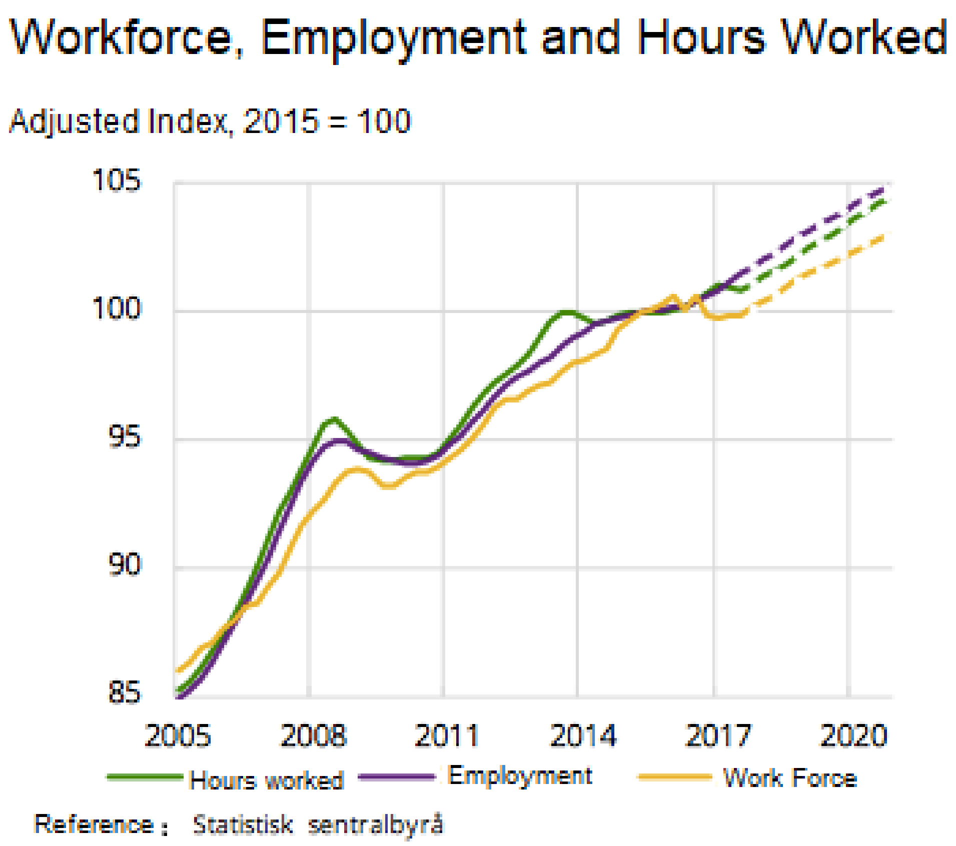

Figure 2 – Workforce, Employment and Hours Worked

3.2 Assets Under Management

Pension funds manage assets, this is called assets under management (AuM) and is defined as "*the total market value of assets that an investment company or financial institution manages on behalf of investors.* (Investopedia). Another way to look at AuM's is as the share of the investors' capital the company controls. In our study, we will limit assets under management to funds where an investor has responsibility for managing of the fund. This means that we exclude bank deposits, mutual funds and cash in our calculations. As we mentioned in the introduction, the total assets under management was 1364 billion NOK in 2016, which is a positive trend from 2015 and 2014, 1283 and 1202 billion NOK.

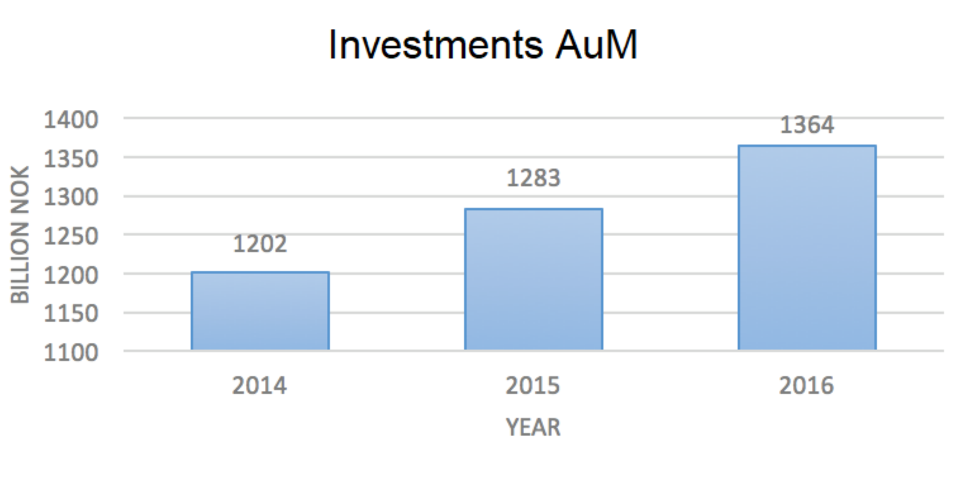

Figure 3 – Investments AuM (Reference: Finans Norge)

Out of the 1364 billion NOK in 2016, the private pension sector was responsible for 551 billion NOK (Finans Norge). This is an indication of employees wanting to ensure their future pensions by investing in private pension funds to prepare themselves for the possible decrease in public welfare benefits. In addition, the life expectancy is increasing which causes a need for higher pensions. Thus, the investments in private pension funds are predicted to increase. It is announced that the profits from the Norwegian Pension Fund will not be sufficient to cover all pension liabilities, which will lead to higher tax rates in Norway (NRK, 2010). We see this as an incentive for saving in private pension funds.

From the graph below, we observe that the intercept between performance benefits and security benefits was in 2014. 2014 was the first year security benefits exceeded performance benefits and the trend continues the subsequent years. In 2016, the premium of security benefits accounted for 66 % of the combined premium in the private sector (Finans Norge).

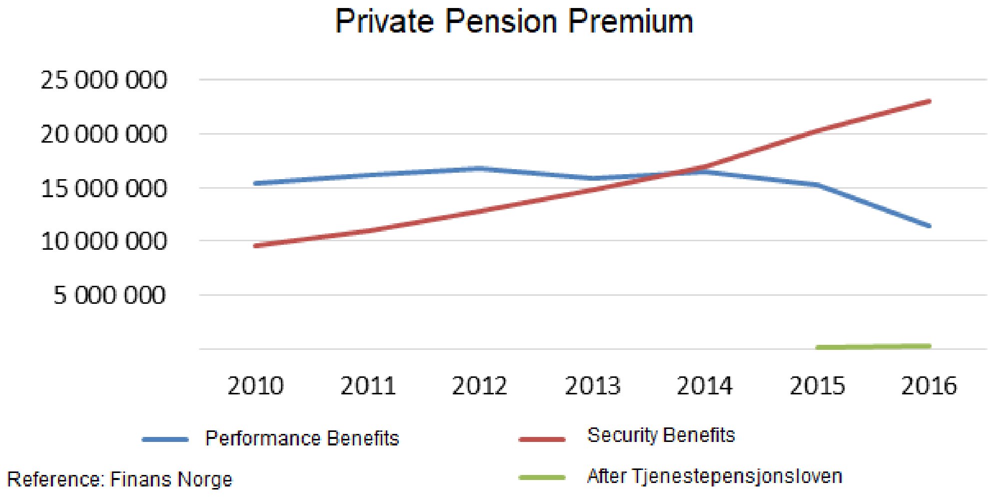

Figure 4 – Private Pension Price

The figure below illustrates the number of insurances and the number of insured for security benefits since 2009. The left axis shows the number of insured, while the right axis shows the number of insurances. When Tjenestepensjonsloven was introduced in 2006, it caused an increase in people taking out insurances according to the minimum demands (Finans Norge) which in 2016 was 2% of salary above 1G. G is a basis amount per year which the Norwegian Government uses to calculate pensions and welfare/insurance benefits, and in 2016, 1G was 92.576 NOK.

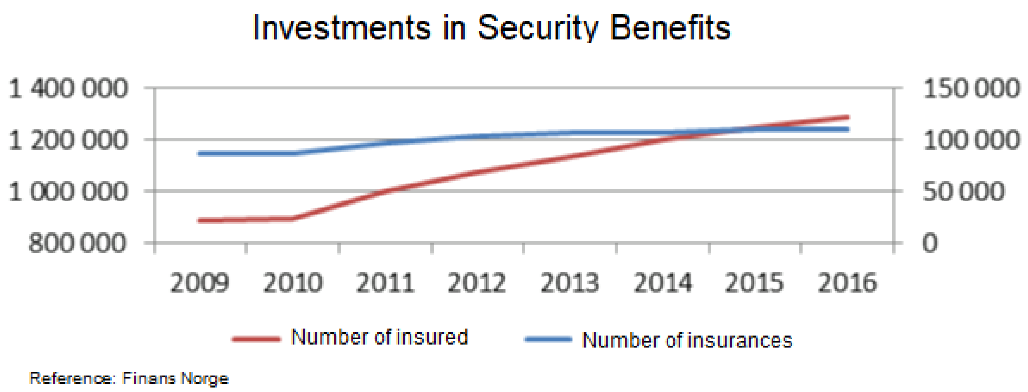

Figure 5 – Investments in Security Benefits

3.3 Efficient Market Hypothesis

The efficient market hypothesis (EMH) implies that prices fully reflect all available information in the market. Market efficiency is desirable because it indicates optimal allocation of capital. However, efficient markets separate from perfect markets due to transaction costs and market imperfections. According to the hypothesis, the ideal market is a market that contains prices which functions as signals for where to allocate resources. This means that we desire a market where it is possible to make investment decisions on the basis of prices that fully reflects all available information. "*A market in which prices "fully reflect" available information is called efficient."* (Fama, 2000).

The hypothesis was first described by Eugene Fama in 1965. According to Fama, it is impossible for investors to outperform the market because prices at all time reflects all information. There are three factors that contribute to efficient markets; rationality, the independent deviation from rationality and arbitrage (Jain, 2012). The first factor, rationality, assumes rational investors that adjust their investments when new information is released. Secondly, independent deviation of rationality states that the optimistic investors are offset by pessimistic investors and thereby creating efficient capital markets. The third assumption is that the market will still be viewed as efficient as long as the rational professional investors outperform the irrational amateurs (Hillier et al., 2016, p. 355-356).

Fama has divided market efficiency into three forms; weak, semi-strong and strong. The weak form of efficiency states that all information available in the market is based on historical costs and prices and previous return information. Semi-strong form of market efficiency says that no investor can earn excess return based on any publicly available information, while strong form states that there is impossible to earn excess return on any information (whether publicly or not, this includes inside information).

However, the definition that we are going to focus on is the semi-strong form since prices never reflect all available information. *"An efficient securities market is one where the prices of securities traded on that market at all times fully reflect all information that is publicly known about those securities"* (Scott, 2015, p. 122).

When there are efficient capital markets, there are several implications for investors and firms. One of the implications is that the market prices will adjust according to the new information once it is released. The investors will not be able to react before the prices reflect the new information. That is, the investors will receive a normal expected return as the market adjusts for new information. (Hillier et al., 2016, p. 367). In the case of efficient markets, the firm will use fair value accounting to value their assets which means that their assets are valued at present value of market price. However, in the real world, there will never be an efficient market since it is impossible to disclose all relevant information.

Another example of an implication is the need for full disclosure (Scott, 2015, p. 127). The firm should disclose all relevant information if the benefit exceeds the cost of developing and reporting the information. The reason for full disclosure is that investors should use all available information when operating in the market, so no information should be wasted. In addition, information reduces information asymmetry which again leads to lower risk for the investors. A third implication is that the chosen accounting policy will not affect security prices, given that there is no cash flow effects. However, the policy should be disclosed.

The EMH is supported by many economists worldwide, one of them is Harvard economist, Michael Jensen. Jensen claims that there exists solid evidence than other research that supports this hypothesis and therefore he believes that the market will outperform the investors. However, there are analysts that do not agree with Famas studies. One of them is Peter Lynch who is claiming to have outperformed the market over a long period of time (Clarke et al., 2001). Other examples of investors outperforming the market, is Warren Buffet.

Further, another critique against EMH is that it is assumed that all participants have the same expectations about stock returns (Shostak, 1997). The question is why the investors should trade when they have homogeneous expectations. Sellers expect a decrease in sale price while buyers expect an increase in purchase price. According to the theory behind EMH is that profits and losses are random phenomena in the market, they can also be viewed as deviations from forecasted return. This indicates that the historical returns are irrelevant since they occur randomly. This substantiates why fair value accounting is the preferred accounting method under efficient markets.

4. Methodology

4.1 Data Collection

To perform an analysis of our research question, we are going to collect a big amount of data and analyze it. We want to collect data from several funds, big and small funds, in order to have a big sample so that it will be easier to generalize the results. By generalizing the results, we hope to achieve a model that can be used by other funds, than those included in our sample. We want to use secondary data because it is easier to collect a big enough sample and hopefully we will get these data from Finansnorge.no. After we have collected our data we will correct possible errors and then define the model that suits our data the best.

In order to perform our analysis, we will need industry data from the Norwegian pension and life insurance market. More specific we will need information regarding pension funds in Norway, total investments in the funds and their profit. In addition, we will need some information regarding the development of the Norwegian market. After researching Finansnorge.no we see that some of the main actors in our chosen market deliver information to their database. The seven suppliers are:

- DNB Liv
- Storebrand
- KLP
- Sparebank 1
- Gjensidige
- Nordea Liv
- Danica

We believe that numbers from these pension fund providers will cause a result that is easily generalized to other companies that are not included in our sample.

4.2 Performance Measures

To analyze the different pension funds, we look at several performance measures. We will focus on profitability ratios and growth rates. When comparing the pension funds using financial ratios, the size of the funds is indifferent because we analyze the relationship between the different parts of the financial information (Hillier et al., 2016, p.73). However, one disadvantage using these ratios is that pension funds may compute their financial information differently, which can lead to a biased comparison. Because of this, we will specify how these measures are computed, making the comparison between the pension funds more accurate.

When analyzing the profitability ratios, it is important to look at changes in the pension funds' profitability. Further, it is significant to analyze the shift in profitability to observe the direction of the funds. The profitability performance is what drives the shifts in value and stock-market returns (Forbes, 2011). The market becomes outperformed when the profitability increases more than the investors' expectations. To illustrate this, we know that even a fund that has huge profit losses may have a positive development in its stock price because the loss is less than the investors expected.

4.2.1 Profitability Measures

The purpose of the profitability analysis is to identify where the source of value comes from. In order to measure the profitability of the pension funds, we will focus on return on assets (ROA), return of equity (ROE), return on invested capital (ROIC) and profitability margin (PM). These four measures are probably the most known and used profitability ratios, and they focus on the net income also known as "Earnings after tax" and "Profit after tax".

In these calculations, we use the book value and not market value. The reason why we do this, is that market value includes the expected value of growth assets which generates future income, and not income today (Damodaran, 2007). The market value includes predictions about future growth of the fund, which is not to be included when calculating the current measures. In addition, when using the market value, we expect the future cost of capital to be equal to the required return of capital because it is not desirable since these two measures are not necessarily equal.

When calculating these ratios, we can use adjusted or non-adjusted figures. The profitability ratios show a more correct measure of the underlying economic performance of the pension funds (Barney, 2014) because these numbers are adjusted for non-recurring items. However, we will use the non-adjusted figures because we believe that adjusted data is not available for us through Finans Norge. If we get access to adjusted data, we will use these figures instead.

4.2.1.1 ROA

The first measure we will focus on is the return on assets (ROA) which is a common measure of profitability. ROA measures the profitability in the percentage of total assets. This measure includes operating and financing activities, however, the interest expense which is a financing activity, is a part of the nominator. (Penman, 2013, p. 71). Since financing assets are a part of the total assets, this measure mixes return on operations with the return on financial assets. The return of operations is usually larger than the return on financial assets, so compared to return on net operating assets (RNOA), we expect to get a lower ROA than RNOA. We can measure ROA as:

$$ROA = \frac{Net\ Income + Interest\ Expense}{Average\ Total\ Assets}$$

4.2.1.2 ROE

The second measure is return on equity (ROE) which is earnings in the percentage of book value of total equity. ROE measures profitability by showing the amount of profit that is generated from the shareholders' investment after the cost of debt has been settled. This measure varies across industries which makes it better to compare ROE within the similar funds within the same industry. Alternatively, it can be beneficial to compare with the funds previous returns to see the development of the fund. To illustrate this, we know that some industries require less invested capital and therefore they will easier get a higher ROE compared to companies that require a substantial amount of capital invested. Because of the varying managing of assets, ROE might be a better measure for comparing performance across different funds.

$$ROE = \frac{Earnings}{Total\ Equity}$$

4.2.1.3 ROIC

The return on invested capital (ROIC) is a measure of the return on the capital invested in a fund. The difference between ROE and ROIC is that ROIC does not take into account if the source of the investment is equity or debt. To calculate this measure, it is important to use operating income after tax in the percentage of book value of the invested capital previous year. (Damodaran, 2007). We use the operating income because we want to include earnings to both shareholders and creditors. It is reasonable to compare ROIC with the cost of capital to observe if the company has invested in profitable funds. One of the main advantages with this measure is that it is easy to compare across different industries because ROIC is not affected by the capital structure (Damodaran, 2007).

$$ROIC = \frac{Operating\ Income_{AT}}{BV\ of\ Invested\ Capital}$$

4.2.1.4 Profit Margin

"The operating profit margin is the profitability of sales, the percentage of a dollar of sales that ends up in operating income after operating expenses." (Penman, 2013, p. 376). A high profit margin is desirable because it indicates high profit and low costs, this shows that the fund is cost efficient. However, one of the weaknesses with this measure is that the capital structure of the fund and the management of assets will cause the profit margin to vary (Hillier et al., 2016, p. 78). There are large differences in profit margins across industries, so it is difficult to compare the measure. The profit margin can be calculated as:

$$PM = \frac{Profit}{Sales}$$

4.2.2 Growth Measure

To compare performance between different pension funds, it is possible to look at the compounded annual growth rate. The compounded annual growth rate (CAGR) is the mean annual growth rate of the investment when the investment grows at a steady state. Using CAGR makes it possible for us to evaluate the development in growth in the funds and it enables us to compare the growth rate across funds. To calculate CAGR, we use ending value and beginning value of index value of fund which means that the compounded annual growth rate can be measured as:

$$CAGR = (\frac{Value\ of\ Index\ of\ Fund_1}{Value\ of\ Index\ Fund_0})^{\frac{1}{Years}} - 1$$

In addition to measure growth in index value of fund, we will measure the growth in assets. This is because pension funds operate with assets, so it is interesting to observe the change in their main source of income. To calculate this measure, we will include both current and non-current assets.

$$Growth\ in\ Assets = \frac{Value\ of\ Assets_1}{Value\ of\ Assets_0}$$

4.3 Hypotheses

Andonov et al. (2012) states that large pension funds would have been more effective if they had been managed passive instead of actively. However, Bauer et al. (2010) do not consider size as an important factor when concluding that actively managed funds have higher expected return than passive managed funds. Our hypothesis is that size is an important factor for the effectiveness of the fund when deciding whether to use active or passive management.

According to Andonov et al. (2012) fund size and liquidity is negatively correlated in American pension funds. "*Large pension funds being unable to respond quickly to news or invest large parts of their portfolio in relatively illiquid stock*s" (Bauer et al, 2010). Therefore, our first hypothesis is that this result can be generalized to Norwegian pension funds.

In accordance with Berk and Green (2004), the performance of pension fund managers is unpredictable from past performance. Nevertheless, pension funds always striving to outperform the market. Based on this, our hypothesis is that the fund that is the most effective will vary because it is impossible to predict from past earnings.

"US public pension funds with a higher percentage of retired participants invest more in risky assets and maintain higher return" (Andonov et al., 2017). Our hypothesis is that retired people invest in less risky pension funds than younger employees. Because of their age and the size of their savings, they are not willing to expose their earned capital to risky investments and they will rather ensure their future income.

According to Bauer et al. (2010) actively managed funds have higher costs than passive managed funds. Our hypothesis is that actively managed funds in Norway has higher costs than passive managed funds. Because the actively managed pension funds require more time and analyzing, it costs more to administrate which decreases profit of the fund.

5. Progression Plan

From	To	Work	Goal
15. Dec.	**15. Jan.**	Preliminary Thesis	Through writing the preliminary thesis we want to get an overview of our chosen topic and collect previous literature. In addition, we will decide what data and methodology is needed for our master thesis. Lastly, we will formulate the research hypothesis.
16. Jan.	**31. Jan.**	Data collection	Collect all necessary data for our analysis.
1. Feb.	**23. Feb.**	Theory and model specification	Specify models we want to use and define relevant theories.
24. Feb.	**15. April**	Testing and results	Testing the hypothesizes and analyze results using our chosen model(s).
16. April	**3. May**	Finish the first draft of the master thesis	Draw conclusions of our research.
4. May		Hand in first draft to our supervisor	
28. May	**1. Sept.**	Finish our master thesis	Revise feedback from our supervisor on the first draft.

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